Dynamic disassembly line balancing in the home appliance industry

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"We cannot solve our problems with the same thinking we used when we created them."

Albert Einstein

Resumo

A transição para uma economia circular requer abordagens inovadoras para o planeamento da desmontagem, particularmente nas indústrias que gerem grandes volumes de produtos em fim de vida (EOL). Esta tese aborda o Problema de Balanceamento Dinâmico da Linha de Desmontagem (DDLBP) para eletrodomésticos em fim de vida (p.e. frigoríficos), propondo um modelo de apoio à decisão baseado em otimização que adapta as operações de desmontagem ao estado de degradação específico de cada produto. O modelo integra dados relacionados com o estado do produto que vão condicionar as tarefas a realizar e os respetivos tempos de processamento. Adicionalmente, inclui ainda recursos fixos e móveis sujeitos a restrições espaciais, temporais e de movimento, no sentido de contribuir para um sistema de produção flexível, capaz de se adaptar rapidamente à variabilidade observada. Implementado em *Python* usando o *Google OR-Tools*, o modelo foi testado a um conjunto abrangente de instâncias, cada uma correspondendo a uma combinação distinta de estados de degradação dos componentes principais do produto. Um algoritmo de agrupamento foi então aplicado aos resultados da otimização, agrupando instâncias EOL com desempenho operacional semelhante em perfis de planeamento representativos. Isto reduziu a complexidade da tomada de decisões, identificando padrões nos resultados do modelo, em vez de se basear apenas nas condições do produto. A análise comparativa com uma linha de base estática revelou ganhos significativos em termos de eficiência, utilização de recursos e otimização do espaço quando se utilizou a configuração dinâmica. Os resultados confirmam o potencial da abordagem proposta para apoiar a tomada de decisão no balanceamento de linhas de desmontagem alinhadas com os princípios da economia circular. Este trabalho foi parcialmente realizado no âmbito do programa de investigação e inovação Horizonte Europa da União Europeia através do projeto RENEE (subvenção n.º 101138415).

Abstract

The transition to a circular economy requires innovative approaches to dismantling planning, particularly in industries that generate large volumes of end-of-life (EOL) products. This thesis addresses the Dynamic Disassembly Line Balancing Problem (DDLBP) for end-of-life appliances (e.g., refrigerators), proposing an optimisation-based decision support model that adapts disassembly operations to the specific degradation state of each product. The model integrates data related to the state of the product that will condition the tasks to be performed and the respective processing times. In addition, it also includes fixed and mobile resources subject to spatial, temporal and movement constraints, in order to contribute to a flexible production system capable of quickly adapting to the observed variability. Implemented in Python using Google OR-Tools, the model was tested on a comprehensive set of instances, each corresponding to a distinct combination of degradation states of the product's main components. A clustering algorithm was then applied to the optimisation results, grouping EOL instances with similar operational performance into representative planning profiles. This reduced the complexity of decision-making by identifying patterns in the model results, rather than relying solely on product conditions. Comparative analysis with a static baseline revealed significant gains in terms of efficiency, resource utilisation, and space optimisation when using the dynamic configuration. The results confirm the potential of the proposed approach to support decision-making in balancing disassembly lines aligned with the principles of the circular economy. This work was partially carried out under the European Union's Horizon Europe research and innovation programme through the RENEE project (grant no. 101138415).

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On a more personal note, I am profoundly grateful to my parents for their constant support, encouragement, and for always believing in me. Their love and dedication have given me the stability and strength to pursue my goals and build the best life possible.

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Acronyms

ACO – Ant Colony Optimization

ALBP – Assembly Line Balancing Problem

CPS – Cyber-Physical Systems

DDLBP – Dynamic Disassembly Line Balancing Problem

DLBP – Disassembly Line Balancing Problem

EOL – End-of-Life

FEUP – Faculdade de Engenharia da Universidade do Porto

GAs – Genetic Algorithms

IoT – Internet of Things

MILP – Mixed-Integer Linear Programming

MMALBP – Multi-Manned Assembly Line Balancing Problem

MMALWW – Multi-Manned Assembly Line Balancing Problem with Walking Workers

PSO – Particle Swarm Optimization

SA – Simulated Annealing

SCIP – Solving Constraint Integer Programs

WEEE – Waste Electrical and Electronic Equipment

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1. Introduction

The transition toward a circular economy is reshaping how industries design, produce, and dismantle products. Within this paradigm, the management of end-of-life (EOL) products plays a critical role - particularly in sectors characterized by high product turnover and material intensity, such as household appliances. Disassembly - the process of deconstructing products into individual components for reuse, recycling, or safe disposal - is a key enabler of sustainable manufacturing. However, disassembly processes remain suboptimal, often constrained by rigid line structures and limited adaptability to product condition variability.

This thesis addresses the Disassembly Line Balancing Problem (DLBP) for EOL home appliances, with particular emphasis on incorporating dynamic elements such as condition-based task selection and the flexible deployment of mobile resources. The main objective is to develop and evaluate a mathematical optimization model that can improve operational efficiency while remaining aligned with circular economy principles and industrial feasibility.

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1.1 Hosting Institution

This dissertation was developed under the research framework of INESC TEC - Institute for Systems and Computer Engineering, Technology and Science, as part of the European RENEE initiative, aimed at enabling more sustainable and reconfigurable disassembly processes. INESC TEC offers a collaborative environment at the intersection of academic research and industrial innovation, with strong expertise in production systems, optimization, and decision support systems.

This work was developed within the scope of the RENEE project (grant no. 101138415), part of the European Union's Horizon Europe research and innovation program.

1.2 Motivation

In recent years, the shift toward more sustainable industrial systems has become a strategic imperative across sectors. Environmental concerns, the depletion of natural resources, and increasing pressure from both legislation and consumer expectations have catalysed the

adoption of the circular economy as a transformative paradigm. Within this context, the effective treatment of end-of-life (EOL) products has gained relevance - not only for environmental protection but also for the economic recovery of components and materials.

Among the key processes enabling circularity, product disassembly plays a crucial role. Unlike recycling or disposal, disassembly allows for the targeted extraction of high-value components, enabling reuse, refurbishment, or material recovery. However, disassembly processes remain underexplored from an operational efficiency standpoint, especially when compared to the decades of optimisation observed in assembly systems. Traditional disassembly lines are often rigid, sequential, and designed without accounting for the variability in the condition of incoming products, limiting their scalability and performance.

At the same time, industrial organisations are increasingly aware that static disassembly lines may be insufficient to cope with the complexity and diversity of modern EOL products. Variability in product condition - ranging from minor wear to severe damage - creates significant challenges in terms of task requirements, resource needs, and execution times. This dynamic nature calls for flexible, data-informed systems capable of adapting disassembly planning to the actual condition of products. Incorporating condition-based information into the planning stage offers a valuable opportunity to improve operational decision-making and control.

This thesis is motivated by the need to bridge the gap between theoretical models in disassembly line optimisation and the practical constraints faced by industrial operations. The focus lies on developing an optimisation-based decision support tool capable of addressing the dynamic line balancing problem in disassembly environments - specifically for EOL home appliances, a class of products characterised by high material diversity, structural complexity, and strong recovery potential.

Furthermore, the integration of both fixed and mobile resources into the model represents a relevant step toward improving operational agility. While many existing models assume static resource assignments, modern disassembly systems can benefit from resources - human or technical - that can be reallocated dynamically across stations, provided that spatial limitations and activation constraints are considered. This hybrid resource framework can enable more compact, efficient, and responsive line configurations, particularly in space-constrained or low-volume production settings.

This work is developed within the scope of the European project RENEE, part of the Horizon Europe programme, which promotes the redesign of disassembly and remanufacturing systems to increase resource recovery, support reuse strategies, and enable the broader implementation of circular economy principles in European manufacturing. In this context, the development of a flexible and adaptive disassembly line optimisation model aligns with both academic research priorities and the operational needs of industry, contributing to the advancement of smarter, more sustainable production systems.

1.3 Objectives

The main objective of this thesis is to develop a decision support tool capable of addressing the Disassembly Line Balancing Problem (DLBP) in a dynamic context, with a particular focus on end-of-life (EOL) home appliances. The proposed model is designed to adapt disassembly planning according to the diagnosed degradation state of each product, adjusting task durations and feasibility based on the condition of key components. Rather than assuming uniform product conditions, the model accommodates variability by using condition-specific input data.

In addition, the model incorporates both fixed and mobile resources, subject to activation times, movement limitations, and station-level spatial constraints. This hybrid resource approach supports greater flexibility in task allocation, contributing to more compact and efficient disassembly layouts.

The optimisation model focuses on minimising the number of active workstations required to complete a valid disassembly plan. Although idle time is not explicitly minimised in the objective function, its reduction is often a natural consequence of effective resource utilisation and balanced task distribution under the model's constraints. It is also essential that the solutions generated are operationally feasible, meaning they respect real-world limitations in terms of time, space, and resource availability on the shop floor.

Beyond model development, this thesis aims to evaluate the model's performance across a diverse set of EOL instances, each representing different combinations of component degradation. A complementary objective is to explore a clustering-based strategy that groups similar instances according to their operational characteristics as observed in the optimisation

results. This post-optimisation analysis aims to simplify short-term planning by identifying representative operational profiles that can be used to inform weekly or daily line configurations.

1.4 Methodology Followed in the Project

The development of this work was structured into five main phases, each building on the previous to support the creation and validation of the proposed optimization model.

The first phase consisted of an in-depth literature review, focused on disassembly planning, Disassembly Line Balancing Problems (DLBP), mobile resource management, and relevant optimization techniques. This review established the theoretical foundations of the study and highlighted open challenges that the present thesis seeks to address.

Next, the problem was defined and the necessary data were gathered. This step involved the characterization of disassembly operations, with initial efforts aimed at applying the model to a real case study provided by the European RENEE project. However, due to delays in obtaining detailed process data, a case study from the literature was selected to ensure timely development and testing of the model. Meetings with project stakeholders and analysis of technical documentation supported this stage and helped in identifying realistic constraints and operational assumptions.

The third phase focused on model development. A mathematical formulation was created and implemented in Python, using the Google OR-Tools solver. The model incorporates precedence constraints, condition-dependent task durations, spatial limitations, and a distinction between fixed and mobile resources. For mobile resources, movement times, activation delays, and space requirements were explicitly modelled to reflect industrial-level constraints.

Following this, an experimental phase was conducted to evaluate the model's behaviour across different product conditions. A total of 81 degradation-based scenarios were simulated, each treated as a distinct instance. These instances were used to generate scenario-specific disassembly plans and collect performance indicators such as efficiency, station usage, and mobile resource deployment. Based on the outputs, a clustering analysis was performed to group operationally similar instances, enabling simplified planning routines.

The final phase consisted of comparative analysis and interpretation. The performance of the dynamic configuration - featuring both fixed and mobile resources - was benchmarked against a static configuration in which resource allocation was fixed and non-optimized. Improvements in key metrics such as workstation usage and resource efficiency were assessed, and the role of clustering in simplifying operational planning was discussed. These steps provided insight into how the model could support real disassembly operations under variable EOL conditions.

The overall timeline of the project is summarised in the Gantt chart presented in Figure 1.

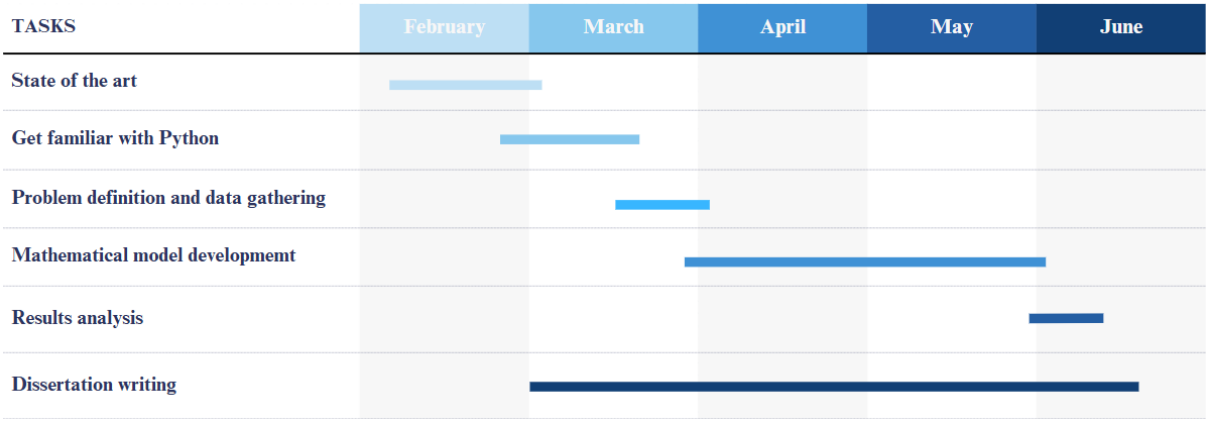


Figure 1 - Gantt diagram of the project.

1.5 Dissertation Structure

This dissertation is organised into six main chapters, offering a progressive and structured exploration of the Disassembly Line Balancing Problem (DLBP) under variable end-of-life (EOL) product conditions and dynamic resource constraints.

Chapter 1 introduces the motivation behind this work, its integration within the broader European RENEE project, and the relevance of disassembly planning in the context of sustainable manufacturing. It also presents the main objectives, the methodology followed throughout the project, and the overall structure of the dissertation.

Chapter 2 provides a comprehensive literature review. It covers key concepts related to disassembly systems and line design, explores the main classifications and extensions of the

DLBP, and analyses how product condition variability influences planning. Special attention is given to models incorporating mobile or reconfigurable resources, as well as to the different resolution strategies proposed in the literature, including mathematical and heuristic approaches.

Chapter 3 presents the problem formulation adopted in this thesis. It outlines the operational context, specifies the model's input requirements, and defines the relevant constraints and assumptions. The chapter introduces the mathematical model used to support disassembly planning, including task precedence, resource compatibility, station-level limits, and condition-based task adjustments.

Chapter 4 describes the implementation of the proposed decision support model. It starts by defining the model's role in tactical disassembly planning, presents the complete mathematical formulation, and explains its implementation using Python and Google OR-Tools. The chapter also describes the dataset used, the structure of input and output data, and the application of clustering as a post-optimization step to support simplified and scalable planning.

Chapter 5 discusses the computational results and their implications. It presents the experimental setup and performance indicators, followed by the model's evaluation across a broad set of EOL scenarios. The chapter includes a comparison between dynamic and static configurations and concludes with the clustering analysis, which groups similar product instances based on their operational behaviour to support more efficient planning.

Chapter 6 offers the main conclusions of the work. It summarizes the contributions made, reflects on the practical relevance of the approach, and identifies future research opportunities, particularly regarding model refinement, real-world validation, and integration with real-time diagnostic systems.

2. Background

2.1 Disassembly Processes and Line Design

Disassembly is defined as the systematic process of separating end-of-life (EOL) products into individual components, subassemblies, or raw materials. It plays a fundamental role in reverse logistics and product recovery systems, enabling reuse, remanufacturing, recycling, and appropriate disposal. Unlike assembly, disassembly involves additional complexities due to the unpredictable nature of EOL products, including deterioration, missing parts, or undocumented repairs (Zhu et al., 2020).

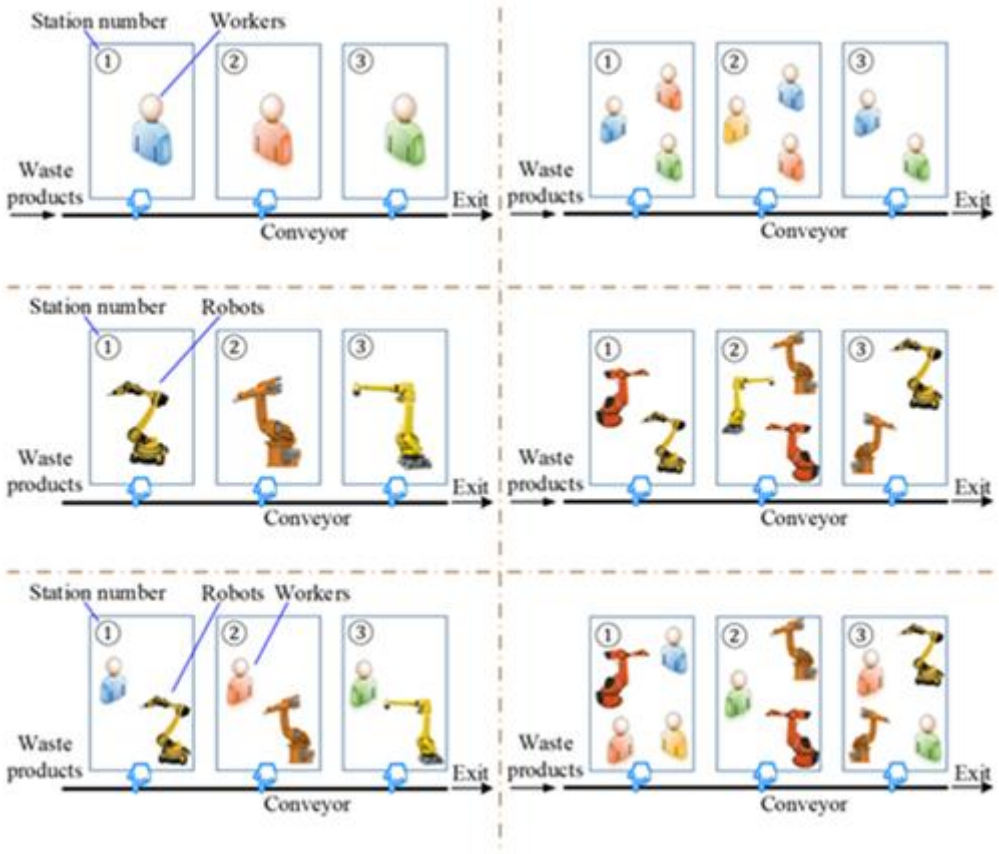
Disassembly operations can follow different configurations, depending on factors such as product complexity, throughput requirements, and available resources. While single workstations or manual disassembly cells are common in low-volume or ad-hoc operations, disassembly lines offer better productivity and workflow standardization, especially in industrial environments (Özceylan et al., 2019).

Several line layouts have been proposed in the literature:

- Straight-line configurations are the most common, adopted in the vast majority of studies. Tasks are arranged sequentially and executed under a fixed cycle time (Zhu et al., 2020);
- U-shaped disassembly lines allow for better space usage and operator mobility. They enable dual-side access, which is useful for heavy or complex products and facilitate shared resource use (Zhang et al., 2025);
- Parallel and two-sided lines are less frequent but may offer advantages in specific applications, such as large appliance disassembly, where task parallelization is feasible (Özceylan et al., 2019).

In large-scale disassembly contexts - such as household appliances - additional challenges emerge due to nonlinear component accessibility, high part counts, and variability in product conditions. To address this, Wang et al. (2021) propose the use of Associated Parts Precedence Graphs, which group tightly connected elements (e.g., screws, nuts, washers) into disassembly units, simplifying both precedence modelling and task grouping.

Figure 2 illustrates various disassembly line configurations, including human-only, robot-only, and hybrid workstations. These represent the increasing flexibility of modern disassembly systems, where task execution can be dynamically adapted to operational requirements and resource availability (adapted from Yin et al., 2025).



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Figure 2-Disassembly line configuration Including Human, Robotic, and Hybrid Workstations. (Yin et al., 2025)

Partial disassembly is also gaining relevance, especially in white goods and Waste Electrical and Electronic Equipment (WEEE) contexts. In these cases, only valuable or hazardous components are removed, as full disassembly may be economically or operationally unfeasible (Jin et al., 2015; Özceylan et al., 2019; Wang et al., 2021). This selective approach significantly influences line balancing strategies and task selection.

From a modelling perspective, several operational constraints must be considered in disassembly line design:

- Precedence relationships, often captured via AND/OR graphs to reflect optional paths;

- Tool changes and directionality, especially for components requiring reorientation or specific tools (Zhang et al., 2025);
- Energy and ergonomic considerations, particularly in manual or semi-automated disassembly of hazardous or heavy parts (Wang et al., 2021).

Recent research also explores the use of walking workers and mobile agents in assembly/disassembly systems. For example, Şahin and Kellegöz (2019) model multi-manned assembly lines with walking workers, where operators can move between adjacent stations, constrained by maximum walking distances. This provides a structural parallel for disassembly lines with mobile resources - human or robotic - that can be reallocated dynamically under well-defined conditions (Kannan and Panneerselvam (2021)).

Overall, disassembly line design is evolving from rigid, linear systems toward more flexible, modular, and condition-responsive structures. These innovations are essential to meet the growing complexity of EOL products and to support optimization models that use product condition data obtained through diagnostic tools or prior inspection (Sultana and Rahman (2020)).

Among the central challenges in this domain lies the Disassembly Line Balancing Problem (DLBP), which involves assigning tasks to stations under precedence and capacity constraints while minimizing inefficiencies. Addressing the DLBP is crucial to ensuring that disassembly systems operate effectively, particularly under variable conditions and in high-mix environments.

This thesis builds upon these developments by proposing a dynamic disassembly line balancing model that accounts for variability in product condition and introduces resource mobility into task allocation. The goal is to enhance operational flexibility and contribute to more sustainable and efficient disassembly systems, particularly in the home appliance sector.

2.2 The Disassembly Line Balancing Problem

The Disassembly Line Balancing Problem (DLBP) plays a critical role in enabling efficient and sustainable recovery of components from end-of-life (EOL) products. Originally derived from the Assembly Line Balancing Problem (ALBP), the DLBP has evolved to reflect the specific challenges of disassembly systems, which are often characterized by variability in

product condition, structural uncertainty, and economic and environmental recovery objectives (Özceylan et al., 2018; Ding et al., 2010).

Formally, the DLBP consists of assigning disassembly tasks to workstations in such a way that precedence constraints are respected, cycle time limits are not exceeded, and one or more performance objectives are optimized. These objectives typically focus on cost reduction, process efficiency, worker safety, and sustainability. The problem is widely recognized as NP-hard - particularly in its multi-objective, real-world variants - which has led to an extensive use of heuristic and metaheuristic solution approaches (Şahin & Kellegöz, 2019; Zhang et al., 2025).

Although structurally related to the ALBP, the disassembly context introduces distinct complexities. Disassembly processes do not necessarily follow the reverse of assembly sequences. Instead, tasks are often selective and guided by the value or environmental impact of specific components rather than the full reconstruction of the product (Tu et al., 2020; Özceylan et al., 2018). Moreover, products received for disassembly frequently exhibit damage, incompleteness, or alterations, which increases operational uncertainty and demands more flexible sequencing and resource assignment (Zhu et al., 2020; Liang et al., 2021).

Task characteristics in the DLBP are also more diverse. Some tasks may be destructive - such as forcibly breaking a casing to access internal parts - or optional, such as the removal of low-value, non-hazardous components. The precedence structure is typically more intricate and can involve AND/OR logic, representing alternative disassembly paths. Furthermore, disassembly lines often need to support synchronous or co-dependent task execution, especially in collaborative or two-sided setups (Liang et al., 2021).

To address these complexities, recent research has proposed models that explicitly incorporate uncertainty through probabilistic or fuzzy task durations (Zhu et al., 2020; (Zhang et al., 2023)), while others suggest hybrid line configurations or human–robot collaboration to enhance efficiency under practical constraints (Zhang et al., 2024).

The objectives pursued in the DLBP are diverse, often involving trade-offs between efficiency, cost, and sustainability. Common objectives include minimizing the number of workstations to reduce fixed operational costs (Tu et al., 2020; Wang et al., 2021), minimizing total idle time and workload imbalance to optimize resource usage (Şahin & Kellegöz, 2019), and maximizing overall line efficiency, particularly in support of circular economy strategies

(Zhang et al., 2025). Some models prioritize the early removal of hazardous or high-value components to comply with environmental regulations or improve economic return (Liang et al., 2021; Özceylan et al., 2018). Others aim to minimize energy consumption, aligning with green manufacturing goals (Wang et al., 2021).

Given the inherent trade-offs among these objectives, multi-objective optimization models have become increasingly prevalent. These often rely on Pareto front approximations or lexicographic ordering to provide decision-makers with a range of optimal solutions from which they can select based on strategic priorities (Zhang et al., 2025).

In summary, the DLBP has emerged as a foundational optimization challenge for implementing flexible and sustainable disassembly systems. Its development has been supported by advances in mathematical modelling, computational intelligence, and EOL product management. However, notable gaps remain in dynamically adapting task allocation to real-time product condition data and in leveraging mobile or reconfigurable resources - precisely the directions in which this thesis seeks to contribute.

2.3 Product Condition and EOL Variability in Disassembly

The condition of end-of-life (EOL) products plays a fundamental role in determining the complexity, feasibility, and efficiency of disassembly operations. Unlike traditional manufacturing, where product characteristics are standardized, disassembly systems must accommodate uncertainty regarding the physical state, completeness, and internal configuration of returned products. This variability - referred to as product state - directly influences task durations, precedence structures, safety considerations, and resource requirements (Zhu et al., 2020; Liang et al., 2021).

In many real-world cases, products exhibit partial deterioration, including corrosion, physical damage, missing parts, or user modifications. These conditions challenge fixed disassembly sequences and require flexible strategies to adapt task allocation dynamically. Zhu et al. (2020) illustrate this by defining 16 EOL states for CRT televisions, each associated with different task times. The resulting task durations are modelled as weighted averages based on the probability of each EOL scenario. Similarly, Tu et al. (2020) adopts an interval-based model to capture uncertainty in disassembly times caused by partial degradation, proposing partial

disassembly as a rational response. Zhang et al (2023) further explores mixed-model disassembly lines under uncertain product conditions, offering adaptive sequencing models.

Although several models account for condition variability using stochastic or fuzzy formulations (Zhang et al., 2025; Özceylan et al., 2018), most rely on predefined probabilities or assumptions. The integration of real-time condition data - such as that obtained through Product State Diagnosis (PSD) - remains underexplored. PSD refers to the use of sensors, diagnostic tools, or embedded systems to assess a product's physical and functional condition prior to or during disassembly. Examples include visual inspection via computer vision, vibration sensors, thermal imaging, or connectivity testing (Xu et al., 2018; Industry 4.0 Review, 2023).

Recent advancements in Industry 4.0 technologies, such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Digital Twins, offer strong potential to support dynamic disassembly planning. These technologies allow for the real-time collection and transmission of condition data, enabling systems to react to degradation indicators and reconfigure task assignments accordingly (Xu et al., 2018; Industry 4.0 Review, 2023). While these approaches are increasingly common in predictive maintenance and smart manufacturing, their application to EOL disassembly systems is still nascent.

To illustrate the spatial and mechanical complexity of product disassembly, Figure 3 presents the physical structure and orientation of components in a typical EOL product. The figure shows the directional angles required to access each part, highlighting that disassembly is not always linear or uniform, especially when parts are degraded or obstructed.

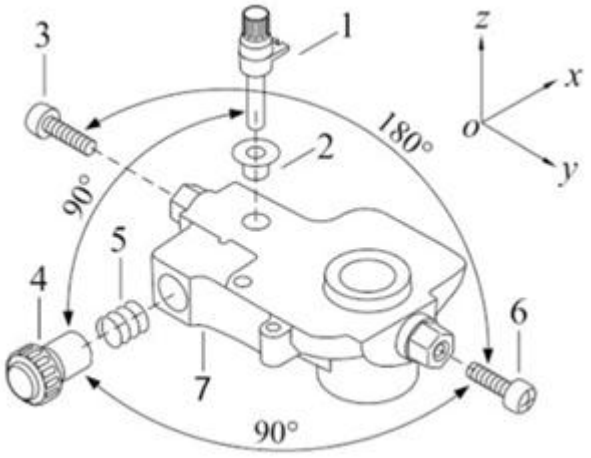


Figure 3 - A schematic diagram of an EOL product sample (Zhou et al., 2023)

In parallel, the logical flexibility required in task sequencing is demonstrated in Figure 4, which shows an AND/OR graph representing the multiple possible disassembly paths for the same product. This structure models how tasks can follow different sequences depending on the product's condition.

Each node in the graph corresponds to a specific state of partial disassembly — i.e., which components have already been removed. Arrows represent feasible next steps depending on the accessibility or condition of the remaining parts. The presence of OR branches indicates that alternative paths are available depending on component degradation (e.g., tasks that can be skipped if a part is missing), while AND branches denote mandatory steps that must be executed in a specific order (Smith and Haas, 2018; Berg and Vance, 2012).

For example, if component 1 is degraded or missing, the task to remove it may be bypassed, altering the path taken in the graph. Conversely, if all components are present and undamaged, the full disassembly sequence must be respected. This graphical representation enables dynamic reconfiguration of the task plan based on the actual condition of each unit, making it highly relevant for real-world EOL product handling (Sanchez and Haas, 2018).

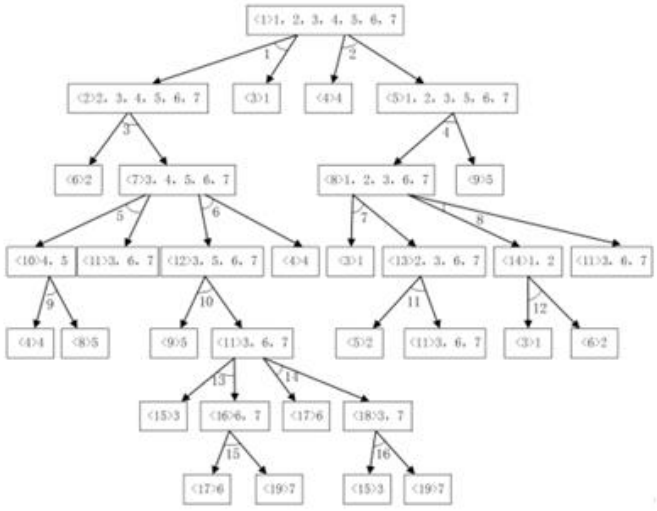


Figure 4 - AND/OR precedence graph representing the conditional disassembly paths of the product shown in Figure 3 (Zhou et al., 2023).

For instance, IoT-enabled diagnostic frameworks can be integrated into smart disassembly cells to identify faulty or damaged components prior to physical intervention. Such data could guide early decision-making, including which components are worth recovering and which require special handling or bypassing. Digital Twins further extend this capability by

simulating disassembly scenarios based on real-time product conditions, supporting operational planning and predictive resource allocation (Industry 4.0 Review, 2023).

The implications of product condition variability go beyond task duration. In some cases, component deterioration may render certain disassembly paths infeasible or dangerous, altering precedence relationships and resource requirements. Liang et al. (2021) note that hazardous parts often require prioritization, while damaged components may necessitate destructive removal techniques. These cases underline the need for disassembly models that are both condition-aware and responsive. Models like those proposed by Zhang et al. (2025) and Özceylan et al. (2018) take steps in this direction, but they remain limited in their integration of real-time data.

The literature thus recognizes the significant impact of EOL product variability on disassembly processes but falls short in integrating real-time diagnostic data. While probabilistic models offer a partial solution, they lack adaptability. The application of PSD, IoT, and Digital Twin technologies represents a critical advancement toward dynamic, data-driven disassembly systems - an approach central to the contribution of this thesis.

2.4 Dynamic Line Balancing with Real-Time Data

Dynamic disassembly line balancing emerges as a promising approach to address the growing complexity and variability in end-of-life (EOL) product recovery systems. As product conditions become increasingly unpredictable, and sustainability requirements demand greater responsiveness, the ability to adapt disassembly operations in near real-time has become a strategic priority. Yet, despite significant theoretical progress in modelling uncertainty, few works in the literature incorporate genuinely dynamic or real-time data into task assignment and sequencing (Zhang et al., 2023).

Existing studies have made initial progresses toward integrating data variability. Zhang et al. (2025) propose a decoder-based mechanism that uses workload thresholds to flexibly assign tasks to different workstation types in a U-shaped disassembly line. Although this method simulates adaptive behaviour, it does not rely on real-time input, and adjustments remain rule-based. Similarly, models based on stochastic programming (Zhu et al., 2020) and

interval uncertainty (Tu et al., 2020) allow for better handling of variability, but they are limited to pre-defined probabilistic scenarios.

The use of real-time or online data to dynamically rebalance disassembly lines is still underexplored. One of the few notable exceptions is Zhang et al. (2023), which models uncertain product conditions across mixed disassembly lines using adaptive sequencing. However, even this work does not incorporate sensor feedback or real-time state diagnosis. Thus, the practical integration of Product State Diagnosis (PSD), enabled by Industry 4.0 technologies, remains a major research gap.

In theory, dynamic line balancing requires a system capable of sensing the product state, analysing its implications, and reassigning tasks accordingly. This may involve changes in task precedence, reassignment to alternative stations, introduction of bypasses or partial sequences, and dynamic buffer management. Some heuristic frameworks, such as those proposed by Zhang et al. (2025), support flexible configurations through constraint-based reasoning. Still, no current model in the DLBP literature actively uses real-time PSD to drive such reconfiguration.

Industry 4.0 frameworks provide the technological foundation to enable these capabilities. The integration of Internet of Things (IoT) devices, Cyber-Physical Systems (CPS), and Digital Twins allows for continuous monitoring of EOL product attributes, real-time decision support, and predictive control of disassembly flows (Xu et al., 2018; Usuga Cadavid et al., 2020). IoT sensors can detect structural defects, component presence, or hazardous conditions, and relay this data to cloud-based or edge processing units. In parallel, Digital Twins can simulate potential disassembly sequences based on current input, anticipating bottlenecks and optimizing resource deployment.

These technologies also support adaptive strategies such as reallocation of tasks in response to detected damage, real-time revision of precedence constraints, or activation of parallel disassembly routes. While these concepts are widely discussed in production planning and control (Usuga Cadavid et al., 2020), their application to EOL disassembly remains largely conceptual. Few studies explicitly model mechanisms like task skipping based on real-time feedback, or dynamic buffer resizing to absorb sequencing variability.

In light of this, the current literature falls short of delivering operationally dynamic DLBP frameworks. Most existing contributions simulate variability using offline methods, failing to capture the temporal responsiveness required in modern circular economy systems.

The integration of PSD data, combined with intelligent control mechanisms, is thus both a necessary and timely evolution. This thesis seeks to contribute directly to this frontier by developing a model that dynamically balances disassembly lines based on the real-time condition of home appliances, enhancing flexibility, efficiency, and sustainability.

2.5 Mobile and Reconfigurable Resources in Disassembly Lines

As disassembly systems evolve to support the principles of circular economy and sustainable production, increasing attention is being paid to the integration of mobile and reconfigurable resources. These resources, which include mobile operators, reconfigurable workstations, and shared tools, offer promising solutions to the challenges of variability, limited space, and task heterogeneity in end-of-life (EOL) product disassembly.

One of the most established research directions in this domain focuses on mobile operators, where workers are allowed to move between stations, performing tasks along a segment of the disassembly line. The Multi-Manned Assembly Line Balancing Problem (MMALBP), extensively studied by Şahin and Kellegöz (2019), provides a formal framework for modelling such systems. In their work, walking workers are assigned to sequential stations, with distance and task compatibility constraints to ensure feasible schedules. This model not only improves labour utilization but also enhances adaptability to variable task durations, which are common in disassembly settings.

In parallel, models involving task sharing and reconfigurable resources have gained traction. A notable example is the flexible disassembly station approach introduced in the Silva et al., 2021, where resources such as tools or specialized robots can be reallocated across multiple workstations. These resources are subject to temporal availability and spatial constraints, often requiring coordination mechanisms to avoid conflicts (Wurster and Seidel, 2022; Aamer and Hassan, 2023). This flexibility is particularly beneficial when dealing with components that demand specific tools or expertise, which would be inefficient to fix permanently to a single location (Nemecek and Lakner, 2023).

Moreover, several disassembly line balancing models incorporate task collaboration between human and robotic agents, where resources dynamically switch roles or stations. The Zhang et al., 2024 and Liang et al., 2021 frameworks explore hybrid systems in which humans

and robots share or alternate tasks depending on workload, precedence, and ergonomic considerations. While these models do not always include physical movement across stations, they establish the groundwork for coordinated reallocation of labour and equipment.

The integration of mobility introduces both advantages and challenges. On the one hand, mobility enhances flexibility, allowing systems to dynamically adapt to product condition, resource availability, or line imbalances. It can reduce idle time by deploying underused resources where needed and increase the robustness of the line by mitigating the effects of bottlenecks or task failure. On the other hand, mobility requires careful control of movement schedules, coordination logic, and setup or activation times. Movement between stations consumes time and space, potentially affecting cycle time and station capacity.

Some models address these challenges by limiting movement distances or defining maximum work zones per mobile agent. In MMALBP, for example, the walking distance within a cycle is constrained, and task assignments are optimized accordingly. Other formulations use shared buffers or overlapping zones, where resources can perform tasks in multiple adjacent stations, thereby facilitating transitions and reducing relocation frequency.

To better illustrate the impact of resource mobility on task assignment, Figure 4 compares two configurations of multi-manned disassembly lines. The top diagram represents a system with fixed worker assignments, while the bottom shows a layout where workers are

allowed to move between stations. As depicted, mobility enables smoother workload distribution, fewer bottlenecks, and more compact task grouping.

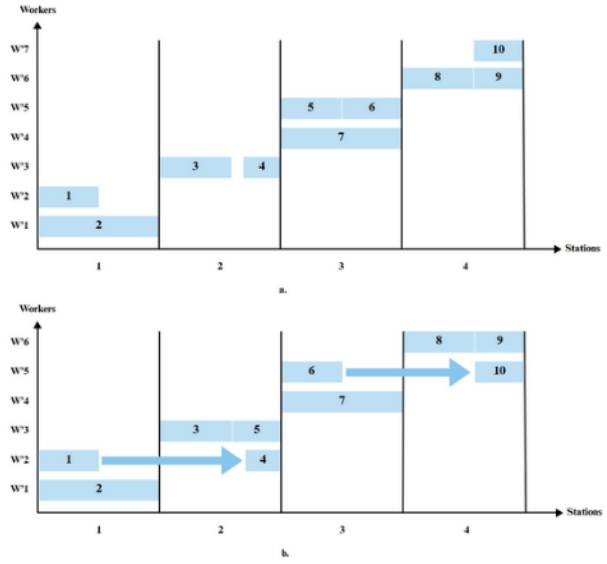


Figure 5 - Comparison between worker allocation strategies in disassembly lines: (a) workers permanently assigned to fixed stations; (b) mobile workers allowed to operate across neighbouring stations.

While the literature provides various modelling approaches for mobile and flexible resource allocation, most studies remain theoretical or simulation based. Practical implementations - especially involving mobile workstations or AGV-supported disassembly platforms - are still rare. Nonetheless, the trend is clear: mobility and reconfigurability are becoming essential elements in the design of future disassembly lines.

This thesis draws directly from these foundations by incorporating mobile resources into the disassembly line balancing model for EOL home appliances. By modelling movement constraints, activation times, and compatibility between mobile resources and disassembly tasks, the proposed system aims to optimize operational efficiency while maintaining spatial feasibility and precedence coherence.

2.6 Solution Approaches

The Disassembly Line Balancing Problem (DLBP) has been addressed using a wide variety of solution approaches, reflecting its combinatorial complexity, real-world constraints, and the presence of multiple, often conflicting, objectives. Gökçen and Toktay (2021) provide a comprehensive overview of the evolution of DLBP models and highlight the increasing

incorporation of environmental and operational constraints into the formulation of disassembly systems. Due to its NP-hard nature, exact methods such as Mixed-Integer Linear Programming (MILP) are typically limited to small-scale instances or theoretical benchmarks. In contrast, the majority of studies adopt heuristic and metaheuristic techniques — including Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization — which are capable of efficiently generating high-quality solutions for larger, more complex problems. Ma and Zhang (2021) systematically compared such algorithms in multi-objective DLBP contexts, concluding that hybrid and adaptive heuristics offer a promising balance between accuracy and computational efficiency. These approaches are especially well-suited to industrial settings, where scalability, adaptability, and responsiveness are essential for handling the variability and unpredictability inherent in EOL disassembly operations. In this regard, Tang and Hu (2021) proposed a parallel mixed-flow disassembly line model to handle multi-variety remanufacturing scenarios, demonstrating the value of flexible line configurations and intelligent sequencing for enhancing system robustness in real-world environments.

Several studies have proposed mathematical programming formulations to capture the structural intricacies of DLBP. Ding et al. (2010) formulated the problem as a multi-objective MILP, optimizing both the number of workstations and the disassembly profit. Similarly, Zhu et al. (2020) developed a multi-objective integer model that incorporates stochastic product states, using weighted scenarios to reflect EOL condition variability. Tu et al. (2020) proposed a model under interval uncertainty, allowing disassembly times to fluctuate within defined bounds, which is particularly useful in the context of degraded or partially incomplete products. These formulations typically include constraints for precedence, cycle time, workstation capacity, and task-resource compatibility, and some extend to model dynamic sequencing or task skipping.

Despite the precision of exact models, their practical application is limited by computational complexity, especially in dynamic or large-scale scenarios. To address this, researchers have increasingly turned to heuristic and metaheuristic methods capable of producing high-quality solutions within acceptable timeframes. One of the earliest and most influential examples is the use of Ant Colony Optimization (ACO) by Ding et al. (2010), adapted to a multi-objective framework (MOACO) for balancing disassembly lines while maximizing economic returns. Zhang et al. (2025) introduced a hybrid method that combines Constraint Programming with a cross-entropy algorithm, effectively navigating large solution spaces in U-shaped disassembly lines under spatial and resource constraints.

Other techniques explored in the literature include Genetic Algorithms (GAs) (Tu et al., 2020), Particle Swarm Optimization (PSO) (Zhang et al., 2025), Simulated Annealing (SA) (Zhu et al., 2020), Ant Colony Optimization (ACO) (Ding et al., 2010) and Electromagnetism Optimization (EMO) (Şahin & Kellegöz, 2019). While each method has its strengths, they share a common advantage: flexibility in modelling real-world complexities, such as operator movement, task reallocation, or non-linear precedence. Studies such as Özceylan et al. (2018) emphasize this point, noting that heuristic methods can easily incorporate industrial nuances that would otherwise be computationally intractable in exact formulations.

A very important theme across the literature is the trade-off between solution quality and computational efficiency. While MILP models can, in principle, find optimal solutions, they often become harder as the number of products, stations, or EOL states increases. In contrast, heuristics offer scalable and adaptable solutions, albeit with no guarantee of global optimality. This balance is particularly relevant in dynamic settings, where disassembly operations must adapt to changing product conditions, task durations, or resource availability in real time (Zhang et al., 2023).

In sum, the choice of the solution method in DLBP must consider the problem's size, complexity, and responsiveness requirements. Exact methods provide clarity and theoretical benchmarks but are often constrained in application. Metaheuristics, on the other hand, align better with the realities of industrial environments, especially when supported by modern computational resources and data-driven modelling. (Mete and Serin (2022))

The model developed in this thesis embraces this practical orientation, employing a hybrid solution framework tailored to dynamically balance the disassembly of EOL home appliances with condition-dependent task times and mobile resource constraints.

3 Problem Definition

The shift toward a circular economy places increasing demands on manufacturers to implement production and recovery systems that support sustainability, resource efficiency, and waste reduction. Within this paradigm, the ability to dismantle End-of-Life (EOL) products efficiently becomes a key operational and environmental requirement. This is particularly relevant in the home appliance sector, where products are typically complex, heterogeneous, and returned in varying conditions after their use phase.

Planning disassembly operations for such products presents multiple challenges. Appliances often consist of a wide range of materials and components with distinct degradation profiles and recovery value. Their internal condition may vary substantially from unit to unit, affecting the feasibility and duration of disassembly tasks. For example, in the case of CRT televisions—commonly studied in the literature—certain components, such as capacitors or cathode-ray tubes, degrade differently over time and require careful removal due to safety or environmental concerns. These examples highlight the need for condition-responsive disassembly strategies that can adapt to the actual state of each product.

This chapter introduces the optimization model proposed in this thesis, which addresses a specific variant of the Disassembly Line Balancing Problem (DLBP): the Dynamic Disassembly Line Balancing Problem (DDLBP). This formulation explicitly accounts for variability in product condition and supports the flexible allocation of both fixed and mobile resources.

The model incorporates operational constraints commonly found in industrial settings, including precedence relations between tasks, resource-task compatibility, spatial limits per workstation, and processing time variations linked to the product's EOL state. The objective is to determine a feasible and efficient configuration of the disassembly line that minimizes the number of active workstations required to process each EOL instance. By integrating dynamic task feasibility and resource mobility, the model aims to offer a more realistic and adaptive approach to disassembly planning in support of circular economy goals.

3.1 Formal Definition and Classification of the Problem

The problem addressed in this thesis is a variant of the Disassembly Line Balancing Problem (DLBP), tailored to the specific context of End-of-Life (EOL) home appliances. In alignment with circular economy principles, this problem formulation aims to enhance material recovery efficiency, reduce operational costs, and improve the adaptability of disassembly systems to product variability.

The model considers a disassembly line designed to process EOL home appliances, each arriving in one of several predefined degradation states. The condition of four key components determines the EOL state of the product. Each component can fall into one of three categories: Good (fully functional and intact), Damaged (partially defective and requiring additional care during removal, thus increasing disassembly time), or Degraded (highly deteriorated or missing, requiring no extraction time due to the ease or redundancy of removal). The combination of these component states results in 81 distinct EOL configurations, each influencing the feasibility and duration of disassembly tasks.

The model assumes that the condition of each product is known in advance through a diagnostic mechanism, such as a Product State Diagnosis (PSD) system. Although the design and implementation of such a system are beyond the scope of this thesis, its availability is considered a prerequisite for applying the proposed approach. This diagnostic information enables the model to tailor disassembly planning according to the actual condition of the product, adjusting task selection and resource allocation accordingly. All assignments must still comply with precedence relations and must fit within predefined workstation constraints, including time, space, and resource compatibility.

Resources are categorized into two types: fixed resources, which are permanently assigned to specific stations, and mobile resources, which can relocate between stations. Mobile resources have limited movement ranges and incur activation times upon arrival at a new station. Each resource, regardless of type, occupies physical space and may only be used in stations where it is assigned or has moved.

The model integrates task setup times, state-dependent processing times, and spatial constraints to ensure realistic feasibility. It enforces rules for station activation, task execution, and resource usage, aiming to capture the dynamic interplay between task variability, precedence, and capacity constraints.

The primary objective of this model is to:

- Minimize the number of active workstations, promoting efficient use of space and labour.

This single-objective formulation is aligned with the practical needs of industrial disassembly systems, where minimizing the number of stations can lead to lower energy consumption, reduced operational costs, and greater flexibility in reconfiguring production lines to handle varied EOL conditions. By introducing task variability driven by product condition and enabling resource mobility within operational constraints, the model extends the classical DLBP framework into a more adaptive and application-oriented formulation suited for the home appliance sector. The next sections provide a detailed explanation of the model's assumptions, parameters, constraints, and objectives.

3.2 Modelling Assumptions and Input Parameters

To model the dynamic disassembly line balancing problem (DDLBP) in a realistic and tractable way, several assumptions and parameters are introduced. These are grounded in practical observations of industrial disassembly lines for home appliances and aim to balance model complexity with computational feasibility.

3.2.1 Assumptions

The following assumptions define the main operational constraints and dynamic of the system:

- Each disassembly task is assigned to exactly one workstation;
- All precedence constraints between tasks must be strictly respected;
- A task is only executable at a station if compatible resources are present;
- Each task has a setup time and a processing time, the latter of which depends on the product's EOL state;
- Mobile resources can move between stations, but only once per cycle and within a limited distance;

- Movement of a mobile resource incurs an activation time upon arrival at the new station;
- Each resource, whether fixed or mobile, occupies a defined area within a station;
- The total occupied area within any station cannot exceed its spatial capacity;
- Workstations are only considered active if they perform at least one disassembly task;
- A mobile resource may only be used in a station if it is assigned to that station or has moved there in the current cycle;
- Resources may only move from stations where they were present in the previous cycle.

These assumptions reflect both the operational constraints of physical disassembly systems and the behavioural logic of mobile resource allocation.

3.2.2 Input data and Parameters

The model takes the following data as input:

- Task set: A complete list of disassembly tasks required for the product;
- Precedence graph: A directed acyclic graph indicating the task dependencies;
- EOL state vector: One of 81 possible combinations of component conditions (Good, Damaged, Degraded);
- Processing times: Task durations adjusted for each EOL state;
- Setup times: Fixed times required to prepare a task;
- Resource set: Includes both fixed and mobile resources;
- Compatibility matrix: Indicates whether resource can perform task;
- Resource area requirements: Physical footprint of each resource;
- Station capacity: Maximum allowable area per workstation;
- Cycle time: Maximum time available per workstation cycle;
- Distance matrix: Physical layout of stations used to constrain resource mobility;
- Movement limits: Maximum distance each mobile resource can travel;
- Activation times: Time required to activate a mobile resource at a new station.

This structured data allows the model to dynamically adapt task allocations and resource assignments according to the specific EOL state of the product, ensuring a realistic representation of operational flexibility in home appliance disassembly lines.

3.3 System Characteristics

The model incorporates two distinct resource types - fixed and mobile - that play a fundamental role in executing disassembly tasks across a sequence of workstations. Each type has operational characteristics that affect both the flexibility and the efficiency of the line. Fixed resources are permanently assigned to specific stations and typically represent tools or equipment that cannot be reallocated during the production cycle. Their main advantage lies in their reliability and immediate availability.

In contrast, mobile resources can be reallocated across different stations during a cycle, allowing for dynamic task execution - particularly useful in situations where workload distribution is uneven or certain tools are only occasionally needed. These mobile units are subject to constraints such as limited movement distance and the need for activation time upon arrival at a new station. Additionally, they must respect continuity rules, meaning they can only move from locations they were previously assigned to. Both types of resources occupy physical space, and their presence contributes to the total spatial load of the workstation. Therefore, the allocation of mobile resources must consider not only task compatibility but also the station's area constraints and the feasibility of movement within the line layout.

Workstations themselves are subject to several operational limitations. The total processing time at a station - including task execution, setup, and any activation time for mobile resources - must not exceed a predefined cycle time. The physical capacity of each station also imposes a constraint: the cumulative area of all resources deployed at a given station must remain within the allowable spatial limit. Moreover, tasks can only be assigned where compatible resources are present. A station is considered active only when it performs at least one task, a condition aligned with the model's objective of minimizing the number of active workstations to improve efficiency and release unused capacity for other operational needs.

Another important aspect of the model is its consideration of product state variability, which is introduced through the use of pre-classified end-of-life (EOL) instances. Each product

entering the disassembly line is assumed to have an identified degradation condition for its main components. This information influences the disassembly process in two fundamental ways. First, task durations are adjusted according to component condition: while components in good condition require standard handling, damaged components necessitate more careful and time-consuming operations, and degraded or missing components may be bypassed or removed with minimal effort. Second, the absence or deterioration of specific components in certain EOL instances may render some tasks infeasible, effectively altering the set of required operations and modifying task precedence structures.

This dynamic behavior transforms the disassembly planning problem into an instance-specific challenge. It demands a high degree of flexibility in task assignment, resource deployment, and station-level cycle management. In doing so, it departs from conventional DLBP formulations, which typically assume static sequences and uniform task durations across all product instances.

3.4 Objectives and Performance Metrics

The model focuses on minimizing the number of active workstations required to disassemble a given end-of-life (EOL) home appliance, based on its identified product condition. This objective aligns with the overarching goals of sustainable and efficient production systems, particularly in the context of circular economy strategies that seek to reduce resource consumption, optimize labour, and enable flexible reuse of industrial infrastructure.

Minimizing the number of active workstations offers several operational advantages:

- Space Optimization**:** Reducing the number of active stations can free physical space on the shop floor, allowing it to be reallocated to other processes or adapted to fluctuating production demands.
- Energy and Cost Reduction: Fewer active stations typically result in lower energy usage, fewer activated tools, and reduced operational overhead.
- Improved Line Reconfigurability: By optimizing resource allocation and task sequencing, the line becomes more adaptable to variations in product condition and volume.

Although the model formally optimizes only the number of active stations, additional performance metrics are indirectly influenced and monitored during implementation and testing:

- Utilization of Mobile Resources: Efficient deployment of mobile resources, respecting distance and activation time constraints, is essential for achieving high flexibility without overloading stations;
- Spatial Occupancy: The balance between resource area requirements and station capacity reflects the physical feasibility and compactness of the solution;
- Cycle Time Compliance: Ensuring that each station's total task, setup, and movement time remains within the allowable cycle time guarantees operational feasibility.

These secondary metrics provide useful indicators of system robustness, resource flexibility, and layout effectiveness, supporting decision-makers in evaluating the model's applicability to real-world disassembly environments.

3.5 Comparison with Existing DLBP Variants

The model presented in this thesis builds upon existing Disassembly Line Balancing Problem (DLBP) formulations by incorporating product condition variability and resource mobility. While many prior approaches focus on static task durations and homogeneous product assumptions, the inclusion of these additional elements aims to increase the model's applicability to more realistic disassembly planning contexts.

Conventional DLBP models often assume that all products arriving at the line are structurally identical and in good condition. As a result, task times are treated as deterministic and fixed, and resource allocation is static. In contrast, the proposed model embraces heterogeneity by considering 81 distinct EOL states, each representing a unique combination of component degradation levels. This fine-grained variability allows for more accurate task timing, better feasibility modelling, and more tailored disassembly sequences.

Furthermore, most classical models rely solely on fixed resources, which limits flexibility in managing variations in workload and task distribution. The inclusion of mobile resources - subject to movement range, activation delay, and spatial constraints - adds a layer

of operational agility, enabling the system to respond dynamically to EOL-driven needs. This is especially important in realistic disassembly environments where some components may be severely degraded or missing, altering both the need for certain tasks and the way they must be executed.

From a line balancing perspective, many prior DLBP approaches share the goal of minimizing the number of stations, idle time, or total cost, and they typically rely on metaheuristic techniques such as Genetic Algorithms, Ant Colony Optimization, or Simulated Annealing to solve large instances. While this model also targets minimization of active workstations, it differentiates itself by embedding:

- EOL-dependent task durations;
- Flexible yet constrained resource mobility;
- Explicit spatial feasibility per station.

It is worth noting that the model differs from traditional mixed-model or multi-product DLBP approaches, which typically address product variation in terms of design or structural differences. In this case, the variability considered relates to internal degradation within a consistent product type (home appliances), which may represent a distinct perspective within the broader DLBP landscape.

In summary, this thesis contributes to the state of the art by addressing three key challenges simultaneously - challenges that are rarely considered in unison in existing literature:

- Variability in product condition (EOL states);
- Mobility and reallocation of disassembly resources;
- Strict spatial and temporal constraints at the workstation level.

This integrated approach positions the model as a forward-looking and application-ready solution for supporting circular economy objectives in the industrial disassembly of home appliances.

4. Proposed Methodology

This chapter describes the methodology followed to formulate, implement, and apply the proposed optimization model. The model was designed to support efficient disassembly planning for End-of-Life (EOL) home appliances, accounting for variability in product condition and the flexible allocation of both fixed and mobile resources. Rather than operating as a real-time control system, the model serves as a tactical decision support tool, generating optimized disassembly line configurations based on pre-identified product conditions.

The optimization framework is particularly relevant for short-term planning scenarios - such as daily or weekly disassembly batches - where grouping similar EOL states enables consistent task assignment and the deactivation of unnecessary workstations. This strategic planning approach allows factories to minimize the number of active stations, reallocate freed-up space to other operations, and improve the overall sustainability and responsiveness of disassembly systems.

4.1 Decision Support Tool

The optimization model developed in this thesis is designed to support short-term tactical planning in disassembly environments. Its purpose is to assist in configuring disassembly lines based on previously identified product conditions, enabling more efficient resource allocation and layout adaptation. The model is not intended for real-time control but rather for the offline planning of disassembly operations over batches of end-of-life (EOL) products.

By incorporating information on the degradation level of key components, the model adapts task selection and processing times to reflect the actual condition of the product. This allows for more accurate task allocation, ensures that only feasible operations are scheduled, and helps avoid the unnecessary use of tools or workstations in cases where certain components are degraded or missing.

The model’s primary function is to determine a valid and efficient assignment of disassembly tasks and resources to workstations, while minimizing the number of active

stations required. As a result, unused stations can potentially be reallocated to other processes, improving overall line flexibility and space utilization.

To achieve this, the model relies on a set of structured inputs that reflect industrial constraints and operational priorities. These include:

- A list of disassembly tasks and their precedence relationships;
- Setup and processing times that depend on the identified product condition;
- A classification of resources into fixed and mobile, and their compatibility with tasks;
- Spatial and temporal constraints at each workstation, including cycle time and area limits;
- A representation of the physical layout of the line, including movement constraints for mobile resources.

The output consists of an optimized assignment of tasks to stations, a deployment plan for mobile resources, and the corresponding set of active workstations. These results serve as decision support for production planners, offering a configuration that is tailored to the characteristics of each product batch and aligned with efficiency and sustainability goals.

This planning approach is particularly relevant for facilities dealing with heterogeneous product conditions and limited shop-floor space. By anticipating variability at the planning stage, rather than reacting to it during execution, the model contributes to a more robust and adaptive disassembly process.

4.2 Mathematical Formulation

A Mixed-Integer Linear Programming (MILP) model is developed in this thesis by building upon two key contributions from the literature. The first foundation comes from Sahin et al. (2019), who proposed a mathematical formulation for balancing multi-manned assembly lines with walking workers. Although focused on assembly contexts, their structural approach to modelling spatially-constrained workstations, mobile agents, and operator movement coordination provided valuable insights for disassembly planning. This work draws from their logic of operator routing and spatial feasibility, adapting it to a reverse logistics setting.

The second foundational influence is drawn from Zhao et al. (2022), who integrated End-of-Life (EOL) product condition variability into a disassembly planning model using stochastic representations. While their work captures EOL uncertainty through probabilistic task feasibility and durations, the approach proposed in this thesis introduces a different perspective: each product instance is assumed to have a known degradation profile, which directly conditions task times, feasibility, and precedence. This allows the model to represent realistic disassembly scenarios more faithfully and to optimize based on concrete product condition data.

Beyond this conceptual combination, several extensions are introduced in this thesis. Notably, the model integrates detailed compatibility between tasks and resources, distinguishes between fixed and mobile resources, and incorporates setup times, activation delays, and area occupancy constraints for each resource at every station. Mobile resources are further constrained by maximum movement distances and spatial limitations along the line layout. These features allow the model to handle high levels of variability in both product condition and resource availability, while maintaining feasibility under industrial constraints such as limited floor space and predefined cycle times.

Altogether, the proposed model extends prior work by embedding condition-aware disassembly logic into a resource-constrained, mobility-enabled optimization framework - tailored to support adaptive planning for home appliance disassembly lines under circular economy objectives.

Sets and Indices

To formally define the optimization model, the following sets and indices are used:

- I: Set of disassembly tasks, indexed by *i*.
- J: Set of workstations, indexed by *j and k*.
- R: Set of all resources, indexed by *r*.
    - $F \subseteq R$: Subset of fixed resources, indexed by *r*.
    - $M \subseteq R$: Subset of mobile resources, indexed by *r*.
- P (i): Set of immediate predecessors of task *i* indexed by *p*.
- C (i): Set of resources compatible with task *i*.
- T: Set of EOL scenarios indexed by *e*.
- E: Set of main component condition defining EOL scenario.

Parameters and Input Data

Additionally, to the defined sets and indices, the model considers the following main parameters and input data:

- t_i**:** Execution time of task i, defined according to the corresponding EOL scenario e. For each model execution, a specific scenario $e \in T$ is considered, and the values of t_i are adapted accordingly.
- s_i**:** Setup time for task *i.*
- a_r: Activation time of mobile resource r.
- y: Time consumed per unit of movement distance.
- $\delta_{i,r} \in \{0,1\}$**:** 1 if resource r can perform task *i*, 0 otherwise.
- $d_{k,j}$**:** Distance between stations k and j.
- D_r: Maximum movement distance allowed for mobile resources *r*.
- A_r: Area Occupied by resource *r*.
- A_{max}: Maximum area available per workstation.
- C: Maximum cycle time allowed per workstation.
- $\phi_r \in \{0,1\}$*:* 1 if resource is mobile, 0 if fixed.
- $f_r \in$ J: Station to which fixed resource $r \in$ F is permanently assigned.

Decision Variable

- $\theta_{i,j} \in \{0,1\}$**:** Binary variable that equals 1 if task *i* is assigned to workstation *j*.
- $\mu_{r,j} \in \{0,1\}$**:** Binary variable that equals 1 if resource *r* is allocated to workstation *j*.
- $\psi_{r,k,j} \in \{0,1\}$**:** Binary variable that equals 1 if mobile resource *r* is moved from workstation *k* to workstation *j*.
- $\omega_j \in \{0,1\}$**:** Binary variable that equals 1 if workstation *j* is active.
- $\tau_j \in R_+$**:** Continuous variable representing the total operation time at workstation *j*, including processing, setup, activation and movement times.
- $O_j \in R_+$**:** Continuous variable representing the idle time at workstation *j*.

Objective Function

The main objective of the proposed model is to minimize the number of active workstations required to execute the disassembly of a single end-of-life (EOL) product configuration. This reflects the industrial goal of optimizing space and resource allocation, especially under the constraints of limited physical area and time. By minimizing the number of workstations, the model contributes to increased compactness of the disassembly line, enabling the release of unused stations for other operations, which is highly valuable in flexible and multifunctional factory environments.

Formally, the objective function is:

$$min \sum_{j \in J} \omega_j$$

Where:

- $\omega_j \in \{0,1\}$: Binary variable that equals 1 if workstation *j* is active.

This formulation encourages solutions that group tasks efficiently across fewer stations, while still respecting all technical, precedence, and capacity constraints. It is particularly relevant in the context of circular economy strategies, where increasing operational efficiency in the disassembly of EOL products plays a central role in waste reduction and resource recovery.

Constraints

$$\sum_j \theta_{i,j} = 1 \; \forall i \in I \tag{4.1}$$

$$\sum_j j * \theta_{i,j} \geq \sum_j j * \theta_{\,p,j} \; \forall i \in I, \forall p \in P(i) \tag{4.2}$$

$$\tau_j \leq C * \omega_j \; \forall j \tag{4.3}$$

$$\tau_j = \sum_i \theta_{i,j} * t_i + \sum_{r \in M} \sum_{k \in J} \psi_{r,k,j} * (y * d_{k,j} + \alpha_r) \quad \forall j \in J \tag{4.4}$$

$$O_j = C * \omega_j - \tau_j \; \forall j \in J \tag{4.5}$$

$$\theta_{i,j} \leq \sum_r \delta_{i,r} * \mu_{r,j} \; \forall i \in I, \forall j \in J \tag{4.6}$$

$$\omega_j \geq \theta_{i,j} \; \forall i \in I, \forall j \in J \tag{4.7}$$

$$\sum_{r \in M} \mu_{i,j} * A_r + \sum_{r \in F} A_r \leq A_{max} \; \forall j \in J \tag{4.8}$$

$$\mu_{r,f_r} = 1 \; \forall r \in F \tag{4.9}$$

$$\mu_{r,j} = 0 \; \forall r \in F, \forall j \in J, j \neq f_r \tag{4.10}$$

$$\sum_{k \in J} \sum_{j \in J} \psi_{r,k,j} * d_{k,j} \leq D_r \; \forall r \in M \tag{4.11}$$

$$\psi_{r,k,j} \leq \mu_{r,k} \; \forall r \in M, \forall k \neq j \tag{4.12}$$

The mathematical formulation developed in this work includes a set of constraints that ensure the feasibility and logical consistency of the disassembly process, while supporting the primary goal of minimizing the number of active workstations. Constraint (4.1) guarantees that each disassembly task is assigned to exactly one workstation, reflecting the operational requirement that tasks cannot be split across stations. Constraint (4.2) ensures that precedence relations between tasks are respected: if a task *p* must precede a task *i*, the model guarantees that task *i* is assigned to a workstation equal to or downstream from the one assigned to task *k*. To respect the maximum allowed cycle time, constraint (4.3) ensures that the total processing time at each station does not exceed the cycle time *C*, thus limiting the workload per station.

In order to calculate this workload, constraint (4.4) defines the total time τ_j of each station as the sum of the processing times of all tasks assigned to it, plus the time required for movements of mobile resources to that station, including their activation times. The idle time of each station is captured by constraint (4.5), which computes it as the difference between the cycle time and the total processing time at that station. This idle time is useful for subsequent performance evaluation and workload balancing.

In terms of resource feasibility, constraint (4.6) ensures that each task is only assigned to stations where at least one compatible resource is present. This is implemented through a compatibility matrix indicating which resources can perform each task. Additionally, constraint (4.7) guarantees that a station is considered active if and only if at least one task is assigned to it, which is essential to link the decision variable ω_j with actual task assignment. The physical constraints of the workstations are considered in constraint (4.8), which ensures that the total area occupied by all resources (fixed and mobile) at each station does not exceed the maximum allowed station area.

Constraints (4.9) and (4.10) ensure the correct allocation of fixed resources. Each fixed resource $r \in F$ is pre-assigned to a specific station f_r, reflecting the immovable nature of equipment or tools. This reflects the physical constraints of fixed equipment in the disassembly line layout and avoids infeasible resource-task assignments. Constraint (4.9) explicitly enforces this condition by setting $\mu_{r,f_r} = 1$, ensuring that the resource is always present at its designated station. Complementarily, constraint (4.10) prevents any fixed resource from being allocated to any other station $j \neq f_r$ by setting $\mu_{r,j} = 0$ for all such cases. These constraints are straightforward because they rely on a known parameter f_r, and do not require additional linearization.

As for mobile resources, constraint (4.11) imposes a global distance restriction by limiting the total movement per cycle to the maximum allowed for each resource. This ensures that mobile tools or operators are not assigned movement plans that exceed their physical capabilities. An alternative formulation could consider individual movement limits per transition, but the total distance formulation is adequate for the current abstraction level and allows for greater flexibility. Finally, constraint (4.12) ensures that a mobile resource can only be moved from a workstation where it is currently allocated**.** This prevents infeasible routing behaviours, such as initiating movement from a station where the resource is not physically present. By enforcing

this condition, the model preserves logical consistency in the movement logic of mobile resources and guarantees that all displacements occur from valid origin points.

4.3 Clustering-Based Application

While the optimization model developed in this thesis produces instance-specific disassembly line configurations, managing each instance individually can be impractical in a real production environment. In particular, as the number of unique degradation conditions increases, the effort required to generate and implement a tailored configuration for every incoming product becomes operationally demanding.

To address this, a clustering-based analysis was explored as an additional post-optimization step. It aims to group similar product instances according to the operational behaviour observed in the model outputs. This approach does not modify or interact with the optimization model itself, but instead serves as a practical tool to simplify planning routines for facilities dealing with high variability in End-of-Life (EOL) product conditions. (Güçdemir (2023))

The clustering was performed after solving all EOL instances individually. For each instance, the model generated a specific solution that included task-to-station assignments, resource usage, and performance metrics. From these outputs, a set of quantitative indicators was extracted to characterize the operational complexity of each solution. These indicators included:

- Number of active workstations;
- Total idle time;
- Average processing time per station;
- Number of mobile resources used;
- Total number of resource movements;
- Total movement time;
- Binary usage flags for each station (e.g., station 1 used: yes/no).

These features were then used as input for a K-means clustering algorithm, which grouped the 81 solved instances into clusters of similar operational profiles. The optimal number of clusters was determined using the Elbow Method, which balances model simplicity

with representation accuracy. In this case, four clusters were identified as a meaningful segmentation of the instance space.

Each cluster represents a group of EOL conditions that, although technically distinct, lead to similar disassembly configurations in terms of workstation usage, resource allocation, and timing. These clusters can thus be interpreted as representative planning profiles, enabling the use of a small number of predefined line configurations rather than planning each instance from scratch.

It is important to stress that this clustering-based strategy is not part of the core optimization model. Rather, it serves as a complementary decision support mechanism, offering a way to generalize the application of model results. Once the clustering has been defined, incoming products can be classified into one of the existing clusters based on their degradation profile, and the corresponding representative configuration can be applied. This enables more efficient scheduling and layout planning over short-term horizons (e.g., daily or weekly), while preserving alignment with product-specific requirements.

By reducing planning complexity without compromising adaptability, the clustering-based application provides a bridge between detailed model outputs and scalable industrial planning practices.

4.4 Resolution Strategy

This section describes the computational strategy used to implement and solve the optimization model for dynamic disassembly line balancing. The proposed methodology combines a rigorous mathematical formulation with practical operational constraints, enabling its application to short-term production planning in settings where End-of-Life (EOL) product conditions vary significantly.

The model was developed in Python using the Google OR-Tools library, with the SCIP solver selected for its capacity to handle complex Mixed-Integer Linear Programming (MILP) problems. These include binary task-resource assignments, precedence relations, station-level spatial constraints, and the allocation of mobile resources. To improve computational efficiency and ensure feasibility, the model automatically filters out infeasible tasks and precedence links

based on the known condition of each product. As such, only viable operations are included in each instance, eliminating the need for runtime adjustments or artificial constraints.

All input data - including disassembly tasks, task precedence structures, component-specific processing and setup times, resource classifications (fixed or mobile), and station constraints (cycle time, area) - were compiled in an Excel file. These data were imported using the Pandas library and used to generate distinct optimization instances, each corresponding to a specific degradation profile of the product. Although the total number of EOL combinations explored was 81, the model was designed to treat each instance independently, reflecting real-world scenarios where the condition of individual units is known prior to disassembly.

For each instance, the model returned a full set of optimized decisions, including:

- Task-to-station assignments;
- Allocation and movement of mobile resources;
- Station-level processing and idle times.

Results were automatically exported into a structured multi-sheet Excel file. One sheet summarized global performance metrics (e.g., number of active stations, total idle time, number of mobile resource movements), while others detailed station assignments and timing breakdowns.

To support practical implementation at the shop floor level, the outputs of all solved instances were further analysed using a K-means clustering algorithm (see Section 4.3). This step grouped instances with similar operational profiles, enabling the definition of representative planning configurations that can be reused across batches. This clustering is performed entirely after model execution, serving as a complementary tool for reducing planning complexity - not as a component of the optimization model itself.

The complete workflow - from data input to the generation of representative plans - is illustrated in Figure 6.

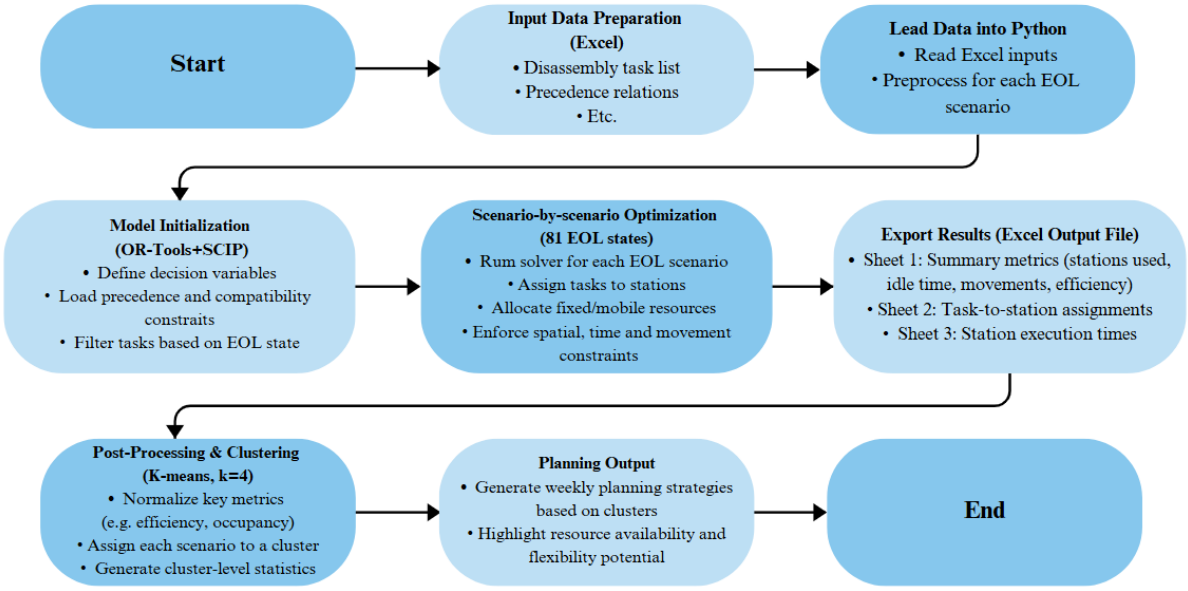


Figure 6 - Optimization and Planning Workflow

This flowchart provides a visual overview of the implementation process. It begins with structured data preparation in Excel (covering task properties, precedence, resource constraints, and layout parameters), followed by the automated resolution of each EOL instance using Python and OR-Tools. After the instance-specific results are generated and exported, performance metrics are compiled and processed through K-means clustering. The resulting clusters form the basis for simplified short-term planning, allowing the selection of a representative layout for each group of similar product conditions. In summary, the proposed methodology is built around an optimization-based model designed to support decision-making in the context of disassembly line problems, combining computational precision with practical applicability.

5. Results and Analysis

This chapter presents the results obtained from applying the proposed optimization model to a realistic disassembly scenario involving end-of-life (EOL) household appliances. The primary aim is to evaluate the model's performance in minimizing the number of active workstations while respecting key industrial constraints such as task precedence, cycle time, station area capacity, and resource mobility.

The analysis is organized into four main sections. Section 5.1 outlines the assumptions made for the experimental implementation, including the structure of the input data, the adopted simplifications, and the simulation setup for each EOL product state. Section 5.2 presents detailed results for all 81 individual EOL scenarios, examining task allocation, resource utilization, and station-level performance metrics. Section 5.3 provides a comparative evaluation between the dynamic line configuration—with mobile resources—and a static baseline where all resources are fixed. This comparison highlights the operational benefits of mobility in reducing active stations and idle time. Section 5.4 explores how clustering techniques can be applied to group similar EOL scenarios, creating reusable disassembly configurations that support short-term planning and improve the adaptability of factory operations. Subsection 5.4.1 describes the clustering composition, while Subsection 5.4.2 focuses on interpreting the clusters and leveraging them for practical line balancing decisions.

Together, these analyses provide structured evidence of the model's flexibility, efficiency, and suitability for supporting adaptive and sustainable disassembly line management in real industrial contexts.

5.1 Case Study

To evaluate the proposed optimization model, a use-case from the literature was adapted from a disassembly line for CRT televisions, as presented in Zhao et al. (2022). This dataset includes 27 disassembly tasks, a precedence graph, estimated task durations, and compatible resource types. However, the original dataset was developed for fixed-resource allocation only and does not account for mobile resources, spatial constraints, EOL-driven task variability, or station capacity. Therefore, several assumptions were made to extend the dataset and enable its use in this more advanced modelling context.

Figure 7 illustrates the precedence relationships among the 27 disassembly tasks, forming a directed acyclic graph with multiple branches and convergence points. The task durations and associated resource types are presented in Table 1, forming the base structure of the implementation.

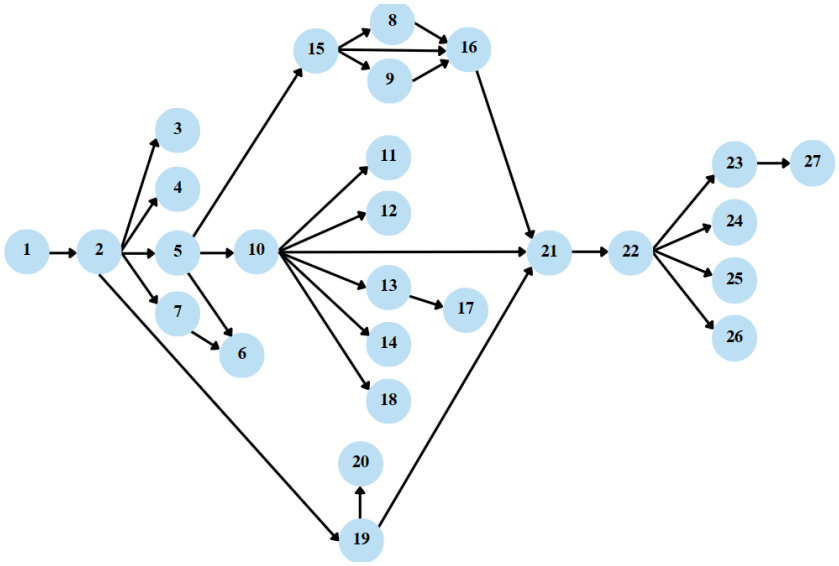


Figure 7 - The baseline disassembly precedence graph of the CRT TV set

Table 1 - The data information of each disassembly task for the CRT TV set

Number	Task	Time/s	Resource type	Number	Task	Time/s	Resource type
1	Screws	50	1	**15**	Eletronic gun end circuit board	4	1, 2, 3
2	Back cover	9	1, 2	**16**	Glass tube	4	1, 3
3	Antenna	3	1, 2	**17**	Electron gun	4	1, 3
4	Horn	7	1, 3	**18**	Explosion protection band	4	5
5	Eletric Wire	24	3	**19**	Screws	17	1
6	Main circuit board	2	1, 3	**20**	Front shell	16	1, 3
7	Power cord	10	2, 3	**21**	CRT	7	1, 3
8	Deflecting coil	18	1, 3	**22**	Conical glass	3	6, 7
9	Polarization adjusting ring	4	1, 3	**23**	Phosphor	3	8
10	High pressure cap	4	4	**24**	Pin	4	4
11	Degaussing coil	4	1, 2, 3	**25**	Anode cap	2	9
12	Ground wire	4	1, 2, 3	**26**	Cathode hood	2	4, 6, 7, 9
13	Transformer	4	1, 2, 3	**27**	Screen glass	2	6, 7
14	Tuner	4	1, 2, 3				

Building on the disassembly structure previously established, four main components were identified and associated with specific disassembly tasks. This classification enabled the systematic generation of EOL instances by varying the condition of key functional elements:

- C1: Tasks 1 and 2;
- C2: Task 6;
- C3: Tasks 19 and 20;
- C4: Tasks 21 to 27.

Extensions of the base case

Based on the degradation states defined for the four main components, multiple End-of-Life (EOL) instances were constructed to reflect diverse combinations of product conditions. Each instance served as input to the optimization model, with task processing times dynamically adjusted according to the condition of the associated components. Tasks linked to damaged components were assigned a 50% increase in processing time to account for the additional care required. In contrast, tasks associated with degraded or missing components were either minimized in duration or excluded entirely from the disassembly plan.

Since the original dataset did not include key parameters required by the proposed model - such as spatial constraints, resource mobility, movement limits, or workstation area - several assumptions were introduced to extend it. These assumptions aimed to simulate realistic industrial conditions and test the full functionality of the model in a flexible and reconfigurable environment.

The main assumptions are as follows:

- Cycle time**:** fixed at 135 seconds per station;
- Maximum station area**:** 3.0 m²;
- Number of workstations: six (linear layout);
- Distances - based on Euclidean spacing between stations (see Table 2);
- Activation time for mobile resources: 0.5 minutes per move;
- Resource classification: resources 1–3 and 9 were considered fixed, while 4–8 was treated as mobile (see table 3);

Table 2 - Workstations distances

From (k)	To (j)	Distance (m)
1	2	**3**
1	3	**6**
1	4	**9**
1	5	**12**
1	6	**15**
2	3	**3**
2	4	**6**
2	5	**9**
2	6	**12**
3	4	**3**
3	5	**6**
3	6	**9**
4	5	**3**
4	6	**6**
5	6	**3**

The assignment of fixed and mobile resources was made based on industrial logic, task distribution, and operational intuition. Resources 1, 2, 3, and 9 were compatible with a wide array of tasks and were assumed to be essential tools or bulky equipment - the kind typically kept at a single station due to their general-purpose nature or setup overhead. To ensure task coverage and simplify configuration, each of these fixed resources was assigned sequentially to stations 1 through 4 (e.g., Resource 1 → Station 1, Resource 2 → Station 2, etc.).

On the other hand, resources 4 to 8 were assumed to be mobile due to their distinct operational profile. These resources were involved in a smaller number of tasks, often linked to specific components such as C2, C3, and C4. Their limited task scope made permanent assignment to a single station inefficient, as they would likely remain underutilized. Additionally, their physical footprint - ranging between 0.6 and 0.8 square meters - suggests they could realistically represent portable tools or mobile manipulators like robotic arms or handheld equipment. Such tools are commonly shared across stations in real industrial

environments. By allowing them to move, the model supports dynamic task reassignment, which helps alleviate bottlenecks, improves station utilization, and promotes more compact and balanced disassembly layouts in response to product variability.

To preserve realism and avoid overestimating mobility, the mobile resources were also constrained by maximum movement distance**,** activation delays**,** and space usage per station**.** This ensured a fair trade-off between flexibility and feasibility, mirroring practical challenges in line reconfiguration and space management.

Table 3 - Resources characteristics

Resources	Mobile	Area (m^2)	Max Distance (m)	Fixed Station	Activation Time (α _ r) (min)
1	0	1	0	1	
2	0	1	0	2	
3	0	1.2	0	3	
4	1	0.8	9		0.5
5	1	0.6	9		0.5
6	1	0.6	6		0.5
7	1	0.7	7		0.5
8	1	0.8	8		0.5
9	0	1.2	0	4	

In summary, the chosen assumptions allowed for the expansion of a static, fixed-resource dataset into a dynamic testbed capable of evaluating the full extent of the proposed model. They enabled simulations that reflect the impact of EOL variability, mobile resource deployment, and spatial constraints - all critical elements in the pursuit of efficient and sustainable disassembly planning.

5.2 Computational Results

This section presents the results obtained from executing the optimization model across the full set of EOL product instances. Each instance represents a unique combination of degradation conditions across four principal components, influencing task availability, precedence relations, processing times, and resource allocation.

The dataset collected from the model includes key performance indicators such as the number of active workstations, cycle time, resource utilization, idle time, mobile resource

usage, and movement statistics. These metrics offer a comprehensive view of how the system responds to product variability under realistic operational constraints.

Table 5.5 summarizes the descriptive statistics across all instances. On average, the model required approximately 3.41 workstations per instance, with values ranging from 2 to 5. The average cycle time was 122.3 minutes, with relatively low variability, suggesting that the model tends to push configurations toward the upper cycle time limit of 135 minutes to maximize station usage. Mobile resources were used in nearly all instances, averaging 3.67 per configuration, with an average of 1.63 total inter-station movements.

Table 4 - Summary statistics of key performance indicators

	Average	Standard Deviation	Min	Max
Workstations Used	3.4	1.0	2	5
Cycle Time (min)	122.3	8.9	102	135
Mobile Resources Used	3.7	1.2	2	5
Total Movements	1.6	1.3	0	4
Efficiency (%)	47%	17%	23%	90%
Utilization Rate (%)	55%	17%	30%	99%

Efficiency and occupancy rate values revealed significant dispersion: efficiency ranged from 23.15% to 89.63%, while occupancy varied between 29.81% and 98.89%. These variations are not model limitations but rather the result of natural disassembly complexity under differing product states. In some cases, degraded or missing components reduce the number of active tasks, leading to low station utilization. In others, complex precedence constraints or fragmented task sets hinder efficient balancing, increasing idle time.

The performance of the solver was consistent across all instances. The model was solved using SCIP through the OR-Tools interface, and all instances were resolved in a total of 48 seconds, corresponding to an average resolution time of less than one second per instance. No runtime limitations were imposed during model execution. Although optimality gaps were not explicitly computed, the short resolution times and the stable convergence behaviour across all instances suggest that the solutions obtained are likely to be optimal or very close to optimal. On average, each instance involved approximately 365 decision variables, including binary task

allocation and resource movement variables, with the total number varying depending on task feasibility and resource combinations.

In addition to aggregated metrics, the model also produced detailed outputs for each instance, including task-to-station assignments and resource allocation plans. These results represent the optimized disassembly line configuration tailored to the specific condition of each product. In other words, for every EOL instance, the model provides a prescriptive layout - indicating how tasks should be grouped, which resources should be deployed, and how workstations should be utilized to achieve the best possible performance under the given constraints.

To illustrate this, Figure 8 and Figure 9 present two contrasting examples generated by the model. These configurations correspond to the best solution identified for each product condition, as determined by the optimization algorithm.

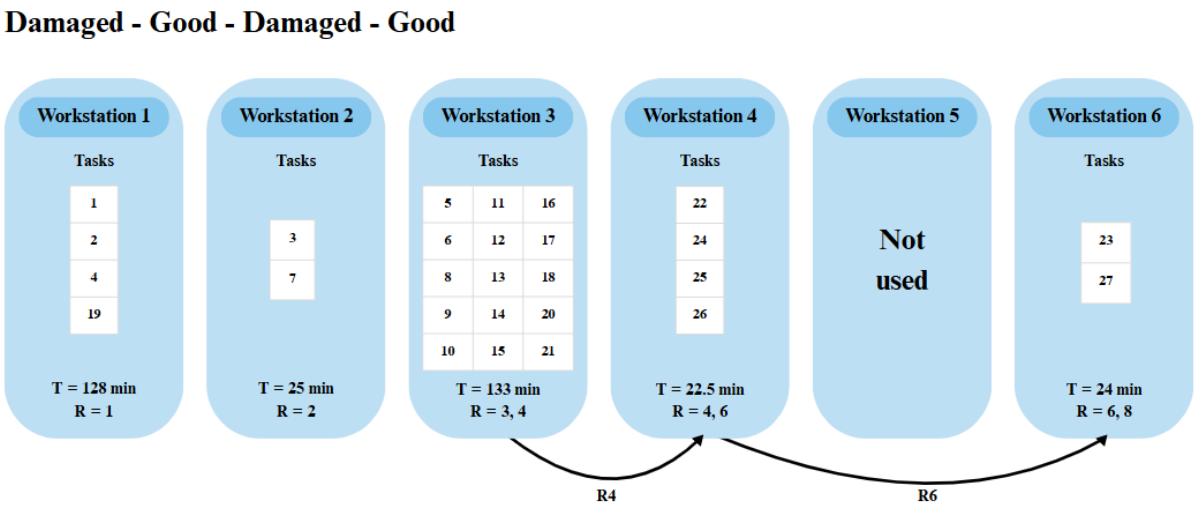


Figure 8 - Disassembly configuration for a low-efficiency instance (23% efficiency, 30% occupancy).

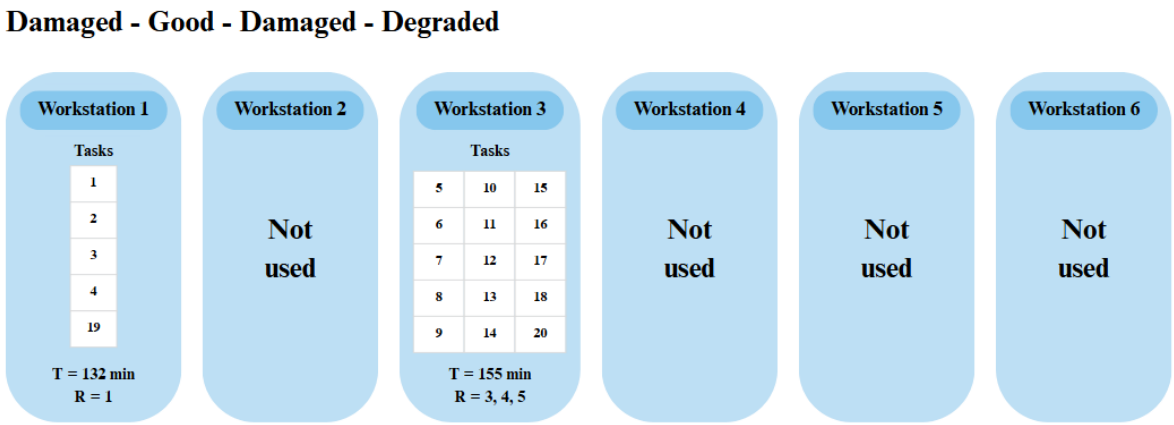


Figure 9 - Disassembly configuration for a high-efficiency instance (90% efficiency, 99% occupancy).

The low-efficiency configuration (efficiency: 23%, occupancy: 30%) results from a more complex or constrained EOL instance. It exhibits fragmented task distribution and lower station utilization, requiring more active stations and leading to longer idle times.

In contrast, the high-efficiency configuration (efficiency: 90%, occupancy: 99%) corresponds to a more favourable EOL state. The solution shows compact task grouping and effective use of both fixed and mobile resources, producing a balanced layout with minimal idle time and fewer active stations.

Although it was not possible to include additional visualizations for all instances, these examples highlight how the model adapts to product conditions and constraints, producing feasible yet diverse configurations.

Finally, while traditional scatter plots were considered for comparing workload balance, the heterogeneity across instances made it difficult to represent the data meaningfully in a single plot. As a result, a matrix-based visualization approach was adopted during analysis to retain detail and interpretability, though not reproduced here in full for clarity.

These results demonstrate that the model is capable of generating consistent and context-sensitive disassembly plans that reflect the complexity and variability inherent to EOL products. The next section explores the specific impact of mobile resources on performance across instances.

5.3 Benefits of the Use of Mobile Resources

To assess the impact of integrating mobile resources and dynamic allocation strategies into the disassembly line, a comparative analysis was conducted between two model configurations: one dynamic and one static. Both were tested on the same dataset of End-of-Life (EOL) product instances. The key difference between the two configurations lies in how physical resources were deployed across workstations.

In the dynamic configuration, mobile resources were allocated by the optimization model, considering task-resource compatibility, movement limits, setup and activation times, and station-level spatial constraints. Fixed resources, in both configurations, were assigned

sequentially to stations in advance. This dynamic allocation capability allowed the line to adapt more effectively to the task requirements of each product condition.

In contrast, the static configuration employed a fixed assignment strategy: all mobile resources were converted into fixed ones and assigned sequentially to stations. More specifically, resources were fixed one-to-one to workstations, following the station index order. The same mathematical model was used in both configurations, with the static version implemented by adjusting constraints to reflect the absence of resource mobility. Task-to-station assignments remained fully optimized in both cases, ensuring that the only degree of freedom was in how resources were allocated and moved.

This comparative analysis serves two complementary purposes. First, it provides a quantitative benchmark to assess the benefits introduced by resource mobility and flexibility. By isolating the variable of interest - resource allocation - it becomes possible to measure the added value of dynamic capabilities within otherwise identical task configurations. Second, the comparison reflects a real-world industrial scenario, where static layouts are still common due to their simplicity and predictability. Demonstrating the potential performance gains of dynamic layouts strengthens the case for more adaptive disassembly systems aligned with circular economy goals.

Table 5 presents the results for the static configuration, where resources were fixed and non-optimized. Compared to the dynamic setup, several differences emerged:

- The average number of workstations used increased from 3.41 to 4.77, representing a 39.86% rise. This suggests that the static layout required more physical space to accommodate the same task set, reducing layout efficiency - an issue also emphasized in the context of spatially constrained lines by Şahin and Kellegöz (2019) and Zhang et al. (2025);
- Efficiency improved significantly under the dynamic configuration, rising from 31.13% to 47.08% - a relative gain of 33.89%. This aligns with the findings of Zhu et al. (2020), who associate flexibility and mobile task assignment with higher throughput and smoother workload distribution;
- The occupancy rate increased from 35.89% to 54.78% in the dynamic setup, a 34.47% improvement. This indicates more deliberate use of space and resource capacity, instead of distributing low-effort tasks across multiple stations;

- The average cycle time increased slightly in the dynamic configuration (from 117.27 to 122.27 seconds). However, this reflects a known trade-off: the model utilizes the available cycle time more fully to reduce the number of stations and idle resources - a strategy similarly reported in flexible disassembly planning by Tu et al. (2020). Importantly, all cycle times remained within the predefined maximum, ensuring industrial feasibility.

Table 5 - Summary statistics of key performance indicators for static line configuration

	Average	Standard Deviation	Min	Max
Workstations Used	4.8	0.6	4	6
Cycle Time (min)	117.3	14.6	71	135
Efficiency (%)	31 %	7 %	19 %	45 %
Occupancy Rate (%)	36 %	7 %	22 %	50 %

To quantify these differences, Table 6 reports the relative percentage changes between static and dynamic configurations for the main performance indicators. These values are expressed with respect to the dynamic configuration as the baseline.

Table 6 - Relative differences between static and dynamic configurations, expressed as percentages with respect to the dynamic line.

	Average	Standard Deviation	Min	Max
Workstations Used	-40 %	39 %	-100 %	-20 %
Cycle Time	4 %	-64%	30 %	0 %
Efficiency (%)	34 %	62 %	20 %	50 %
Occupancy Rate (%)	35 %	61 %	27 %	50 %

The results suggest that resource mobility contributes meaningfully to operational efficiency. By allowing resources to be shared and reallocated as needed, the dynamic configuration supports more compact layouts, improved utilization, and greater adaptability to varying product conditions.

While static setups remain common in industry due to their simplicity, they struggle to cope with the inherent variability of EOL disassembly. As the literature suggests, disassembly environments benefit significantly from the ability to adapt resource usage to product state, especially when space, tools, and specialized labour are constrained (Özceylan et al., 2018; Industry 4.0 Review, 2023).

Because the task allocation remained constant across both experiments, the observed differences are directly attributable to the resource allocation method. This strengthens the argument that mobility is not merely a fine-tuning mechanism, but a core enabler of responsive, space-efficient, and sustainable disassembly planning.

5.4 EOL Clustering and Operational Implications

Another contribution of this thesis is the transformation of a highly detailed, instance-specific optimization model into a scalable decision-support system for industrial disassembly planning. While the model is capable of optimizing disassembly for any given End-of-Life (EOL) state individually, managing such a large number of distinct configurations (in this case, 81 states) would be operationally infeasible on the factory floor. Manually reconfiguring the line for every incoming product variant would result in excessive planning overhead, setup times, and disruption.

To address this, a data-driven clustering approach was introduced. By analysing the operational outcomes of all 81 individual EOL scenarios - such as the number of workstations used, idle time, cycle time, resource allocation, and movement statistics - it is possible to group similar scenarios into a smaller number of representative clusters. Each cluster groups together EOL states that exhibit similar performance profiles and resource demands when optimized by the model.

This allows production managers to treat entire groups of product conditions as one “type” when scheduling operations. Instead of adapting the line configuration for every EOL product received, they can define weekly or daily plans based on the expected distribution of clusters.

This clustering mechanism serves as a practical link between the detailed optimization results and the broader need for operational feasibility. While it does not replace the model’s instance-specific recommendations, it offers a complementary strategy to simplify planning and

improve applicability in real-world settings. The remainder of this section presents the clustering process, summarizes the characteristics of each group, and discusses how such segmentation can support short-term planning in disassembly operations.

5.4.1 Clustering Composition

To support the practical use of the optimization model in disassembly operations, a clustering analysis was conducted based on the outputs generated for all 81 EOL product instances. Rather than relying on predefined degradation categories, the clustering was performed on the model's operational results - capturing how the system behaves under each condition. This ensures that the grouping reflects not the physical state of the product directly, but the corresponding impact on task allocation, resource use, and system performance.

The K-means algorithm was applied to a set of operational indicators extracted from the model results, including metrics related to workstation usage, task distribution, mobile resource deployment, and spatial configuration. These indicators - described previously in Section 4.3 - were chosen to reflect the practical behaviour of the disassembly system under each EOL condition, rather than the physical degradation alone.

The number of clusters was defined using the Elbow Method, which indicated that four groups offered a good balance between descriptive accuracy and planning simplicity. The final distribution of instances was uneven, reflecting the diversity of degradation profiles:

- Cluster 1 included 29 instances
- Cluster 2 contained 27 instances
- Cluster 3 grouped 20 instances
- Cluster 0 concentrated the remaining 5 instances

This composition suggests that certain disassembly profiles are more prevalent than others, which has practical implications. For example, clusters with more instances may justify the development of standardized line configurations, while rarer cases may require more flexible or manual handling strategies. The next section provides a detailed analysis of each cluster and discusses how these patterns can be used to support disassembly line planning.

5.4.2 Cluster Analysis and Use in Line Balancing

The clustering process resulted in four distinct groups of EOL instances, each reflecting a typical system response in terms of resource usage, timing, and workstation configuration. This segmentation allows planners to replace instance-specific solutions with a reduced number of representative operational profiles, making the model more applicable in real industrial environments.

Table 7 summarizes the average performance indicators for each cluster, including efficiency, utilization rate, and number of active workstations. These figures illustrate clear differences between groups in terms of layout compactness, resource demand, and task consolidation.

Table 7 - Summary of key indicators and workstation usage per cluster

Cluster	Efficiency (%)	Utilization Rate (%)	Number of Active Workstations	Active Workstations *per* Cluster
0	25 %	31 %	4.0	2, 3, 4, 5
1	39 %	47 %	4.1	1, 3, 4, 6
2	66 %	74 %	2.0	1, 3
3	39 %	47 %	4.0	1, 3, 4, 5

Cluster 2 stands out as the most efficient group, using on average only two workstations (most commonly stations 1 and 3), and achieving high efficiency and utilization. These scenarios reflect relatively simple disassembly operations, where tasks are easily grouped and mobile resource usage is limited. Their compact layout makes them well suited for low-staffing periods or for scheduling alongside other parallel operations.

In contrast, Cluster 0 presents the lowest performance, despite requiring four workstations. It concentrates task execution in stations 2 to 5, with lower occupancy rates and efficiency, indicating fragmented or imbalanced workloads - likely caused by challenging precedence structures or degraded components. These scenarios should be addressed during full-staffing periods, and may benefit from pre-sorting or additional planning to mitigate inefficiencies.

Clusters 1 and 3 represent more moderate profiles, both requiring around four workstations, with similar performance levels. The difference lies in station allocation patterns: Cluster 1 relies more frequently on stations 1, 3, 4, and 6, while Cluster 3 avoids station 6 and uses 1, 3, 4, and 5. These subtle differences may reflect variations in task duration, precedence, or resource compatibility. Both clusters are suitable for standard shift planning, where moderate flexibility is available.

The ability to associate clusters not only with performance indicators but also with spatial configurations adds an extra layer of value for planning. It allows factory managers to anticipate which stations will be required under each configuration, helping to schedule maintenance, avoid station overlap, or reallocate unused space for secondary operations.

This segmentation thus simplifies daily or weekly planning. Rather than treating every EOL product as a unique case, products can be grouped by cluster and processed using a common line configuration. This not only reduces the planning burden but also enables resource reallocation, avoids redundant reconfiguration, and increases overall flexibility - especially important in environments where disassembly operations compete for shared tools, operators, or floor space.

Beyond simplification, clustering brings clear strategic benefits to disassembly operations. It enables production teams to establish a limited set of pre-tested line configurations that correspond to typical degradation profiles. These configurations can be reused across different planning cycles, reducing not only planning effort but also the likelihood of execution errors on the shop floor. Furthermore, by identifying low-complexity clusters in advance, managers can anticipate when stations and operators may become available, reallocating those resources to other value-adding tasks such as diagnostics, repair, or parallel disassembly lines. This approach transforms the model from a purely prescriptive tool into a repeatable operational strategy, enhancing responsiveness, space management, and workforce flexibility.

6. Conclusion and Future Work

This thesis addressed the challenge of planning disassembly operations for End-of-Life (EOL) products under realistic and variable conditions, with a focus on industrial applicability. In particular, the work proposed a mathematical optimization model that aims to minimize the number of active workstations required to disassemble a product, while accounting for condition-based task feasibility, precedence relations, processing times, spatial constraints, and the distinction between fixed and mobile resources.

The model was designed to be used at a tactical planning level, assuming that information about the condition of incoming products is available before execution. Rather than handling disassembly variability in an abstract or stochastic manner, the formulation takes a condition-specific approach - tailoring task assignment and resource allocation based on the degradation status of key components. In doing so, the model provides feasible and adaptive plans that are better aligned with the heterogeneous nature of EOL flows.

To evaluate its performance, the model was applied across a wide range of input configurations, each representing different degradation combinations. The results showed that incorporating mobile resources can significantly improve layout compactness, increase task consolidation, and reduce idle time when compared to a static configuration with fixed resources only. These gains were achieved while respecting practical operational limits such as setup and activation times, cycle time bounds, spatial availability, and movement constraints. The consistent convergence times and quality of the solutions obtained suggest that the model is computationally tractable and potentially suitable for industrial integration.

Recognizing, however, that treating each product condition as a distinct planning problem may not be scalable in real production environments, this work also proposed a complementary clustering-based approach. By grouping similar instances based on their optimization outputs - rather than solely on physical degradation - a reduced number of representative profiles was identified. These clusters capture typical system responses and can be used to define a small set of pre-planned line configurations. This enables more agile and predictable scheduling, supports better allocation of mobile tools and operator effort, and helps reduce the operational burden associated with constant reconfiguration. In particular, the ability to distinguish low-complexity groups from high-demand ones creates new opportunities for more intelligent shift planning, resource reuse, and space optimization in highly variable disassembly environments.

Nonetheless, this work is not without limitations. The dataset used to implement and test the model was derived from a case study originally designed for static disassembly planning and had to be extended through several assumptions. These included the classification of resources as fixed or mobile, estimates for activation times and spatial occupation, and the definition of degradation profiles. While these additions were grounded in industrial literature and logical reasoning, they were not validated against real-world operational data. Furthermore, the implementation was limited to a single product type, and the solutions were generated in a batch mode rather than through integration with real-time data streams.

In light of these constraints, several directions for future research emerge. First, the model could be extended to handle multi-product environments and shared-resource settings. This would improve its scalability and relevance in factories where diverse EOL products are disassembled in parallel. Second, more advanced modelling of mobile resource behaviour could be introduced - capturing routing complexity, congestion effects, or interaction between mobile agents. This would further enhance the realism of the planning logic and its responsiveness to dynamic shop-floor conditions.

Third, the integration with real-time condition monitoring systems - such as digital twins, computer vision, or sensor networks - would enable the model to move from pre-emptive to reactive or semi-dynamic planning. Instead of relying on predefined degradation profiles, line configurations could be adapted continuously based on incoming diagnostic data, potentially through rolling horizon optimization or hybrid online-offline strategies.

Additionally, future research could incorporate sustainability-oriented objectives into the optimization model. Rather than minimizing only the number of workstations or idle time, the objective function could be expanded to include environmental or economic criteria - such as energy consumption, emissions, or recovery value. This would link operational planning directly to the broader goals of the circular economy.

Finally, a key next step would involve testing the model in an industrial pilot environment. Such a validation would provide empirical insight into the model’s practicality, identify potential gaps between planning logic and execution constraints, and allow for the calibration of key parameters based on real data.

In conclusion, this thesis contributes a flexible and operationally grounded framework for disassembly line balancing under EOL variability. By integrating condition-driven

planning, spatial constraints, mobile resource allocation, and clustering-based simplification, the approach bridges the gap between mathematical rigour and factory-floor feasibility. While there remain avenues for extension and validation, the work presented here offers a solid foundation for more adaptive, scalable, and sustainable disassembly planning systems aligned with the demands of circular production.

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UN Sustainable Development Goals

The United Nations Sustainable Development Goals (SDGs) represent a global framework for fostering sustainable development across social, environmental, and economic dimensions. This dissertation, focused on the dynamic disassembly line balancing of end-of-life (EoL) home appliances, supports multiple SDGs through the promotion of circular economy principles, resource efficiency, and technological innovation. In particular, it aligns most directly with SDG 7 – Affordable and Clean Energy and SDG 9 – Industry, Innovation and Infrastructure.

SDG 7 – Affordable and Clean Energy calls for ensuring universal access to modern, reliable and sustainable energy. While the core of this dissertation is not centred on energy generation, it contributes significantly to energy-related goals by enhancing the efficiency of disassembly systems. The optimization model developed minimizes the number of active workstations required, thereby reducing energy consumption per unit processed. Furthermore, by adapting operations to the actual condition of each product, unnecessary energy-intensive tasks are avoided. This supports the broader aim of reducing the energy intensity of industrial processes. In the context of circular supply chains, the selective recovery of components from appliances may also enable the reuse of parts within renewable energy systems, indirectly supporting clean energy availability and system longevity.

SDG 9 – Industry, Innovation and Infrastructure emphasizes the importance of building resilient infrastructure, fostering inclusive and sustainable industrialization, and promoting innovation. This dissertation contributes directly to this goal by developing a condition-aware, optimization-based decision support tool capable of dynamically adapting disassembly operations. The integration of mobile resources, task-condition mapping, and space-aware planning reflects a shift toward more intelligent and responsive industrial systems. The methodology builds upon modern principles of flexible manufacturing and supports the digital transformation of reverse logistics processes, particularly relevant for industries dealing with high product variability and end-of-life uncertainties. By doing so, it reinforces the innovation potential of sustainable production systems and supports the development of infrastructure that is both efficient and adaptable.