Critical raw materials in telecommunication products: current circular practices and future strategies

Master Thesis in collaboration with a Dutch telecom company

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kpn

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by

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For the Master's programme of Industrial Ecology
at the University of Leiden and
Delft University of Technology.

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Cover photo: Cm-sized pyrochlore rare earth ore, Sarfartoq, West Greenland. Photo credit: M.T. Hutchison 2007

Executive Summary

Most electronic devices depend on Critical Raw Materials (CRMs) to be produced or repaired. As such, this increasing dependency represents an emerging threat to the resilience of modern technological systems; without these materials, essential devices such as servers and modems could become inaccessible. Most CRMs lack short-term substitutes and are often sourced from regions with low levels of governance or complex geopolitical relationships with the European Union (EU). In addition to supply risks, the primary production of CRMs is associated with environmental impacts such as resource depletion, acidification, biodiversity and greenhouse gas emissions. These dynamics emphasize the need for innovative solutions that reduce dependency on primary materials, for which a suggested approach is increased circularity.

Therefore, this study addresses the dependency on primary CRMs by exploring strategies to reduce or slow primary material inflow through circular practices, focusing on the end-of-life (EoL) stage of consumer telecommunication products. This is done through static (bookkeeping) and dynamic Material Flow Analysis (MFA), applied within the Dutch context and in collaboration with telecom provider KPN.

KPN currently applies circular measures, such as product reuse and recycling, to some of its distributed devices. However, a comprehensive overview of CRM quantities within product flows, as well as a structured outlook for future CRM circularity, were not yet developed. Consequently, this study addresses this gap by providing insights in applied CRM circularity practices and future strategies, based on one of KPN's most distributed products. The outcome offers pragmatic insights for KPN to slow primary CRM demand, aligning with the EU Critical Raw Materials Act and the company's own sustainability objectives to achieve net-zero emissions in the value chain by 2040.

Of the circular practices applied to an internet modem as use case, reuse shows the highest potential: compared to the total primary production and transport, the total emission reduction through reuse could amount to roughly 0.814% of emissions in the Dutch communications sector over the y to y+14 period. From a materials perspective, this research identified fifteen CRMs in the product under study. For these materials, reuse and recycling could prevent the need for 624 kg of CRMs on the printed circuit board. Including aluminium from the heatsink, material savings increase to a total of 241 tonnes, which equates to a Global Warming Potential (GWP) impact score prevention of up to 83.5% over the device's total material production. Herein, mainly recycling has some limitations as KPN only applies open-loop recycling to a limited set of CRMs.

Furthermore, the study evaluates the potential of future circular strategies, such as improved waste management, product lifetime extension, and increased CRM recycling. These scenarios suggest that additional material savings could reach up to 10.7 tonnes, with an additional GWP impact score prevention of around 3.89%. Increasing total GWP prevention from 83.5% to 87.4%.

However, as this study uses a single product as use case, scaling this study's approach across a broader range of telecommunication or other similar products is recommended to confirm whether substantial company- or sector-wide impact can be identified. In addition, this study recommends to also explore further possibilities to increase circularity; such as advancing on the R-ladder through refusing, rethinking and reducing the use of CRMs and critically assess how EU recycling targets could still be met within the limited remaining time.

Finally, this study contributes to the scientific debate by exploring the underexamined area of CRM flows in telecom equipment through circular strategies. By taking an industrial ecology (IE) perspective, it applies a systems approach to position KPN's supply chain within its wider environmental context, offering both practical implications and theoretical insights.

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Contents

List of Abbreviations

General Abbreviations

CRMA	Critical Raw Materials Act
CRM	Critical Raw Material
EC	European Commission
EI	Economic Importance
EoL	End-of-Life
EoL-RIR	End-of-Life Recycling Input Rate
ER	Energy Recovery
EU	European Union
GWP	Global Warming Potential
IE	Industrial Ecology
ILCD	International Life Cycle Data System
IT	Information Technology
IV	Impact Variable
CO_2-eq	CO_2-equivalent
LCM	Life Cycle Management
LCIA	Life Cycle Impact Assessment
LCA	Life Cycle Assessment
LF	Land Fill
MCS	Monte Carlo Simulation
MFA	Material Flow Analysis
MR	Material Recovery
PCB	Printed Circuit Board
PM	Precious Metal
SFA	Substance Flow Analysis
SR	Supply Risk
WEEE	Waste Electrical and Electronic Equipment

Relevant Periodic Element Abbreviations

Ba	Barium
Be	Beryllium
Bi	Bismuth
B	Boron
Ce	Cerium
Co	Cobalt
Ga	Gallium
In	Indium
Mg	Magnesium
Pd	Palladium
P	Phosphorus
Rh	Rhodium
Ru	Ruthenium
Sb	Antimony
Si	Silicon
W	Tungsten

List of Tables

Appendix Tables

List of Figures

Appendix Figures

1 Introduction and Research Objective

Modern technology is deeply embedded in today's society, powering everything from individual devices to complex organizational systems (Naikoo et al., 2018). Organizations and individuals alike rely heavily on technological devices, such as computers, servers, and modems, for critical operations. Ranging from management of essential infrastructure to a growing reliance on communication technologies, which accelerated substantially during the COVID-19 pandemic (Lukings and Habibi Lashkari, 2021; Neuby, 2016). Yet this dependency rests on the assumption that technology will remain readily available, introducing significant risks when key technological components are disrupted. Ivanov et al. (2018, pp. 8) identified several main supply chain vulnerabilities: single sourcing, low risk-mitigation inventory, capacity overuse, insufficient safety technologies, and missing contingency plans. A product group which is argued as subject to most of these factors and stands out as vital in modern information technologies (IT) is Critical Raw Materials (CRMs).

CRMs are defined by the European Union (EU) as "those raw materials that are economically and strategically important for the European economy but have a high-risk associated with their supply" (Ferro and Bonollo, 2019b, pp. 1). Besides this overarching definition, CRMs are described as materials used in sectors vital for economic growth and development such as sustainable and consumer technology, health and aviation sectors (Ferro and Bonollo, 2019b). However, these materials, vital for the production, repair, and replacement of hardware, are predominantly sourced from politically unstable regions or areas with low levels of governance such as China (Kalantzakos, 2020). This creates supply chain vulnerabilities, intensified by geopolitical tensions and trade restrictions (Girtan et al., 2021). In addition to supply shortages, the reliance on CRMs poses a secondary threat: the environmental impact of primary production, which often involves high greenhouse gas emissions, acidification and resource depletion (Jo and Myung, 2019).

As a result, the problem statement of this study relates to the current dependency of Europe, and specifically the Netherlands, on primary CRM inflows for the functioning of essential hardware within its society. While previous research has explored CRM supply chains and recycling technologies, the End-of-Life (EoL) stage of telecom equipment remains underexplored. This research aims to fill that gap by assessing CRM flows and proposing mitigation strategies to enhance circularity and reduce environmental impacts from the perspective of the Dutch telecom provider KPN.

From a societal perspective, ensuring a stable supply of CRMs is essential for economic resilience and technological advancement. Especially for the Netherlands, which relies on advanced technological systems to support its large service sector and network readiness, ensuring a stable CRM supply is critical (Baller et al., 2016). Scientifically, this study contributes to the underexplored topic of circular CRM strategies in telecom equipment and adds to literature by exploring the potential of reuse as described by Cooper and Gutowski (2017). Also, this study contributes to the field of industrial ecology (IE), by applying static and dynamic Material Flow Analysis (MFA) as typical IE tools and through offering pragmatic solutions for KPN to slow CRM demand, aiming to reduce environmental impacts and improve sustainability in the telecom sector (Graedel, 2019).

To address the problem statement, and derive strategies for mitigating CRM dependency in the context of the Dutch telecom sector, KPN provided insights into their EoL supply chain. MFA is a method designed to map material flows and identify opportunities for intervention, was applied as the main research method (Laner and Rechberger, 2016). As the research combined static (bookkeeping) and dynamic MFA, it provides insights through both a systemic overview of CRM flows and the temporal effect under different circular strategies, such as reuse, recycling and life time extension. The overarching goal is to support KPN in aligning with the EU Critical Raw Materials Act (CRMA) and achieving its own sustainability objectives.

1.1 Context of Critical Raw Materials

CRMs receive extensive attention in scientific literature, official reports, and databases; a reflection of their economic and geopolitical importance that pushes countries worldwide to evaluate their positions and dependencies (Girtan et al., 2021). This focus has led to the development of a wide range of methodological approaches to assess material criticality, which in turn further increases national engagement with the topic.

Schrijvers et al. (2020) examined 42 criticality assessment methods, analyzing both their unique and overlapping characteristics. The methods range from assessments at the product, technology, or company level to those at the country, regional, or global scale. The indicators found, were witnessed to differentiate between geological, environmental, technological, geopolitical, and social factors, while their temporal frames vary from a few years to several decades.

However, with these differences between methodologies in mind, Schrijvers et al. (2020) defined a common denominator: most based their core principle on the United States National Research Council's approach to criticality. This approach is based on two parameters, one for supply risk and the other for the impact of supply restrictions, as illustrated in Figure 1.

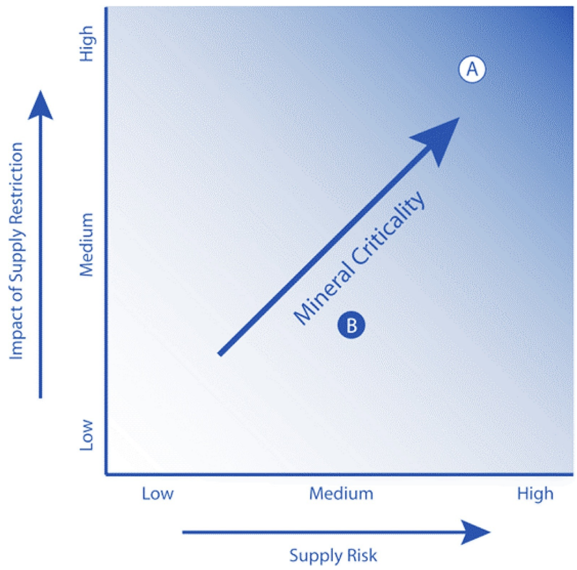


Figure 1: Graphical representation of the US National Research Council's approach to criticality. *Note: point A indicates a material with a higher criticality score than the material in point B. Source: National Research Council (2008).*

1.1.1 Critical raw materials from the EU and KPN's perspective

For this study, the EU perspective serves as a contextual framework, given that KPN, the Dutch telecom company central to this research, aligns its operational goals with EU legislation and forecasts (KPN, 2024a). Which materials are included in the EU list of CRMs is re-evaluated every three years by the European Commission (EC). This evaluation is based on two main indicators: economic importance (EI) and supply risk (SR). EI relates to the impact of supply restrictions by Schrijvers et al. (2020), reflecting whether these materials are essential for products critical to the EU market. SR encompasses factors such as EU mining capacities, governance quality in exporting regions, and recycling or substitution potential (Domaracka et al., 2022; Schrijvers et al., 2020).

Figure 2 illustrates the overall structure of the EU criticality methodology. Herein several factors, such as global supply, recycling and potential substitutes all influence the two main parameters of EI and SR.

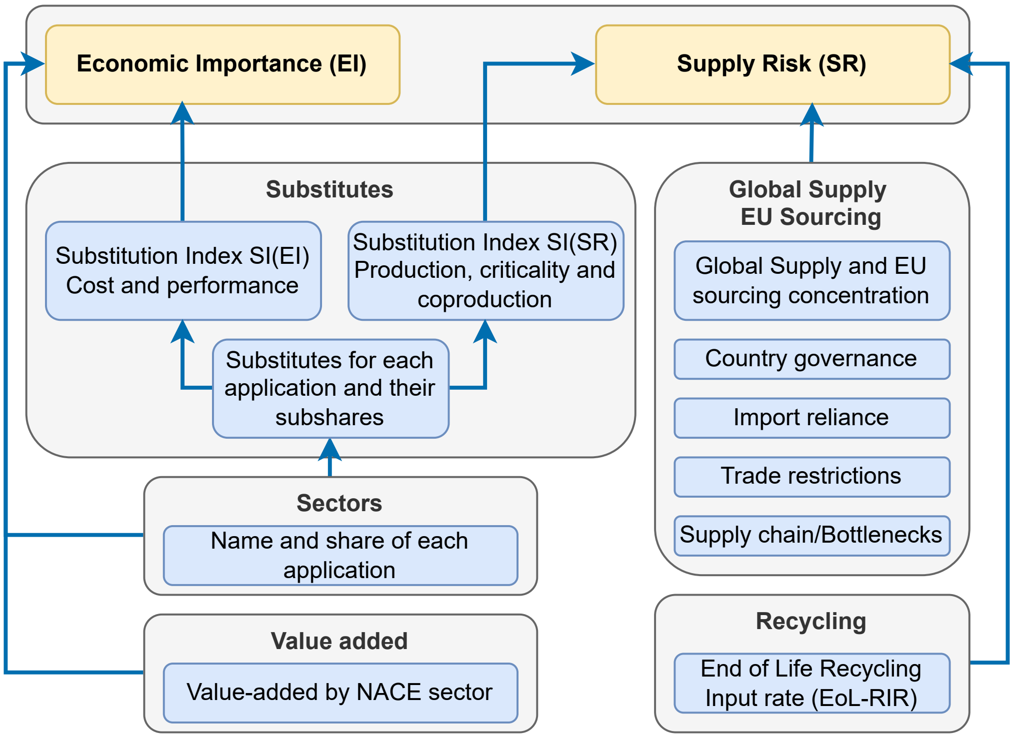


Figure 2: Overall structure of the EU criticality methodology. *Based on: Grohol and Veeh (2023).*

As discussed in the introduction, modern society is becoming increasingly dependent on the availability of CRMs (Ferro and Bonollo, 2019b). As a result, strategies are discussed in literature which aim to mitigate supply dependencies and provide a relieve. One of these solutions, discussed by Månberger (2023), is the 'circular economy' strategy; when applied to CRMs this strategy aims to reduce or slow primary material inflows, following three core principles:

1. *Closing the loop:* Enhancing recycling to keep CRMs within a circular system, reducing the reliance on primary materials.
2. *Narrowing the loop:* Decreasing CRM usage by innovating designs that require fewer materials or limiting the production of CRM-intensive goods.
3. *Slowing the loop:* Prolonging the lifespan of products containing CRMs through repair and reuse to reduce demand for new materials.

While promising, these approaches are not complete solutions. Even in optimal scenarios, recycling efficiencies and other practical limitations necessitate some level of primary material input (Månberger, 2023). Hool et al. (2024) outlined other incentives to reduce the uncertainty around CRM supplies within the EU under the CRMA, emphasizing the importance of capacity building through strategic projects and advanced risk monitoring (European Union, 2024). Alternatively, Hofmann et al. (2018) introduced a perspective from the material science community, emphasizing how material scientists and engineers often ignore material criticality, as CRM thinking is mainly contained within the environmental-, chemistry- and resource management sciences.

KPN identified the issues around CRMs and overall material criticality in their annual report (KPN, 2024b). Defining scarcity of (critical) raw materials as a potential factor for increased service and production costs which could affect their market position. Herein the key risks are identified in network and customer equipment due to the concentration of CRM production in certain countries. KPN indicated they wish to reduce this risk through circular incentives and environmental perspectives such as designing for reduced CRM use, extended product lifetimes and increased reuse and recycling.

1.1.2 Specific approaches to critical raw materials

The literature discussed above mainly outlines overarching mitigation methods. These broader methods have functioned as a base for more practical approaches. This section narrows down on possible mitigation methods to address CRM dependency and promote circularity in the context of KPN.

One such method is reuse, which extends product lifespans by reconditioning CRM-intensive equipment like servers and other IT-equipment (Bashroush et al., 2020). KPN already makes use of this strategy to some extent, reusing certain products within its supply chain. Therefore, elaborating on such strategies, with a specific focus on CRMs, could further slow down the need for primary material inputs and reduce operational costs while also positively impacting sustainability (Cooper and Gutowski, 2017). However, successful implementation requires restructured logistics and consumer acceptance (Patwa et al., 2020).

Another approach is mechanical recycling, which recovers CRMs from EoL electronics such as printed circuit boards (PCBs) and telecom hardware. Işıldar et al. (2018) described CRM recovery from Waste Electrical and Electronic Equipment (WEEE), defining advancements in separating metals from polymetallic products as crucial for improving circularity. However, this process faces challenges with material purity and efficiency, especially for complex equipment (Vermeșan et al., 2019). More sustainable alternatives were also investigated, such as hydrometallurgy and bioleaching, but their scalability for complex telecom equipment remains limited (Auerbach et al., 2019; Işıldar et al., 2019).

Material substitution is also described as a solution. As material efficiency advances, shifting to materials which are less critical, could reduce CRM uptake (Månberger, 2023). Ferro and Bonollo (2019a) added to this approach by emphasizing CRM reduction at the design stage. They argue that product design, targeting to increase End-of-Life Recycling Input Rates (EoL-RIR) – the proportion of secondary materials from EoL scrap in total input – can significantly enhance circularity and reduce CRM dependency. While theoretically promising, material substitution often involves loss in quality and performance, making them challenging to apply universally. Additionally, materials that could function as substitutes are often critical as well (Tkaczyk et al., 2018).

1.1.3 Methodological approaches to critical raw materials and reuse

Building on the literature, this study adopts methods to assess CRMs in EoL products. Life Cycle Assessment (LCA) and MFA are highlighted by Withanage and Habib (2021) as underused yet valuable tools for WEEE information management. They emphasize the potential of cradle-to-gate and cradle-to-grave studies to improve CRM flow insights while addressing data limitations to reduce assumptions.

Islam and Huda (2019) similarly recommended MFA as an effective approach to trace material flows within systems, especially for CRM-containing WEEE. While challenges such as data quality and availability are a common issue, they emphasized MFA's value in guiding material flows and point out existing research as a foundation for further exploration.

One such study, by Ueberschaar et al. (2017), focused on challenges in CRM recovery from WEEE. Through the application of MFA, their findings showed promise for thermal treatment and manual separation in chip recycling but also highlighted the limitations of current technologies for complex materials, stressing the need for continued innovation in CRM recovery methods.

As these innovations would likely take time to become available, Cooper and Gutowski (2017) studied the environmental impacts of reuse. They found repair and reuse to almost always be less energy intensive than new production. However, products and supply chains must be suited for this process and reused products can only result in net-environmental benefits when they displace otherwise newly produced products.

1.1.4 Conceptual framework of MFA

MFA serves as an environmental decision-support tool, mapping material flows and stocks within systems (Laner and Rechberger, 2016). To effectively design and communicate an MFA model, a clear understanding of key concepts is provided, as described by Laner and Rechberger (2016):

Materials, substances, and goods: MFA focusses on materials or substances; i.e. Substance Flow Analysis (SFA), examining their behaviour within a system. Materials and substances each represent a single unit. Goods, however, often include multiple materials or substances and typically carry economic value (potentially negative when goods are defined as waste).

Flows, processes, and stocks: MFA models how materials, substances, and goods move through a system. Processes perform actions such as transport, transformation, or storage. Flows connect these processes and transfer materials from one to another. Stocks emerge when in- and outflows differ, causing accumulations or reductions. Transfer coefficients determine in- and outflows.

System and system boundaries: The system consists of specified flows, processes, and materials, aligned with the research objectives. An open system permits indirect inputs and outputs (e.g., energy use), whereas a closed system includes only explicitly defined interactions.

1.2 Research Gap, Objective & Research Question

1.2.1 Research gap

Telecom devices, which are widely used and indispensable across Dutch society, often contain CRMs. However, detailed quantification, recycling, reuse or reduction strategies for CRM contents in this context remain insufficiently explored. Although, KPN already applies circular strategies from a practical standpoint (e.g. reuse and recycling), a clear overview of CRM reduction through these actions is missing. Since insights into this topic could strengthen production chain resilience and lower environmental impacts tied to primary CRM production (Jo and Myung, 2019), this study aims to fill this gap by providing an overview of circular approaches to KPN's CRM flows.

This gap poses a challenge for KPN to critically assess its current position and decide on improvement strategies, especially since they strive for reduced CRM use and net-zero emissions in the value chain by 2040 (KPN, 2024b). To aid in this goal, this study provides insights into KPN's current position regarding CRM circularity, while also assessing the impact of future strategies such as increased recycling and product lifetime extension.

From a scientific perspective, the MFA method has been recognized as promising for understanding WEEE flows (Withanage and Habib, 2021), however, its application to assess the circularity of CRM flows in telecom equipment remains limited. This study narrows down on this gap, applying and improving MFA models, to map- and potentially slow down primary CRM inflows. Additionally, by focusing on telecom equipment and combining MFA insights with future strategies, this study contributes to knowledge on improving circularity and reducing environmental impact in general, as well as specifically through reuse as described by Cooper and Gutowski (2017).

1.2.2 Research objective

In practical context, the research objective is to provide KPN with a well-documented overview of CRM quantities in current EoL product flows and, if present, where these flows follow circular practices. Aiming to provide clarity on KPN's current position in terms of circularity and thus opening up the possibility for future improvements and future directories to reach net-zero emissions (e.g. increased reuse, recycling or novel approaches).

From a scientific viewpoint, through applying MFA, the objective of this study is to provide novel scientific insights in the context of slowing down CRM demand for essential telecom equipment while simultaneously lowering the upstream environmental impacts associated with primary material extraction and production.

1.2.3 The industrial ecology perspective

The field of IE adopts a multidisciplinary systems-based approach in which environmental, technical, and social dimensions are viewed as interconnected and mutually influential. Rather than treating industrial systems as isolated operations, IE positions them within the broader dynamics of natural systems (den Hond, 2000). In line with this methodology, the principles of IE are embedded in this study's research objective.

Through a technical assessment of the system, the research aims to deepen the understanding of critical material flows and identify any existing circular practices. This understanding forms the basis for discussing future-oriented strategies to enhance CRM circularity. From an IE perspective, the overarching objective is to mitigate environmental impacts by reducing reliance on primary material extraction and to decrease societal risks by strengthening material security and reducing indirect environmental consequences.

1.2.4 Main research question and sub-research questions

To achieve the research objective, this study follows the main research question: *"To what extent can circular practices, regarding CRMs in KPN's products, be identified and potentially further developed to slow primary CRM demand?"*. With this question the aim is to assess if KPN already applies circular practices in the context of CRMs to some extent and which role these play in their EoL logistics. Additionally, this question seeks to answer whether there is room to initiate or further develop circular practices in the context of EoL CRM flows for KPN. The main research question is designed to provide a framework for the study and is supported by three sub-research questions:

1. *How is KPN's most supplied product currently characterized in terms of criticality, material recovery and environmental impacts?*
2. *To what extent are KPN's current CRM flows circular, based on static MFA modelling output?*
3. *Which future oriented strategy shows the highest potential to slow primary CRM demand, based on dynamic MFA modelling output?*

Herein the first subquestion aims to select a specific product or a set of products, providing a use case which can be researched within this study's timeframe. The second subquestion elaborates on this use case to gain accurate insights into KPN's EoL material flows and circular practices. The third subquestion extends this view into the future to assess the effect of different circular scenarios.

1.3 Outline and Reading Guide

To address the research and sub-research questions outlined above, this document is structured as follows: Chapter 2 summarizes the methodology and offers a reproducible framework for addressing each sub-question. Since each of the three subquestions follows a different methodological approach, these chapters also begin with a more in-depth overview of that chapter's specific methodology.

Chapter 3 focuses on the first sub-question, introducing Product A as a use case and providing a characterization of this device in terms of criticality and environmental impact. Chapter 4 introduces the static, bookkeeping MFA model to evaluate the product and material flows within the system and to identify existing circular practices. Chapter 5 builds on these results by presenting the dynamic MFA model, which examines product and material flows over time and serves as the basis for scenario analysis. Chapter 6 interprets the findings and explores their broader implications from KPN's perspective as well as within the context of external factors. Finally, Chapter 7 offers the overall discussion, conclusions, recommendations, and a reflection on the applied methodology.

2 Research Approach and Methods

2.1 Application of Methods and Data Requirements

To provide a reproducible framework, this chapter provides an outline of the applied methods, data requirements, and expected outputs. Due to the application of three different methods, this chapter first provides a concise overview of the methodology per subquestion. In the beginning of chapter 3, 4 and 5 the respective methodology's application is further specified to provide an orderly structure. Since a modelling approach is used in Chapter 5, this methodological framework also includes a section on the modelling concept and scenario development.

A central principle throughout this study's methodology is the assumption of *ceteris paribus*; the assumption that all variables outside the defined methodological and modelling boundaries remain constant (Schurz, 2014). This assumption is applied due to the highly dynamic geopolitical context surrounding CRMs, allowing for focused analysis within a controlled system scope (Schicho and Espinoza, 2024).

2.1.1 Methodological Overview

Subquestion 1: *How is KPN's most supplied product currently characterized in terms of criticality, material recovery and environmental impacts?*

The first subquestion aimed to narrow down the broad range of products offered by KPN. The intended output was a single product, or a selected group of products, with the highest CRM uptake. To maximise impact regarding CRM use and circularity, the ideal approach would have been to assess CRM quantities per product and link this to the number of units supplied, allowing identification of the most impactful products. Data requirements included detailed CRM composition per product and information on the quantity of products distributed to customers.

However, due to data limitations, from KPN's suppliers as well as literature on CRMs in electronics, this approach was adjusted. Instead, the method was based on identifying the most frequently used or supplied products containing a PCB, with the underlying idea that most CRMs in IT hardware are located on the PCB (Srivastava et al., 2020). Therefore, selecting the most distributed PCB-containing product provided an impactful context in the context of CRM use.

The next step was product characterisation, which involved breaking the product down into relevant components and properties. As this study focused exclusively on CRMs, detailed data on CRM content was essential. Moreover, since such data could only be obtained for one product that met the selection criteria, the analysis continued with a single use case. For this product, a detailed CRM report was available and compared to scientific literature to further describe the included materials. To provide context on total CRM uptake, CRM quantities were multiplied by the total number of devices procured by KPN.

Subsequent steps included characterising the selected CRMs in terms of criticality, requiring data on each material's EI and SR, and in terms of their EoL-RIR, using the rates defined by the EC in Grohol and Veeh (2023). Finally, the environmental impact for the impact category of climate change was assessed. This assessment was conducted per material by using KPN figures and each CRM's Global Warming Potential (GWP) for primary extraction, expressed in kg CO_2-equivalent (kg CO_2-eq). This study used the Ecoinvent 9.3 cut-off database and the CML v4.8 2016 Life Cycle Impact Assessment (LCIA) method.

Subquestion 2: ***To what extent are KPN's current CRM flows circular, based on static MFA modelling output?***

The second subquestion's objective was to identify which materials are most critical for KPN and to what extent circular practices in EoL CRM flows could be detected. The primary method was static, bookkeeping MFA in STAN software. The output was a model that traces CRMs from the point they enter the system until their EoL, including reuse, repair, recycling, and other stages. Reuse and repair were identified as the main focus at this stage, as these are the strategies KPN actively applies to retain products within its supply chain. Other strategies, such as recycling, are also implemented, but they typically take place further downstream in the supply chain and are less directly influenced by KPN's operational control.

Designing the model began with defining the goal and scope, including which materials and system boundaries to consider. Data collection and model development followed an iterative process. Several data requirements were already fulfilled by the first subquestion, particularly on CRM quantities, which are essential to the model. Additional data was required on system flow quantities, transfer coefficients, and stock accumulations. Specifically, these were inputs such as yearly primary inflow, collected and recovered products, repair volumes, and the rates of recycling, energy recovery, and landfill for both industrial and municipal waste streams.

Two model types were developed: one MFA model that traced the full CRM set (excluding aluminium due to its abundance), and a set of SFA models that tracked flow quantities per individual CRM. To construct the models, an initial overview of the EoL process was provided by KPN's EoL manager. This was restructured into a detailed flowchart, from which key flows and processes were selected for inclusion in the final MFA and SFA models.

To validate the MFA model and assess uncertainty, the stepwise procedure by Laner et al. (2014) was applied. This was not repeated for the SFA models, as they use identical transfer coefficients and are therefore assumed to share the same uncertainty. To calculate these uncertainties standard deviations for uncertain values were used. A second validation measure involved informal discussions with experts from KPN and EoL manager A. Their insights were used to evaluate both the model structure and its output in relation to real-world conditions.

Subquestion 3: ***Which future oriented strategy shows the highest potential to slow primary CRM demand, based on dynamic MFA modelling output?***

Lastly, the third subquestion aimed to gain insights into KPN's CRM flows and the effect of circular strategies over time. Through modelling with dynamic MFA in Python, this produced a prospective baseline scenario. With this baseline in place, the effect of future scenarios was evaluated. Data requirements from the previous two subquestions remained relevant, as the model depends on CRM quantities and transfer coefficients to determine flows to reuse, recycling, and waste management. Two additional inputs were required: yearly stock data for the product under study and the survival curve as defined by European Commission (2024a).

Using this information, this study utilized the dynamic MFA approach, initially outlined by D. B. Müller (2005). For this study an adjusted modelling formula, which included a discrete yearly dimension and explicit inflows as described by Fishman (2023), was applied. This formula enabled the calculation and visualization of yearly cohorts. At this stage, the model operated on the product level; the material context was incorporated in a later step.

The following steps, defined elaborations to the base formula, resolving some of its limitations by embedding more variables and the possibility to directly connect environmental impact calculations. To begin, reuse was included as a parameter, which calculates the amount of primary inflow that can be substituted by reused products based on a predefined rate. The number of products that cannot be reused and thus flow to either industrial or municipal waste processes, including recycling, energy recovery, or landfill, were also calculated. Finally, two impact variables were introduced to quantify material and GWP impact. This was done by multiplying the reused or recycled quantities by the material content per device or the GWP per material in kg CO_2-eq.

This methodology resulted in a baseline scenario designed to project the inflows and outflows of a device over time, along with the corresponding material and GWP impacts. This model was then used to assess various scenarios by embedding the model in a Python function, allowing multiple parameter adjustments to be ran simultaneously and produce comparable scenario outputs. To validate the model and quantify uncertainty, the stepwise procedure by Laner et al. (2014) and informal expert interviews with KPN were also applied to the dynamic MFA.

2.1.2 Methodology on recycling, repairing and reuse impact

This study identifies three indicators for circularity in KPN's EoL flows: repair, recycling and reuse. Herein recycling is defined as processes which displace expected primary material inflows and the burdens associated with their primary production. Overall, recycling processes have lower impacts than those for primary production, however, when compared through a life cycle or systems perspective, some deviations could occur (Gheewala, 2024). The use of alloying materials, logistics or economy-wide effects could create instances where primary production shows lower overall impacts. In the context of Product A, open-loop recycling is applied to aluminium and some CRMs; therefore this strategy contributes to overall material retention but not for KPN specifically as it is uncertain where these downstream flows are applied in secondary processes.

Repairing is defined as producers retrieving used products and, through minimal interventions, restoring them to their original state (Lindkvist Haziri and Sundin, 2020). For KPN this practice is applied to product A if the device's lifetime can be increased through cost-efficient repairs.

Lastly, the process of reintegrating products into the supply chain without repairs is defined as reuse in the context of this study; this is the main process of KPN's EoL manager (Gharfalkar et al., 2016). In this process the products' data is removed, they are cleaned and if no further repairs are required they are reused. If necessary, the devices are directed to repair, as listed above, or become waste. Moreover, this study defines the impact of reuse in line with Cooper and Gutowski (2017), who found that reuse mostly provides net environmental benefits when it displaces a newly produced alternative. In such cases, savings depend on whether the reused product would otherwise have been sent for waste treatment or recycling:

- *If destined for waste treatment:* reuse avoids the impacts of primary production.
- *If destined for recycling:* reuse avoids the impacts of secondary production, although material retention is partial due to recycling inefficiencies.

This study applied this distinction by assigning primary CRM savings to each reuse iteration, as reused products displace new production. All in all, these three strategies reflect three of the nine R's on the R-ladder as defined by Potting et al. (2017). On this ladder, ranging from EoL strategies descriptive of a linear economy to circular economy, reuse is rated as R3, repairing as R4 and recycling as R8. R9 for recovery is also identified for Product A's waste streams which is defined as the least circular strategy on the R-ladder. The three most circular R's are refuse (R0), rethink (R1) and reduce (R2).

2.1.3 Modelling levels: product and individual materials

Within the context of this study, Product A, and the CRMs within this product, are discussed and modelled on different levels. Most importantly, this study only traces the materials in Product A which are identified as CRMs according to the EC's 2023 CRM list and found through the product's CRM assessment in **Appendix B** (Grohol and Veeh, 2023). Therefore, when this study refers to Product A, this always entails only the CRMs in product A, as other materials are excluded. Herein, all CRMs are identified on the PCB except for aluminium which is used in the heatsink; a component designed to distribute heat emitted by the device (Mjallal et al., 2018).

Additionally, since reuse mainly refers to reusing the product entirely, the impact of reusing a single product equals the reuse of all the CRMs within this product. Herein, only an exception is made when products require repairs as discussed in Chapter 4.2. The static and dynamic models first define flows on the product (i.e. CRM and aluminium) level. As a subsequent measure these flows are then dissected into individual CRM flows to assess the impact of reuse and recycling per material. In summary, throughout this study CRM flows are researched and modelled on two levels:

1. *Product level:* all CRMs in Product A which, in practice, refers to the PCB and heatsink. Sometimes aluminium (i.e. the heatsink) is excluded due to its abundance compared to other CRMs which obstructs interpretation of the results; if so this is clearly mentioned.
2. *Material level:* measured as an individual material which is identified in Product A and listed as critical by the EC's 2023 report.

2.1.4 Methodological considerations

A limitation for the first subquestion lies in the product selection. While the applied steps are documented, ensuring reproducibility, the method still includes arbitrary elements. As KPN offers a wide range of products across consumer and business markets, and data is scattered across multiple datasets, there is a chance a more relevant device was unintentionally overlooked. Additionally, for the materials, which were identified in Product A as compounds, the pure fractions were derived using molar mass calculations. While this does provide an indication of the primary materials that would have to be extracted for primary production, the complicated dynamics of material compounds are further neglected.

Another limitation lies in the use of the EI and SR to determine material criticality. Although these are argued as the best available indicators, being developed by the EC which closely monitors EU material criticality rates, these rates remain dynamic. Even more so when the current political arena is accounted for, the level of criticality is subject to time, geographic positioning and local shortages (Schicho and Espinoza, 2024).

The same is argued for the EoL-RIR, which represents macro-level EU averages. KPN's downstream processes, wherein these EoL materials likely do not travel further than the Netherland's neighbouring countries, could deviate from these generalized rates. Another approximation was the use of the climate change impact family and GWP indicator to assess environmental impact. While useful, this too was based on selected LCIA methods and their assumptions, and should be interpreted as indicative rather than exact (Joint Research Centre, 2010).

Furthermore, MFA itself introduces methodological uncertainty. Defining materials, processes, and system boundaries always involves some degree of subjectivity (Laner and Rechberger, 2016). Although the MFA model was designed to closely follow available data, the selection of categories and parameter values could vary per person. Resulting in the possibility of an independent reproduction of the MFA model to contain different system boundaries, processes or other parameters.

These uncertainties also extend to the dynamic MFA model, which relied on transfer coefficients from the static MFA. Moreover, it used generalised values to project flows over time. While this was hard to avoid in prospective modelling, reuse and recycling rates will differ from year to year. The model therefore does not claim to predict exact outcomes, but aimed to approximate future developments based on currently available information. Results should be interpreted accordingly, with awareness of potential data limitations and future deviations from the modelled scenario.

Lastly, KPN provided the practical framework for this research, as a telecom provider they're argued to be a reliable source of data regarding IT equipment in the Netherlands. However, other companies might use different partners or approaches, driven by varying objectives and motivations which could result have resulted in the study's outcomes to be overly KPN-oriented (Clarke and Davison, 2020). As a result, any generalization of outcomes must be interpreted with caution, mainly when discussing or applying lessons beyond the scope of KPN.

2.2 Research Flow Diagram

Figure 3 illustrates the research approach described above. Herein, the three subquestions follow each other up, leading to a description of the results and implications and an answer to the main research question. Specific steps per question are shown on the right. Below each subquestion the required outputs are described.

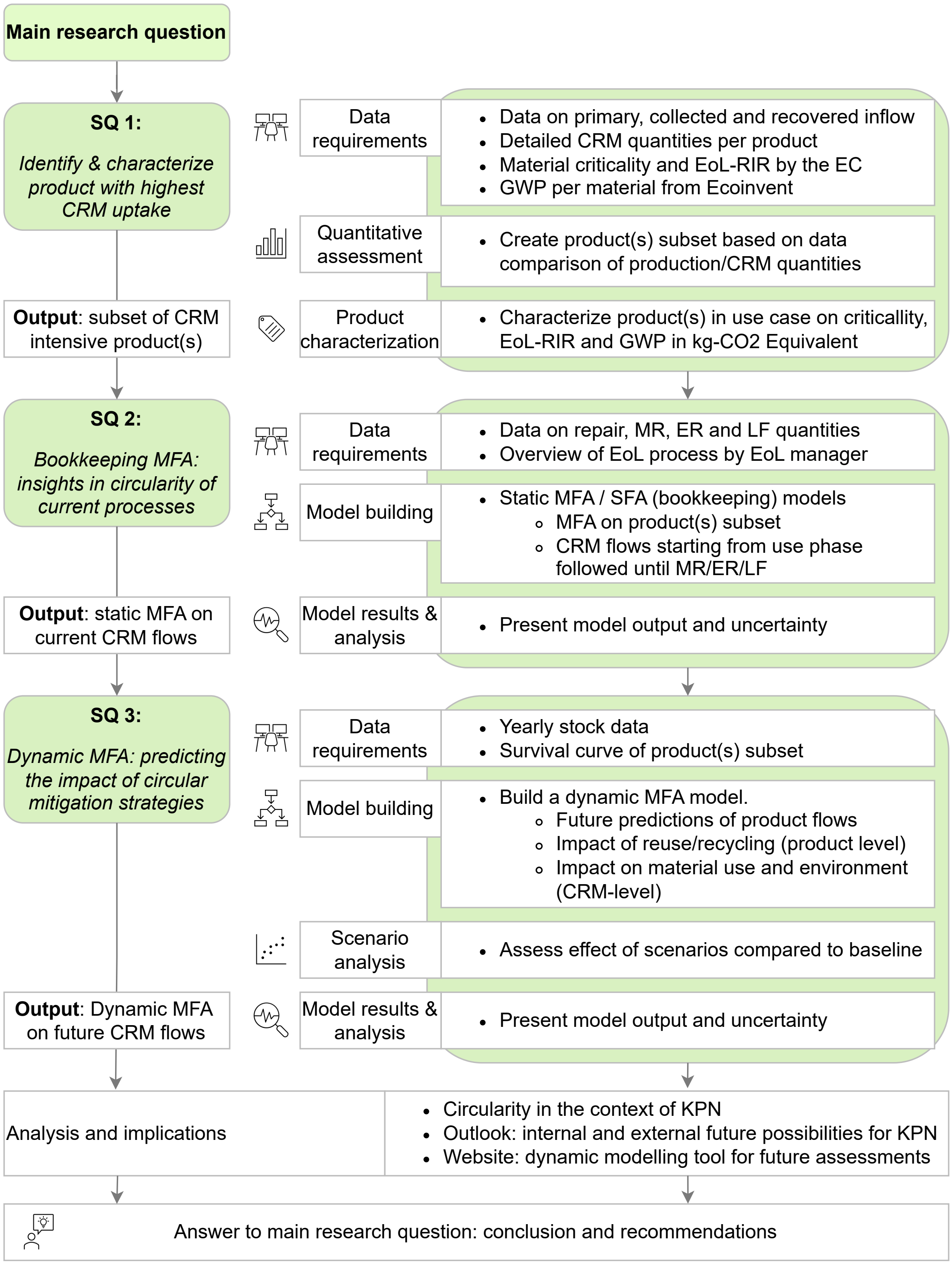


Figure 3: Research flow diagram. *Note: MR = material recovery (recycling), ER = energy recovery and LF = landfill.*

3 Defining the Most Critical Products

As the landscape of CRMs in the Dutch telecom sector is both extensive and dynamic, the initial objective of this study was to develop a framework, which renders this complexity in a structured and comprehensive manner. Therefore, this chapter focuses on refining KPN's broad portfolio of telecom products and equipment to a select subset deemed significant. This process followed a structured approach, beginning with the definition of "significant" products, followed by an evaluation of their characteristics based on material composition, criticality scores, environmental impact and role in the (EoL) supply chain.

3.1 Methodology: Product Selection and Characterization

A fundamental factor in determining product significance within the framework of this study was the quantity and criticality of the CRMs a product contains. Ideally, an assessment would have been conducted on KPN's entire product portfolio to identify those requiring the highest amount of CRMs, as these products pose the greatest risk regarding supply chain disruptions. However, due to the scarcity of data on product CRM compositions, an alternative approach was applied.

To define a representative subset of products, data from year y's total supplies and returns was analysed to identify the most used products in terms of total weight (kg). Additionally, a secondary criterion was the requirement for products to contain a PCB, as these are generally recognized to contain the highest quantity of CRMs within waste electronic devices (Srivastava et al., 2020). While this methodology did not measure the absolute weight and criticality of CRMs within each product, it provided a reasonable estimate of those products that likely contribute substantially to overall CRM consumption. The result of this selection process was product A (name modified in line with non disclosure agreement) as the main topic of study, since this product was expected to contribute significantly in regard to KPN's primary CRM uptake. An overview of the product groups and products included in the analysis is provided in **Appendix A**.

3.1.1 Product data sources

The specific material in- and outflows, along with the processes product A undergoes, were identified through primary data provided by KPN and its partner organizations responsible for supply and EoL management. For each data level in Table 1, suppliers and EoL managers provided insights into their respective processes. An overview of the contact roles, data- and information sources, is listed in Table 1.

Table 1: Data level, contact roles and provided information for Product A.

Data level	**Contact role**	**Provided information**
Supplier data	(partial) Manufacturer A	Material / CRM quantities, component level
Use phase data	Service provider (KPN)	Total inflow from supplier and recovered inflow, product level
EoL data	EoL manager A	EoL management data, product and product group level
Waste management data	Recycler A	Recycling, recovery and waste data, process level

As shown in Table 1, data on specific CRM quantities for product A was provided by the partial manufacturer of the product. The manufacturer is defined as 'partial' since they assemble the end-products but do not necessarily produce all individual components. Components such as the PCB, which generally contain the highest concentration of CRMs, are often produced by upstream manufacturing partners (Srivastava et al., 2020). Nevertheless, since this upstream manufacturer proved difficult to contact, the partial manufacturer was found to possess the most comprehensive knowledge of CRM quantities within the scope of this study's data collection.

The total inflow of products into the use phase originates from two sources: the manufacturer and recovered inflows. This information was obtained from KPN's internal data, which was identified as the most well-documented and accessible source.

EoL management data was provided by EoL manager A, responsible for a subset of KPN's EoL products. They offered insights into the specific EoL processes that the products undergo, as well as quantitative data at either the product or product group level for each process.

Lastly, data from recycling partners was provided by EoL manager A and used to quantify recovered materials, energy recovery, thermal decomposition, and landfill streams. While the previous data sources consist of primary data for the included products, the recycling data is slightly older (2019) and pertains to processed ICT telecom components as a whole rather than individual products. However, since CRM recovery techniques from WEEE have not undergone significant advancements within this period, this data was deemed the most reliable and available source, though subject to necessary precautions (Lapko et al., 2019).

3.1.2 Criticality calculation of identified materials

To assess material criticality, the EC's methodology was applied, they developed a framework for criticality rankings that considers supply risk (SR) and economic importance (EI) (Grohol and Veeh, 2023). Each material is assigned a value between 0 and 1, reflecting its replaceability across all applications defined in the EC annual report (Grohol and Veeh, 2023). The SR evaluates the likelihood of supply disruptions based on factors such as geographical concentration, political stability of supplier countries, and material availability, as shown in Equation 1 (Nuss and Ciuta, 2018).

$$SR = \left[(HHI_{WGI,t})_{GS} \cdot \frac{IR}{2} + (HHI_{WGI,t})_{EU\,sourcing} \cdot \left(1 - \frac{IR}{2}\right) \right] \cdot (1 - EoL_{RIR}) \cdot SI_{SR} \qquad (1)$$

In Equation 1, the SR is calculated through the combination of multiple factors. The Herfindahl-Hirschman index (HHI) measures the geographical concentration of materials in specific countries and is evaluated alongside the scaled World Governance Index (WGI) and the trade parameter (t), all of which are multiplied by total import reliance. The same calculation is applied to materials that could be sourced within the EU. The combined outcome of these steps is multiplied by the $EoL - RIR$, which quantifies the proportion of secondary materials used in primary production. Finally, this value is multiplied by the substitution index (SI) related to SR.

Alternatively, the EI is based on the material's role in the production process and its impact on the economy, including its contribution to technological performance and overall value creation, as shown in Equation 2 (Nuss and Ciuta, 2018).

$$EI = \sum_s (A_s \cdot Q_s) \cdot SI_{EI} \qquad (2)$$

In Equation 2, the EI is calculated by multiplying the total quantity of materials used in a sector (s) with the share of end-use in sectors that exceed a predefined threshold of importance for the EU's functioning (As and Qs), along with the SI.

3.1.3 End-of-Life recycling input rate calculation

As this study focusses specifically on the circularity of products within KPN's scope, a key parameter besides the EI and SR methodologies described above, is whether, and to what extend, the above named materials are reused and recycled. As discussed in the previous section, Equation 1 and 2 are designed as holistic approaches, incorporating as many variables related to the respective output fields of EI and SR as possible. Within this framework, one section of Equation 1 evaluates the proportion of recycled materials from waste streams used in the production of new goods, as shown in Equation 3 (Nuss and Ciuta, 2018).

$$EoL-RIR = \frac{(\text{secondary material}_{EU})}{(\text{primary metal}_{EU}) + (\text{secondary metal}_{EU})} \tag{3}$$

In equation 3 only metals that are separated and recycled with the intention of reuse in material production processes, specifically for generating secondary metals or metal alloys, are included (Ferro and Bonollo, 2019a). The application of equation 3 to each of the materials identified in product A, results in generalized values regarding their current recycling rates on the EU level. While these values are not directly applicable to KPN, this initial step provides preliminary insights into the status quo of CRMs used in Product A. The EoL-RIR per material is shown in Table 2.

3.1.4 Environmental impact calculation

With the methodology on material composition and characterization in terms of quantity, criticality, and recycling established, another key parameter in this study was the environmental impact of the included materials. As conducting a full LCA is beyond the scope of this research, environmental impacts are calculated only through the impact category of climate change as one of the most pressing environmental issues; herein GWP is the indicator for each materials' impact scores (Abdurahman Mume et al., 2024; Jang et al., 2022). To assess this, each material's GWP100 impact score was extracted from the Ecoinvent database (version: 3.9 cutoff). While GWP accounts for only a portion of the overall environmental impact, excluding factors such as acidification and ecotoxicity, it is considered a comprehensive and widely applied method for assessing CO_2 impact calculations (Lynch et al., 2020).

The CML v4.8 (2016) LCIA method was applied and selected for several reasons. Primarily, it is used as an explorative measure into the GWP impact score per material, which benefits from relying on a widely recommended and commonly applied method to avoid ambiguous outcomes when compared with other studies. Earlier versions of the CML method have been recommended within the International Reference Life Cycle Data System (ILCD) framework, as they assess resource scarcity by considering the dynamics between extraction rates and available reserves. Additionally, the CML methods include most of the CRMs identified by the EC, offering a sustainable methodological approach for future research (Joint Research Centre, 2010).

3.2 Results: Product Characterization and Impact Assessments

3.2.1 Product characterization: internet modem for household use

The product under study, product A, is a modem designed for household use. In year y this product had a total primary inflow (from the manufacturer) of 176 tonnes and a recovered inflow (from the EoL manager) of 54.9 tonnes. As is typical for modems, these units circulate among users for a predetermined period. Generally, customers receive a modem when signing or renewing a contract, after which the device remains in use for approximately five years before being phased out and replaced with a newer model ([redacted], personal communication, [redacted]). This modem was introduced in year y, since then a total of $1.18 \cdot 10^6$ kg of total primary inflow has been supplied to consumers, and 272 tonnes of this primary inflow is recovered until the end of year y.

Materials in Product A

The identified CRMs are derived from a CRM analysis by manufacturer A. This assessment, which serves as the primary data source for quantifying CRM content in Product A, was conducted in 2020, which was around the time of the product's introduction to KPN's customer base. This assessment employed a combination of supply chain inquiries and the collection and analysis of full material declarations from suppliers to evaluate the CRM content.

All materials included in the analysis of Product A are categorized as either strategic or critical. Notably, two materials – indium and barium – are incorporated in the CRM assessment by Manufacturer A, even though they are no longer classified as critical in the 2023 EC report. These materials were considered critical in the 2020 EC CRMs list, which corresponds with the time frame during which the CRM assessment was conducted (European Commission, 2020; Grohol and Veeh, 2023).

The final report identified a total of 1,162 components integrated into the product. Of these, 83%, equivalent to 968 components, were successfully analysed. The study reports high coverage of surface mount device (SMD) commodities (primarily resistors and capacitors) and the main chipsets. However, certain components require further investigation, including cables, the power supply unit, a minor number of integrated circuits, and connectors. The identified materials, and an indication of their used quantity, are shown in on the periodic table in Figure 4.

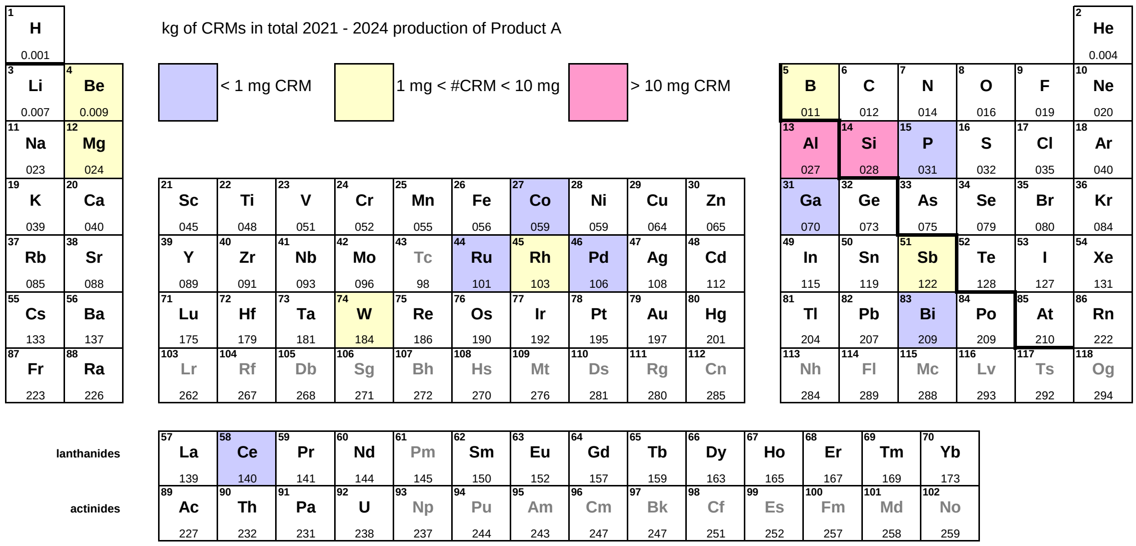


Figure 4: Material composition product A. *Note: blue indicates less than 1.00 mg of a material is identified in Product A, yellow indicates the material quantity is between 1.00 and 10.0 mg and red indicates more than 10.0 mg of a material is identified in Product A.*

In Figure 4, all fifteen CRMs identified by manufacturer A in product A are coloured on the periodic table to illustrate which materials and from which material-groups are mostly used. Three groups are identified as mostly present: the platinum, boron and nitrogen group. Platinum group elements often occur together in nature and mostly without natural abundances (Rauch and Morrison, 2008). From the boron group, boron is the only metalloid while the others are metals (Häussermann et al., 2003). From the nitrogen group elements phosphorus is identified, which naturally occurs as a non-metal and antimony and bismuth which naturally occur in metallic forms (Strohfeldt, 2015).

Other elements are beryllium, which occurs in small quantities in the natural soil, and magnesium, which is abundantly present and essential for plant growth (Gunn, 2014). Tungsten occurs as a compound metal, mainly as a result of subduction-related plate tectonics (Gunn, 2014). Silicon is the most abundant of all elements on the Earth's surface. However, the critical variant is silicon metal, which is derived through advanced processing, clustered mainly in China (European Commission, 2014; Snyder et al., 2007). Lastly, cerium is a metallic element and the most abundant of the lanthanides, also referred to as rare earth elements (REE) (Chandra and Tomar, 2023).

Most of these materials are identified as a combination of pure materials and compounds in Product A, a detailed description of the quantities and molar mass calculations is included in **Appendix B**. Below is a concise overview of the CRMs in Product A and their functionalities.

- **Antimony (Sb):** tin solder of mechanical switch, in plating components and as post plating for internal components.
- **Barium (Ba):** solder mask for the PCB and electrical connection for the flash memory and LED lights.
- **Beryllium (Be):** to adapt mechanical properties of copper alloy in shield fingers (small metal blades to ensure contact).
- **Bismuth (Bi):** tin solder of mechanical switch, plating of internal components.
- **Boron (B):** glass coat of resistors, electrodes, resistive film and protective coat of resistors.
- **Cobalt (Co):** in iron nickel alloy of diodes, copper alloy of shield fingers and class resistors.
- **Indium (In):** in chip of green LED light.
- **Gallium (Ga):** in chip of green LED light.
- **Magnesium (Mg):** in resistors substrate.
- **Phosphorus (P):** in copper and nickel alloys and as mold compound (flame retardant).
- **Silicon metal (Si):** chip of semiconductors, backside layer of resistors and as overcoat of resistors.
- **Tungsten (W):** die of RAM memory and ceramic base of resistors and capacitors.
- **Ruthenium (Ru):** glass layer and resistive film of resistors.
- **Palladium (Pd):** in electrodes, resistive layer and protective coat of resistors.
- **Cerium (Ce):** tin plating for brack of manual switch (push button).
- **Rhodium (Rh):** in resistors and capacitors.

To contextualize the production-level quantity of the identified individual materials, Figure 5 shows the amount of CRMs used by multiplying the product-level CRM quantities with the primary inflow between year y to y+4 of 1.34 million devices.

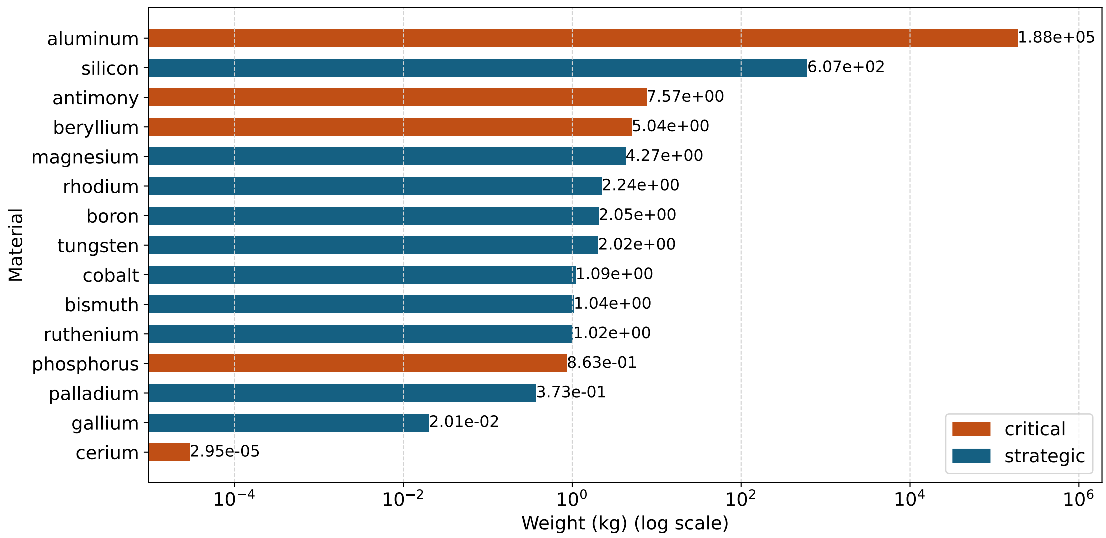


Figure 5: Material composition product A, multiplied by total produced quantity in the year y to y+4 period.

All materials for which the specific weight is known are included in the quantification shown in Figure 5, summing up to 188 tonnes of the total 1.18 million kg of product inflows. Other materials, which are unaccounted for are primarily used in the hard cover of the modem which is made of polycarbonate and not defined as critical or strategic at this moment (Grohol and Veeh, 2023). **Appendix C** provides an overview of the component-level weights in product A.

3.2.2 Criticality calculation of identified materials

With an identification of the product under study, along with its primary characteristics, the next step was to assess the material criticality. This was done using the criticality methodology developed by the EC, which is applied to the materials identified within the selected products. This methodology is based on two key parameters: SR (equation 1) and EI (equation 2) (European Commission, 2017), an overview of the materials, identified in product A, and their positioning in relation to SR and EI is provided in Figure 6.

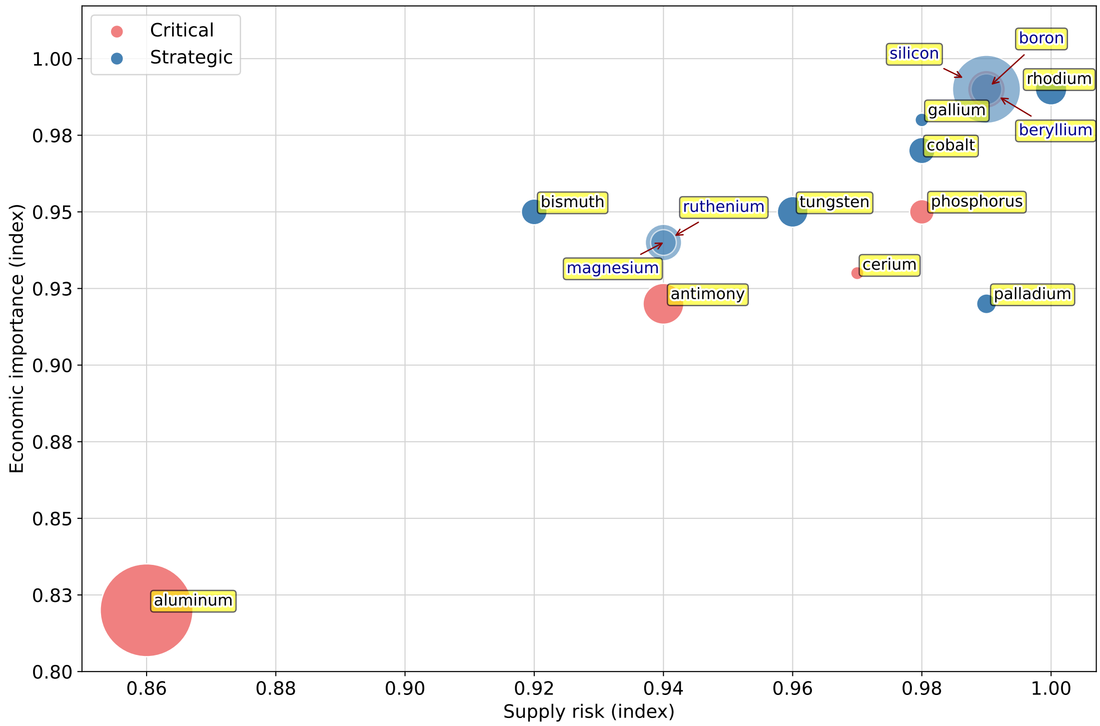


Figure 6: Substitution Index: EI and SR. *Note: bubbles sized to quantity of material in device (subject to max and min values). Based on SR and EI values from European Union (2024).*

As shown in Figure 6, four materials in product A have high criticality rates in terms of both SR and EI: rhodium, beryllium, boron and silicon metal. Phosphorus and palladium also display relatively high SR values but pose lower risks in terms of EI. Antimony, bismuth and aluminum rank lower on both SR and EI, the remaining materials fall within an intermediate range.

When accounting for whether a material is defined as strategic or critical, materials such as beryllium, rhodium, and boron fall within the higher ranges in terms of SR and EI. However, mainly aluminium presents relatively low criticality within the context of this product while defined as critical. This is due to the difference within the definition of these subgroups; CRMs are identified by their EI and SR (European Commission, 2024b), whereas strategic materials are designated by additional factors such as a high dependence for vital technologies, substantially high supply risks or concentrated geographical distribution (Hool et al., 2024).

3.2.3 End-of-Life recycling input rate calculation

The last step in characterizing Product A, applied each material's EoL-RIR as calculated with Equation 3 by the EC (Grohol and Veeh, 2023). The results per material are shown in Table 2.

Table 2: EoL-RIR per material identified in product A.

Material	EoL-RIR (%)	Material	EoL-RIR (%)	Material	EoL-RIR (%)
Tungsten	42	Cobalt	22	Gallium	0
Silicon metal	0	Cerium	1	Bismuth	0
Ruthenium	12	Boron	1	Antimony	28
Rhodium	12	Beryllium	0		
Phosphorus	0	Aluminium	32		
Palladium	12	Magnesium	13		

Note: ruthenium, rhodium and palladium fall under a collective EoL-RIR of 12% which may vary per specific material, source: Grohol and Veeh (2023).

Table 2 indicates that most materials in Product A have a low or non-existent EoL-RIR. This is often due to inadequate recycling processes, a challenge reflected in the overall recycling rate used for production input in the EU, which stood at just 7.3% in 2023 (van Gaalen and Slootweg, 2025).

Among the materials with a more substantial EoL-RIR, tungsten (42%), cobalt (22%), aluminium (32%), magnesium (13%), and antimony (28%) show higher levels of recycling. For these materials, there may be opportunities to enhance circularity for KPN. In contrast, materials with marginal or non-existent EoL-RIR are expected to present greater challenges at this stage, largely depending on shifts in economic value and the advancement of more sophisticated recycling technologies capable of improving recovery rates (Charles et al., 2020; Karali and Shah, 2022).

3.2.4 Prevented GWP calculation

Figure 7 presents the GWP impact score per material, calculated by multiplying the total material weight by its kg CO_2-eq in terms of GWP per kilogram of primary production. Each light red bar represents the total GWP in kg CO_2-eq for the year y to y+4 production of the respective material.

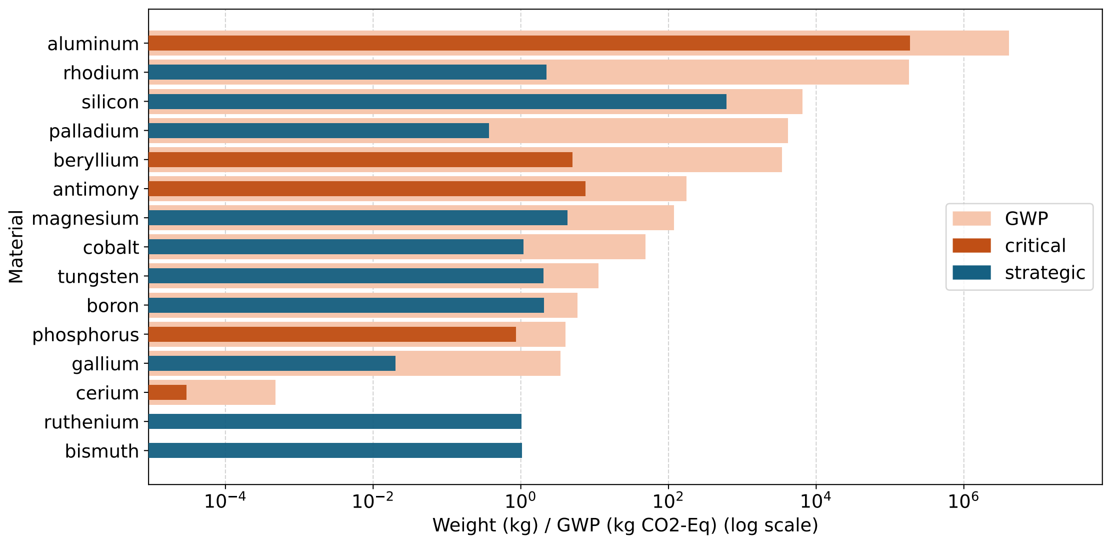


Figure 7: kg CO_2-eq of GWP compared to material usage over year y to y+4 period (LCIA method: CML v4.8 2016). *Note: no Ecoinvent data on ruthenium and bismuth, figure based on values from Ecoinvent database (Appendix B).*

In Figure 7, the GWP bars for materials with a high GWP per kilogram extend the material weight bars in the graph by a greater distance than those with lower GWP values. As a result, materials used in large quantities but with a relatively low GWP per kilogram, such as aluminium, have GWP bars positioned only slightly beyond their corresponding material weight bars. In contrast, rhodium production generates $80.4 \cdot 10^3$ kg CO_2-eq per kilogram, causing its GWP bars to extend significantly beyond the bar for material weight. This extreme value, which is also a topic of debate in scientific literature, is described as a result of rhodium occurring in extremely low ore concentrations, requiring highly-fossil intensive extraction and complex refinery, a trend which is similarly observed for palladium and platinum group metals in general (Ecoinvent, 2019; Nuss and Eckelman, 2014).

Additionally, if the above listed production of materials could be slowed through circular practices, this would also potentially reduce the amount of GWP impact scores. Therefore, this 'prevented GWP' through slowed material inflows, might slow the process of climate change to some extent.

These GWP values, compared to total material quantities, provide a preliminary insight into the relative impact score to climate change of each material. However, they also relied on subjective parameters such as LCIA methodology- and characterization factor selection. Therefore, any decision-making based on these values should account for the potential implications of other characterization factors or LCIA methods.

Another metric for the calculation of environmental impact comes from an internal KPN study. While the underlying calculations are not traceable, this study provided 12.47 kg CO_2 emissions for the total production phase per device and 0.04 kg CO_2 for the overall transport. In total this amounts to 12.51 kg CO_2 per newly produced item of Product A. Following the reuse logic by Cooper and Gutowski (2017), this could thus be the total emissions saved with each reused device when supplied instead of a newly produced device.

Since this value can not be dissected into individual material contributions, this can only be used for high-level emissions calculations. Notably, this impact is expressed in kg CO_2, not kg CO_2-eq, such as the GWP. Additionally, due to the absence of detailed calculation specifications, this value's results should be interpreted with additional caution.

4 System Analysis: Current Circular Practices

With an overview of the included product, its CRM quantities, and CRM characterizations in place, this chapter examines the system through which these variables flow. Since the circularity of CRMs within KPN's context cannot be assessed solely through high-level calculations, as presented in the previous chapter, the EoL supply chain for Product A was analysed. This analysis aims to both identify and quantify existing circular practices, while also determining if and where significant CRM losses occur.

4.1 Methodology: Static MFA and SFA Models

4.1.1 System analysis

All products within the scope of this study are processed by an EoL manager once they exit the use phase at the customer. The specific processing steps and associated quantities were verified through factory visits and primary data provided by EoL manager A.

The central focus of these processes is reuse, returning products to the market with minimal repairs or hardware replacements. Consequently, reuse, and to some extent repair, are the dominant circular strategies within KPN's ownership scope. For products deemed unsuitable for these approaches, recycling is the preferred fallback, with remaining fractions being directed to energy recovery and landfills.

EoL-manager A

Figure 8 presents a simplified schematic overview of the EoL product chain from the perspective of EoL-manager A, with a focus on product A. This overview is based on the detailed supply chain shown in **Appendix D** and has been streamlined to clearly visualize the key processes relevant to this study.

As visualized in Figure 8, data on the material composition of product A is provided by the manufacturer (purple section), from whom KPN procures the products. Once acquired, the products enter the 'in-scope KPN' stage (grey section) and are defined as falling under KPN's ownership. Therefore, any actions to enhance circularity at this stage of the product chain have a direct influence on KPN's resilience and sustainability objectives.

Consequently, the 'EoL management' stage (green section) is particularly of interest in the context of this study, as it offers insights into the circular practices currently applied. Reused products cleaned and tested beforehand. Some products require repairs, after which they are sent back to the testing and reuse process. Products deemed unfit for reuse or repair are sent to 'waste management' (blue section). In the context of this study EoL management is defined as all processes occupied with the collection of products from KPN's customers and the determination of product flows to reuse, repair or waste streams.

At the 'waste management' stage, the products are no longer economically viable for direct reintegration into the consumer market. However, this does not mean they are entirely without value. On the contrary, this phase involves material extraction processes, which represent a key opportunity for CRM recovery (Charles et al., 2020).

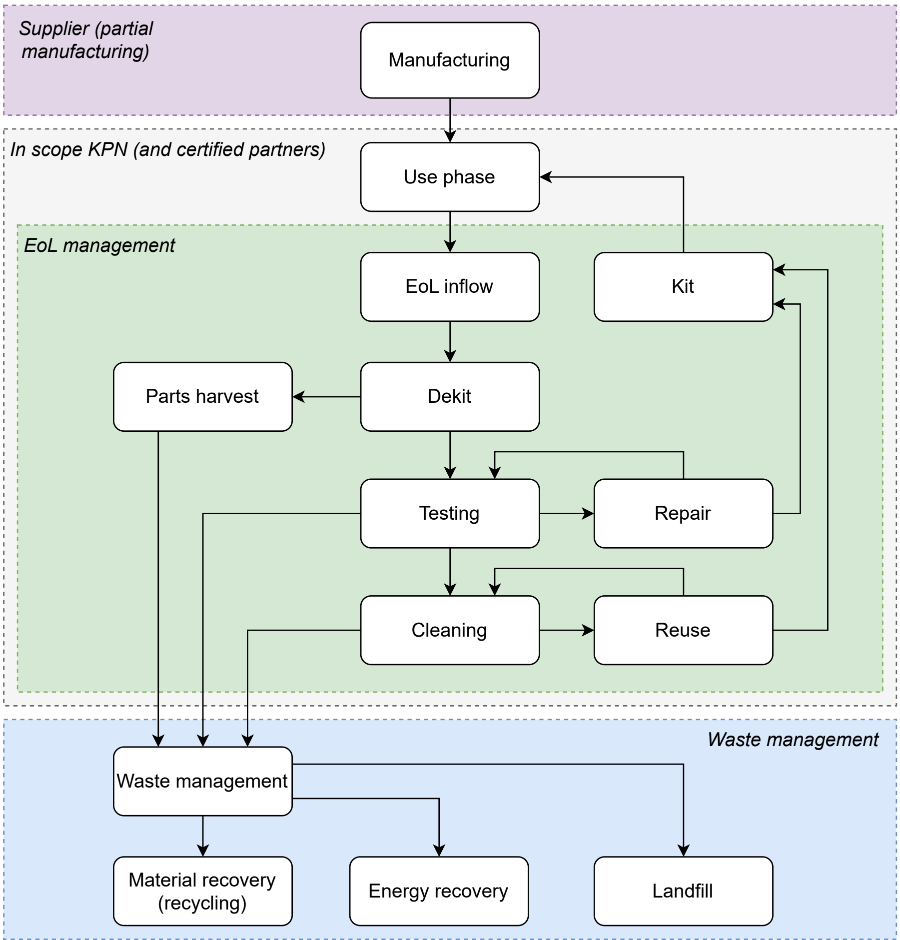


Figure 8: EoL-manager A: EoL supply chain.

4.1.2 Static MFA / SFA Model: Goal and Scope Definition

To assess the current level of circularity of CRMs in KPN's EoL supply chain, the simplified schematic overview, in Figure 8, was translated into a static MFA / SFA bookkeeping model using STAN software. STAN is specifically designed for MFA purposes, enabling graphical modelling with integrated translation into a mathematical model. It calculates flow values based on transfer coefficients and stock accumulation, visualized in a Sankey-style layout (Brunner and Rechberger, 2016).

System goal and boundaries

The goal was to identify where CRMs in Product A exit the system, accumulate, and whether they recirculate through static, bookkeeping MFA.

E. Müller et al. (2014) define MFA as static when it captures a system through a snapshot in time. While often a single year, the static definition also applies here, as the models represent the product and material flows of the entire quantity of Product A produced between year y to y+4, condensed into a single observable frame. Additionally, SFA modelling is applied to assess the individual materials flows in product A in section 5.4.

The system boundaries for the static MFA model are closed and based on the flows and processes shown in Figure 8. This selection is based on two considerations. First, the relevance of flows and processes within the context of this study, specifically, those that provide insight into CRM behaviour within the system and disposal pathways. Second, the data availability: only flows and processes deemed relevant and supported by sufficient data are included.

Included processes

The green processes in Figure 9 untill 13 fall within KPN's direct scope and are supported by available, product-level data. For the blue processes, outside KPN's scope, data was also documented but not at product level. These flows are based on average percentages from the EoL manager's year y to y+4 waste treatment, resulting in lower accuracy than the product-specific flows.

Product definition

The static MFA traces Product A from the moment it is delivered to a KPN customer up to the point where it is either recycled into smaller components, incinerated for energy recovery, or landfilled. It is important to note that the model follows the CRMs in Product A as a single 'bundle', which remains intact from the moment it enters the system boundaries until it exits.

According to the CRM report (**Appendix B**), all identified CRMs – except aluminium, which is excluded from the product-level model – are located on the PCB. EoL Manager A confirmed the PCB remains mostly intact for reuse processes, allowing the CRM composition to be treated as unchanged within the system boundaries ([redacted], personal communication, [redacted]) [redacted] The PCB's CRM composition is only subject to change during repair, as in- and outlets, buttons and other PCB-connections are repaired during this process.

4.1.3 Static MFA model validation and uncertainty analysis

The static MFA model, as outlined in the previous sections, must be evaluated in terms of how its defined goal and scope, data quality, and uncertainty affect the overall results. To structure this, the stepwise procedure for addressing uncertainty in MFA as described by Laner et al. (2014), is applied. This procedure builds on the MFA framework introduced in the 2004 edition of the *Handbook of Materials Flow Analysis* by Brunner and Rechberger (2016).

According to this procedure, a distinction is made between descriptive and exploratory MFAs. Descriptive MFA typically focuses on quantifying material flows within a defined system to characterize material turnover. In contrast, exploratory MFA aims to gain deeper insights into the processes driving these dynamics. Although the overall goal of this study is exploratory, this approach is primarily implemented in the dynamic MFA described in Chapter 5. The static MFA presented in this chapter is best characterized as descriptive. For this type of MFA, Laner et al. (2014) indicated that the first four steps of their uncertainty assessment procedure should be applied. These steps are addressed in Chapter 4.4.

For the SFA models, this process was not repeated as these apply identical transfer coefficients to the MFA model. Therefore, the validation and uncertainty analysis should be identical as well, since only the input value is altered and not the model's structure.

4.2 Results: MFA Model - Product Flows

4.2.1 year y to y+4 period

Besides the inflow quantities, the main parameters for the y to y+4 model are the transfer coefficients as shown in Table 3, detailed calculations for these values can be found in **Appendix E**. These rates define the quantity of material flows between processes.

Mainly the outflows from the Use phase and from the EoL management processes come with a high reliability as they are based on well-maintained datasets by KPN. For the Collection and sorting outflow there is a distinction in the outflows; those coming from waste products follow different rates than those coming from non-return waste products, as also visualized in Figure 11.

Additionally, the CRM outflow rate contains only precious metals (PMs) as only these and aluminium – which is not included in the MFA model, only the SFA – were found to be recycled in this context. The non-recovered CRMs flow refers to the remainder of CRMs which flow to recycling processes but are not effectively recovered.

Table 3: Overview of main transfer coefficients

Process	Outflows	Rate (%)
Use phase	Collected products	31.8
	In use	55.6
	Non-return waste products	12.7
EoL management	Reuse products	81.2
	Waste products	12.6
	Sent for repair	6.14
Collection and sorting: *From waste products*	Waste to recycling	70.0
	Waste to energy	30.0
	Landfilled	0.0
Collection and sorting: *From non-return waste products*	Waste to recycling	64.2
	Waste to energy	31.2
	Landfilled	4.64
Recycling	CRM outflow	0.0801
	Non-recovered CRMs	99.9

Note: waste management uses different transfer coefficients per inflow as visualized in Figure 11.

The static MFA model, visualized in Figure 9, illustrates flow quantities through the relative width of each stream. As a result, the primary inflow, *CRM use*, is the largest, since 100% of the CRM bundle enters the system. The other flows are scaled to the inflow of *CRM use* and represent the fragmented streams on a product level (extensive flows Table in **Appendix F**).

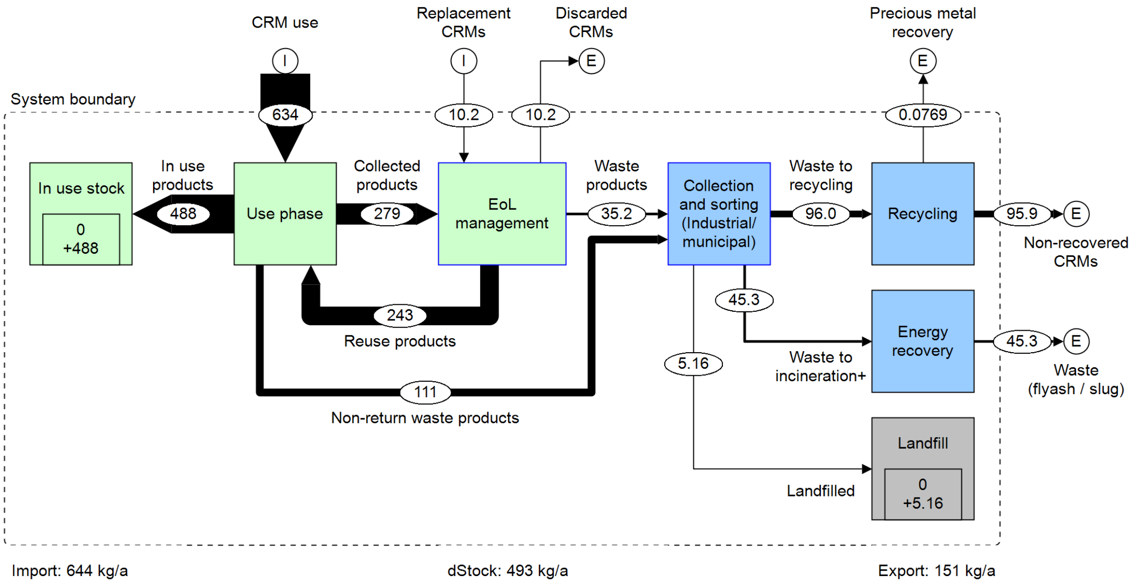


Figure 9: Static MFA model of CRM flows in product A: year y to y+4 period. *Note: values in kg, green processes are within- and blue and grey are outside KPN's scope, aluminium not included, blue process outline indicates subsystem.*

As shown in Figure 9, the static MFA model encompasses all primary inflows and corresponding outflows. When the product, or more specific: its added up CRM bundles of 634 kg, are introduced into the system, it first enters the use phase. Due to STAN's limitation in assigning both stock accumulation and a transfer coefficient within a single process, the products in use are represented as accumulating in a separate *in-use stock*. This stock reflects all units located at KPN customers' households, amounting to a total CRM accumulation of 488 kg over the y to y+4 period.

When a product is no longer allocated to a customer, such as when a user switches providers or requires a new modem, it enters the *collected products* stream, representing 279 kg of CRMs, and is transferred to the *EoL management* process. Within this process, various steps are taken to assess the device's reusability and, if applicable, reuse or repair it (details in **Appendix D**). Since mainly the reused quantity of products, retaining the unaltered CRM bundle, is relevant to this study, the *EoL management* stage is modelled as a subsystem wherein a quality assessment determines if a product is sent for reuse, repair or to waste as shown in Figure 10.

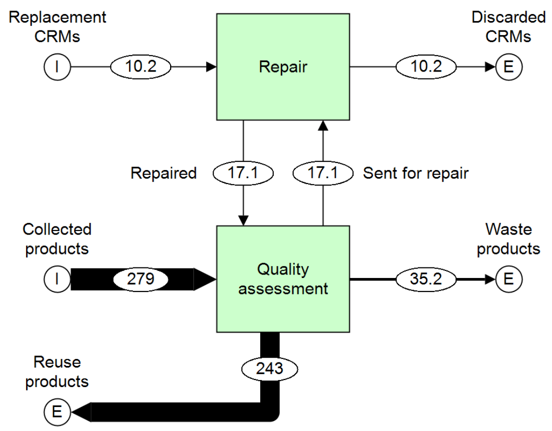


Figure 10: Sub-system of EoL management in static MFA model: y to y+4 period. *Note: values in kg, green processes are within KPN's scope, aluminium not included.*

As shown in the *EoL management* subsystem in Figure 10, this stage determines whether a device is fit to return to the use phase, which applies to a total of 243 kg of CRMs (including those passing through reuse and repair).

The quality assessment within the *EoL management* subsystem determines whether a product requires to be repaired resulting in CRMs flowing out of the system at this stage due to repair-related losses from the PCB, which are replaced by new CRMs prior to the product recirculating to the *reuse products* flow. Based on repair data, a distinction was made between repairs involving the PCB and those concerning other components of Product A. In order to maintain a conservative estimation of CRM reuse, all PCB-related repairs were modelled as requiring CRM replacements. This assumption led to an estimated CRM outflow of 10.2 kg. Consequently, an equivalent inflow of 10.2 kg of CRMs was introduced into the system, representing the material required for these replacements. This approach accounts for potential CRM losses during repair while ensuring the mass balance of the model remains intact.

When a product is deemed unfit for reuse or repair by the EoL manager, it is directed to *the collection and sorting process*, accounting for 35.2 kg of CRMs. This process also receives an inflow of 111 kg directly from the use phase, representing products not returned by consumers to KPN's EoL managers. These devices typically end up in municipal recycling centres or general waste streams. As such, this process is labelled *collection and sorting (industrial/municipal).*

To maintain model clarity, this is defined as a single process. However, within it, the *waste products* and *non-return waste products* streams each have their own transfer coefficients, determining their respective contributions to *recycling*, *energy recovery*, and *landfill*. These subsequent processes are modelled as a sub-system, as illustrated in Figure 11.

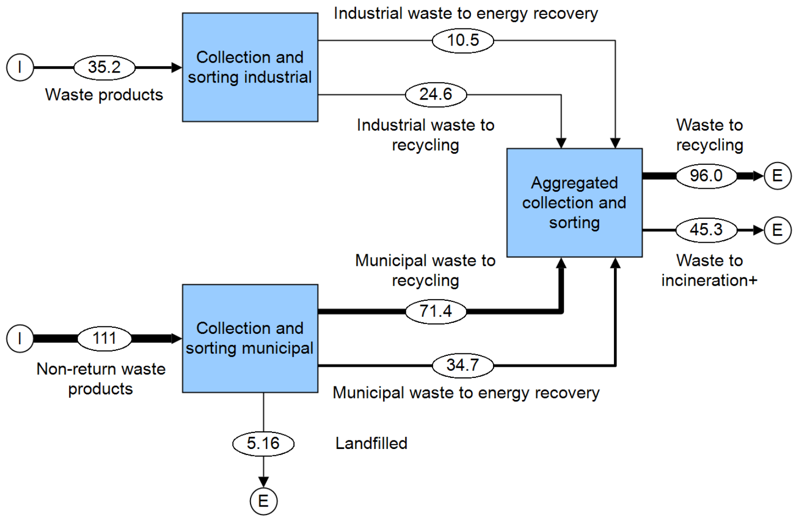


Figure 11: Sub-system of waste management (industrial & municipal) in static MFA model of CRM flows in product A: y to y+4 period. *Note: values in kg, blue processes are outside KPN's scope, aluminium not included.*

Following the *collection ans sorting* process, devices enter different EoL streams: 95.9 kg is *recycled* (open-loop), 45.3 kg is incinerated for *energy recovery*, and 5.16 kg is *landfilled*. From this stage onward, the data carries a higher degree of uncertainty, as the percentages used, reflect general trends for modem treatment rather than product-specific data for Product A. This increases the likelihood of 'leakage,' where rounded percentages introduce small deviations, thereby reducing the model's precision and its direct applicability to real-world conditions.

CRM recovery has been found to occur only in a small quantity of 0.0769 kg through the recycling process. The recovered CRMs belong to a specific subset known as PMs, which include rare metallic elements with high economic value such as gold, silver, and the platinum group metals (platinum, palladium, rhodium, iridium, osmium and ruthenium) (European Commission, 2015). In recent years, platinum group metals have particularly gained increasing industrial relevance due to widespread use in industrial applications (Karim and Ting, 2021).

The estimated *PM recovery* is based on the quantity of palladium, rhodium and ruthenium identified in product A. In contrast to the other CRMs, these PMs are frequently recovered in recycling streams due to their high economic value and relatively low cost of extraction from WEEE, especially when compared to virgin mining (Xia and Ghahreman, 2024). This economic motivation for PM recovery also reflects why other CRMs are rarely recovered, most lack sufficient market value to justify their extraction from complex EoL products.

4.2.2 Hypothetical scenario: discontinuation

As mentioned in the previous section, the majority of the CRMs are directed into the *in-use stock*, representing their primary application. Once products reach the end of their use phase, the flows become more fragmented: while most transition to *EoL management*, a portion enters municipal waste streams. These downstream flows gradually thin out, with the bulk of CRMs accumulating in the *in-use stock*, while the remainder exits the system in relatively small quantities.

This accumulation in the *in-use stock* is particularly important to monitor, as it represents a substantial quantity of CRMs for which the y to y+4 system does not account for final processing. As stated in Chapter 3, the product in question is discontinued and phased out following the introduction of a newer model. This leads to an outflow, where Product A is no longer reused and instead moves entirely to *recycling*, *energy recovery*, or *landfill*.

This transition necessitates a restructured model in which the CRM inflow from outside the system boundary is set to zero, and the primary input is the 488 kg of accumulated CRMs in the *in-use stock*. Furthermore, the transfer coefficient for reuse is also set to zero, reflecting that discontinued products are no longer reintroduced into the use phase. The restructured model is presented in Figure 12 (subsystem illustrations included in **Appendix G**).

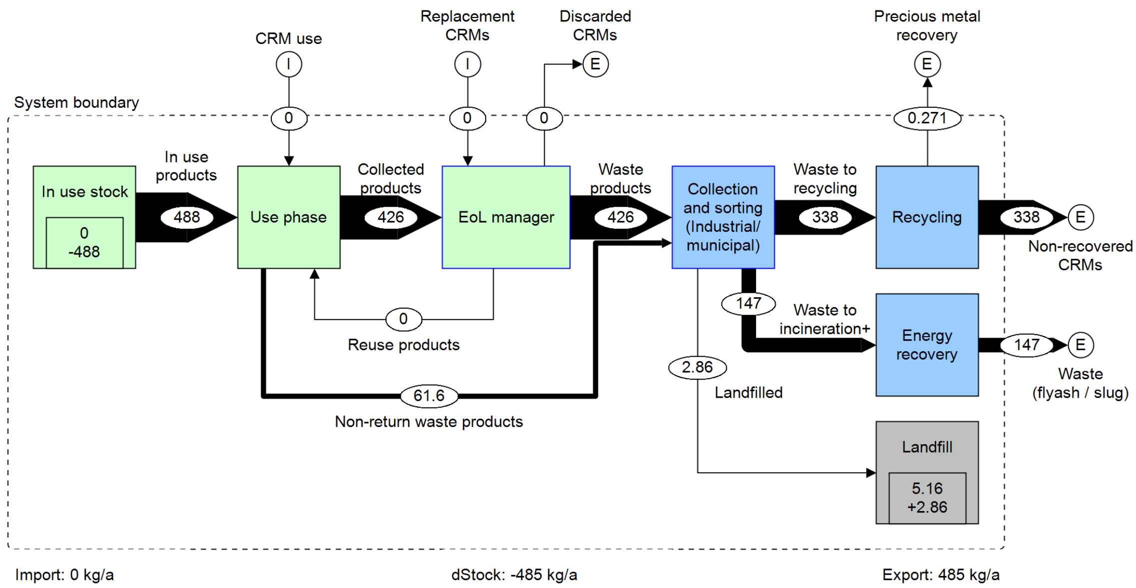


Figure 12: Static MFA model of CRM flows in product A: discontinuation. *Note: values in kg, green processes are within- and blue and grey are outside KPN's scope, aluminium not included. subsystem illustrations in Appendix G, blue process outline indicates subsystem.*

The key distinction illustrated in Figure 12, as compared to Figure 9, is the fully linear trajectory of the CRMs. For Product A, no new CRMs are introduced into the system, as no new units are produced, and all existing products ultimately end up in *recycling*, *energy recovery*, or *landfill*.

This outcome demonstrates that while reuse and repair contribute to circularity, they remain finite strategies. In both the y to y+4 and discontinuation models, CRMs are ultimately directed into linear EoL processes, with minimal recovery through recycling.

The modelling approach used for Figure 12 does, however, introduce additional uncertainties. The model introduced here assumes a sudden discontinuation wherein all products are phased out in a single, linear stream, which mainly serves the purpose of accounting for the EoL-scenario in which the *in use stock* will eventually dry up. However, in a real word scenario, this outflow of products would be less sudden, following a gradual transition from the current device in customer households to a newer one.

Additionally, due to the lack of precise data on the discontinuation phase, certain flow quantities may shift during phase-out, potentially affecting CRM recovery outcomes of this scenario. However, this scenario is modelled as a means of showing the behaviour of the system when Product A would no longer be required on the consumer market and the current absence of circularity in this context. This shows how KPN's system for devices such as modems is likely circular through reuse as long as these devices are required. When a new device is introduced there seems to be no clear circular strategy to recover these CRMs, indicating room for improvement. However, this functions differently for aluminium, not included in this model, as this has a higher recycling rate and would thus provide better results when product A is discontinued.

4.3 Results: SFA Model - Material Flows

The models in Figure 9 until 12, follow all CRMs (excluding aluminium) as a bundle, assuming the PCB in which they're used remains intact within the systems boundaries. To assess the material flows in more detail, a similar modelling approach is used for each material separately. The characterization of a product on the material level falls under the definition of Substance Flow Analysis (SFA), an approach which is mainly similar to MFA in its core principles but specified for individual substances (Islam and Huda, 2019).

4.3.1 SFA models: product level

The following section presents the modelling outputs of all CRMs in Product A at the product level. It is important to note that these results are based on the y to y+4 model and therefore do not account for the discontinuation phase, during which all materials are gradually phased out. Therefore, values such as the *reuse (flow)* or the *recovered (outflow)* could increase over time as a substantial amount of these materials is still accumulated in the use phase.

Aluminium flows

As indicated at the beginning of this chapter, aluminium is the only CRM in Product A that is not located on the PCB. Instead, it is used as a heatsink, aiding in the absorption and distribution of heat to prevent the device from overheating (Mjallal et al., 2018). Because of this function, the total amount of aluminium in Product A is significantly higher than that of the other CRMs, which are present in much smaller quantities on the PCB.

Of the total 140.553 grams of CRMs in Product A, aluminium accounts for 140 grams, while the remaining CRMs together make up just 0.553 grams. Therefore, it is excluded from the main MFA model and instead included in a separate SFA model. Furthermore, aluminium is expected to follow a higher recycling rate. The results of this model are shown below in Table 4 , and a visual representation of the model can be found in **Appendix H–1**.

Table 4: SFA results: aluminium in product A.

CRM	Use (inflow)	Reuse (flow)	Recovered (outflow)	Non-recovered (outflow)	Waste (outflow)	Landfill (stock)	Unit
Al	140	53.8	17.3	3.90	9.99	+ 1.14	g

Note: aluminium recovery rate modelled as 81.6%, values rounded to three significant figures.

As shown in Table 4, 140 grams of aluminium is used in the manufacturing of a single product. Based on Recycler A's report (**Appendix E**), a 81.6% recycling rate is assumed for aluminium, resulting in 17.3 grams being recovered over the y to y+4 period. In addition, the table presents the *non-recovered* outflow, *waste*, and *landfill* quantities, following the same structure as the MFA model described in the previous section.

Precious metal flows

A second, distinct group of CRMs in Product A consists of the PMs. As outlined in Section 5.3, these materials are among the few CRMs that are currently widely recycled, approximately 12% according to the EC, primarily due to their high economic value (Grohol and Veeh, 2023; Xia and Ghahreman, 2024). In a report by KPN's recycler, a percentage of 14.0% could be derived for PMs (**Appendix E**), consequently, this recovery rate was also applied in the SFA models. The SFA modelling results are presented in Table 5, with a visual representation available in **Appendix H–2**.

Table 5: SFA results: platinum group metals in product A.

CRM	Use (inflow)	Reuse (flow)	Recovered (outflow)	Non-recovered (outflow)	Waste (outflow)	Landfill (stock)	Unit
Pd	0.278	0.107	0.00588	0.0362	0.0198	+ 0.00226	mg
Rh	1.67	0.603	0.0347	0.214	0.117	+ 0.0134	mg
Ru	0.764	0.293	0.0162	0.0995	0.0545	+ 0.00828	mg

Note: platinum group metals recovery rate modelled as 14.0%, values rounded to three significant figures.

Table 5 provides an overview of the CRM flows and stock related to the platinum group metals in Product A. Compared to aluminium, a smaller percentage of these metals is recovered, with the remaining quantities ending up in *non-recovered, waste, or landfill* streams.

Remaining CRM flows

Lastly, an SFA model was developed for each of the remaining CRMs. According to KPN's recycling partner, only aluminium and PMs are currently recycled, while the other materials, likely due to their limited economic value, are not. As a result, the recovery rate for the materials in Table 6 is modelled at 0.00%. **Appendix H–3** contains a visual representation of these models.

Table 6: SFA results: remaining CRMs in product A.

CRM	Use (inflow)	Reuse (flow)	Recovered (outflow)	Non-recovered (outflow)	Waste (outflow)	Landfill (stock)	Unit
Sb	$5.64 \cdot 10^3$	$2.17 \cdot 10^3$	0.00	$8.54 \cdot 10^2$	$4.03 \cdot 10^2$	$+ 4.59 \cdot 10^1$	µg
Be	$3.76 \cdot 10^3$	$1.44 \cdot 10^3$	0.00	$5.69 \cdot 10^2$	$2.68 \cdot 10^2$	$+ 3.06 \cdot 10^1$	µg
Bi	$7.74 \cdot 10^2$	$2.97 \cdot 10^2$	0.00	$1.17 \cdot 10^2$	$5.53 \cdot 10^1$	+ 6.30	µg
B	$1.53 \cdot 10^3$	$5.88 \cdot 10^2$	0.00	$2.32 \cdot 10^2$	$1.09 \cdot 10^2$	$+ 1.25 \cdot 10^1$	µg
Ce	$2.20 \cdot 10^{-2}$	$8.45 \cdot 10^{-3}$	0.00	$3.33 \cdot 10^{-3}$	$1.57 \cdot 10^{-3}$	$+ 1.70 \cdot 10^{-4}$	µg
Co	$8.14 \cdot 10^2$	$3.13 \cdot 10^2$	0.00	$1.23 \cdot 10^2$	$5.81 \cdot 10^1$	+ 6.63	µg
Ga	$1.50 \cdot 10^1$	5.76	0.00	2.27	1.07	$+ 1.22 \cdot 10^{-1}$	µg
Mg	$3.19 \cdot 10^3$	$1.22 \cdot 10^3$	0.00	$4.83 \cdot 10^2$	$2.28 \cdot 10^2$	$+ 2.60 \cdot 10^1$	µg
P	$6.43 \cdot 10^2$	$2.47 \cdot 10^2$	0.00	$9.74 \cdot 10^1$	$4.59 \cdot 10^1$	+ 5.24	µg
Si	$4.52 \cdot 10^5$	$1.74 \cdot 10^5$	0.00	$6.84 \cdot 10^4$	$3.23 \cdot 10^4$	$+ 3.68 \cdot 10^3$	µg
W	$1.51 \cdot 10^3$	$5.79 \cdot 10^2$	0.00	$2.28 \cdot 10^2$	$1.08 \cdot 10^2$	$+ 1.23 \cdot 10^1$	µg

Note: CRM recovery rate modelled as 0.00%, values rounded to three significant figures.

Since these materials are not included in the current recycling process, the *recovered* column remains at 0.00 for all remaining CRMs. This outcome will remain unchanged even if Product A is discontinued, which would only increase the total outflow and stock quantities. The majority of these materials end up as *non-recovered* outflow, while a portion is directed toward *energy recovery*, and a smaller fraction is ultimately *landfilled*.

4.3.2 SFA models: production level

Whereas the previous section presented the SFA modelling output at the product level, this section scales those values to reflect the total production volume of Product A between year y to y+4. To calculate these results, each value from the product-level model is multiplied by the number of units produced, of 1.34 million units. Since the original values are already normalized per product, a uniform multiplication is applied across all figures. This yields the total inflows, outflows, and landfill stock accumulation over the y to y+4 period, as shown in Table 7.

Table 7: SFA results: CRM quantities over total year y to y+4 production.

CRM	Use (inflow)	Reuse (flow)	Recovered (outflow)	Non-recovered (outflow)	Waste (outflow)	Landfill (stock)	Unit
Al	$1.88 \cdot 10^{5}$	$7.22 \cdot 10^{4}$	$2.32 \cdot 10^{4}$	$5.23 \cdot 10^{3}$	$1.34 \cdot 10^{4}$	$1.53 \cdot 10^{3}$	kg
Pd	$3.73 \cdot 10^{-1}$	$1.44 \cdot 10^{-1}$	$7.90 \cdot 10^{-3}$	$4.86 \cdot 10^{-2}$	$2.66 \cdot 10^{-2}$	$3.03 \cdot 10^{-3}$	kg
Rh	2.24	$8.09 \cdot 10^{-1}$	$4.65 \cdot 10^{-2}$	$2.87 \cdot 10^{-1}$	$1.57 \cdot 10^{-1}$	$1.80 \cdot 10^{-2}$	kg
Ru	1.02	$3.93 \cdot 10^{-1}$	$2.17 \cdot 10^{-2}$	$1.33 \cdot 10^{-1}$	$7.31 \cdot 10^{-2}$	$8.34 \cdot 10^{-3}$	kg
Sb	7.56	2.91	0.00	1.15	$5.41 \cdot 10^{-1}$	$6.16 \cdot 10^{-2}$	kg
Be	5.04	1.93	0.00	$7.63 \cdot 10^{-1}$	$3.59 \cdot 10^{-1}$	$4.10 \cdot 10^{-2}$	kg
Bi	1.04	$3.98 \cdot 10^{-1}$	0.00	$1.57 \cdot 10^{-1}$	$7.42 \cdot 10^{-2}$	$8.45 \cdot 10^{-3}$	kg
B	2.05	$7.89 \cdot 10^{-1}$	0.00	$3.11 \cdot 10^{-1}$	$1.46 \cdot 10^{-1}$	$1.68 \cdot 10^{-2}$	kg
Ce	$3.00 \cdot 10^{-5}$	$1.13 \cdot 10^{-5}$	0.00	$4.47 \cdot 10^{-6}$	$2.11 \cdot 10^{-6}$	$2.28 \cdot 10^{-7}$	kg
Co	1.09	$4.20 \cdot 10^{-1}$	0.00	$1.65 \cdot 10^{-1}$	$7.79 \cdot 10^{-2}$	$8.89 \cdot 10^{-3}$	kg
Ga	$2.01 \cdot 10^{-2}$	$7.73 \cdot 10^{-3}$	0.00	$3.04 \cdot 10^{-3}$	$1.44 \cdot 10^{-3}$	$1.60 \cdot 10^{-4}$	kg
Mg	4.28	1.64	0.00	$6.48 \cdot 10^{-1}$	$3.06 \cdot 10^{-1}$	$3.49 \cdot 10^{-2}$	kg
P	$8.62 \cdot 10^{-1}$	$3.31 \cdot 10^{-1}$	0.00	$1.31 \cdot 10^{-1}$	$6.16 \cdot 10^{-2}$	$7.03 \cdot 10^{-3}$	kg
Si	$6.06 \cdot 10^{2}$	$2.33 \cdot 10^{2}$	0.00	$9.17 \cdot 10^{1}$	$4.33 \cdot 10^{1}$	4.94	kg
W	2.02	$7.77 \cdot 10^{-1}$	0.00	$3.06 \cdot 10^{-1}$	$1.45 \cdot 10^{-1}$	$1.65 \cdot 10^{-2}$	kg

Note: aluminium recovery rate modelled as 81.6%, Platinum group metals recovery rate modelled as 14.0%, remaining CRM recovery rate modelled as 0.00%, values rounded to three significant figures.

The data in Table 7 provides an overview of all the in- and outflows in regard to the y to y+4 period wherein Product A is introduced to KPN's consumers and a substantial amount has already been collected and thus sent through a variety of *EoL management* streams. While all of these data points could be beneficial to assess the impact of KPN's methodology in some context, the main circular practice which stands out in this table is the effect of reuse. All data included is related to materials flowing in- and out of the system except for one; the *reuse products* flow, as this flow is argued to provide a significant contribution to the system's circularity.

Without the products, which need additional CRMs to be repaired included, a line of reasoning is suggested that every product reused could equal one less product which had to be supplied from primary inflow and thus manufacturing (Cooper and Gutowski, 2017). With KPN's manufacturer indicating most of the products components originate from China, the inclusion of closed loop recycled CRMs seems even more unlikely, suggesting that every reuse could equal the whole set of CRMs to be prevented from primary extraction to some extent.

Either way, within the modelled y to y+4 period the *reuse products* flow contributes significantly to saving CRMs either through preventing new CRMs from being extracted or by delaying the need for recycling processes which often result in material loss (Ciacci et al., 2015). Even with the factor of repairs which require additional CRMs included, this process only requires those CRMs instead of the whole device, and thus PCB, being inefficiently recycled. Additionally, as presented in Chapter 4.2.2 when the device would be discontinued which stops the reuse, recycling processes are often ineffective in regard to CRM recovery, making reuse a viable option to extend the time in which CRMs could remain in the loop.

4.4 Results: Model Validation and Uncertainty Analysis

4.4.1 1. Establishing the mathematical model

In the first step, the system elements and their interrelationships must be clearly defined. This is addressed in Chapter 4.1, where the goal, scope, and overall processes are introduced, and further elaborated in Chapter 4.2, which describes the relationships between processes and flows, supported by modelling output over the y to y+4 period.

One key parameter related to model correctness in static MFA, that has not yet been discussed, is the principle of mass balance. In line with the law of conservation of matter, MFA outcomes can be verified by checking whether the combined material inputs, outputs, and stock changes are balanced (Brunner and Rechberger, 2016). In other words, the total material inflow should equal the sum of the total outflow and the material accumulated in stocks. Table 8 illustrates how this principle is respected in both the y to y+4 MFA model and the hypothesized discontinuation scenario. The SFA models apply identical transfer coefficients as the y to y+4 model and are therefore not shown, but are also consistent with the mass balance principle.

Table 8: Mass balance calculations for MFA models.

Model	**Import(I)**	**Delta stock (dStock)**	**Export (E)**	**I - (dStock + E)**	**Mass balance**
y to y+4	644.3	+ 492,8	151,5	0	Yes
Discontinuation	0.00	- 485	485	0	Yes

4.4.2 2. Characterize data uncertainty

The second step involves characterizing data uncertainty in the model, for which two approaches were applied. First, processes were grouped as either within KPN's scope (green coloured processes) or outside it (blue coloured processes). In-scope processes are primarily of interest to this study as they reflect reuse potential. Out-of-scope processes are included for downstream context but rely on more aggregated data due to missing product-level information, leading to greater uncertainty in their transfer coefficients.

Therefore, the quantifiable approach, based on including uncertainty factors in the STAN model, was applied primarily to the in-scope processes where uncertainty was detected. These uncertainty factors are based on the standard deviation of selected transfer coefficients, as detailed in **Appendix E - Table 20**.

As collection, repair, waste, and reuse flows are tracked via product-specific barcodes scanned at process entry and exit points, their uncertainty is set at zero. The *non-return waste products flow*, however, is more uncertain; based on an average of four annual values, a standard deviation of 0.0390 was calculated. This uncertainty also affects the derived *in use products* flow and is accordingly included through the STAN software's calculation of an unknown value.

Although not prioritized, the same quantification was applied to the flows leaving the *collection and sorting municipal* process since data was available, aimed at enhancing model quality. For two out-of-scope processes, however, quantifying uncertainty remained challenging:

1. **Industrial recycling** relies on a 70.0% minimum recovery target for PCBs. While data from a downstream partner suggests this target is rather exceeded than not, exact uncertainty remains hard to quantify.
2. **Precious metal recycling** uses material-specific data from 2019 on IT and telecom equipment. Though relevant, the data's age adds an element of uncertainty which is difficult to quantify.

4.4.3 3. Combine data and mathematical model

The third step entails inserting the data into the mathematical model, followed by cross-checking and plausibility assessment. These validation steps were undertaken through informal discussions with the senior product manager of Product A, a strategist from the energy and environment division, and a manager from KPN's EoL partner ([redacted], personal communication, [redacted])[redacted] The resulting model is calibrated based on the best available data. As previously discussed, the in-scope sections are considered to offer an accurate representation of reality, while the out-of-scope components provide a realistic contextual insight into downstream flows.

An additional source of uncertainty in the model lies within the repair process of the EoL management subsystem. Since the modelling logic requires all discarded CRMs to be replaced, the inflow of replacement CRMs should equal the outflow of discarded ones. However, introducing replacement CRMs as inflow eventually results in more discarded CRMs as they end up in repaired products from which some are later repaired again. To address this, a modelling step was introduced where the replacement CRM inflow was initially set to zero, allowing it to be balanced against the discarded outflow. While argued to be a method with some ad-hoc characteristics, the system's mass balance is respected, resulting in the expectations for increased uncertainties to be marginal.

4.4.4 4. Calculate the uncertainty

As outlined in the stepwise procedure, uncertainty in a static MFA model can be propagated either analytically or through mathematical techniques (Laner et al., 2014). In this case, the analytical approach was chosen, as the primary flows of interest are based on KPN's internal datasets and are therefore considered to carry low uncertainty. Accordingly, the uncertainties defined in the second step were propagated through the model by incorporating them into the relevant transfer coefficients. This approach is reflected by the uncertainty indicators shown in Figure 13.

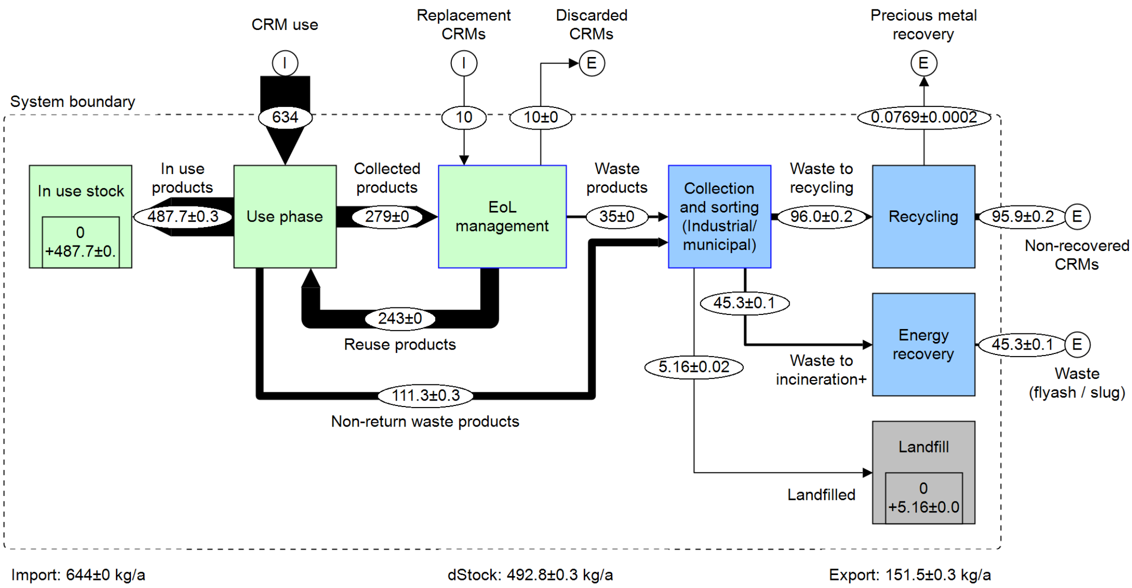


Figure 13: Uncertainy in static MFA model of CRM flows in product A: y to y+4 period. *Note: values in kg, green processes are within- and blue and grey are outside KPN's scope, aluminium not included, blue process outline indicates subsystem.*

Figure 13, presents the final modelling result for the y to y+4 MFA, including the associated uncertainty. To preserve readability, most values are rounded by the software, which may cause minor deviations from the original input. These do not affect the correctness of the output.

With uncertainty incorporated into the flow values, the STAN software assesses how uncertainty in one flow propagates throughout the system. This makes it possible to observe the impact of uncertainty on individual flows and on the model as a whole.

For example, the *non-return waste products* flow has an uncertainty of 0.300, which also affects the *in use products* flow, as the latter is derived through mass balancing of the use phase's in- and outflows. Alternatively, the *collected products* flow remains unaffected since it was modelled with zero uncertainty, and thus does not propagate uncertainty downstream from the *non-return waste products* flow.

The uncertainty associated with the *non-return waste products* flow does, however, propagate into the downstream municipal waste flows, *recycling*, *energy recovery*, and *landfill*, contributing to aggregated uncertainty. Besides the flow-specific values shown in Figure 13, the overall uncertainty- and model quality are presented in Table 9.

Table 9: Uncertainty parameters for MFA models.

Model	Import	Delta stock	Export	Degree of overdetermination	Quality of reconciliation	z-value
y to y+4	± 0.00	± 0.300	± 0.300	1.00	1.00	0 < 0.05 = 100%
Discontinuation	± 0.200	± 0.0100	± 0.100	1.00	1.00	0 < 0.05 = 100%

As Table 9 illustrates, the total uncertainty values for import, stock change, and export range between 0.00 and 0.300. When considered relative to the total model quantities, these values do not indicate worrisome uncertainties. Nevertheless, to confirm the robustness of the results, the model's quality was assessed quantitatively using metrics provided by the STAN software: the degree of overdetermination, the reconciliation quality, and the z-values.

The degree of overdetermination is used to assess the ratio of independent balance equations to unknown variables. A model is considered overdetermined when more input flows are specified than necessary, leaving fewer values to be calculated through the modelling software (Klinglmair et al., 2016). In both models, used in this study, STAN provided a degree of overdetermination of 1.00, indicating the model is sufficiently capable of assessing the flow data based on the provided inputs.

Reconciliation quality, also reported as 1.00 for both models, reflects the success of the least-squares optimization process used to adjust input data for internal consistency (Klinglmair et al., 2016). A value of 1.00 indicates the reconciliation is successful and that the observed data matches perfectly with the expected data, with further confirms the model's internal consistency.

Lastly, all identified z-values in the model fall between 0.00 and 0.500 which indicates the reconciliated values closely match the expected values, with no significant deviations observed. This indicates that the model is well-calibrated to the available data and provides a high degree of confidence in data output.

5 System Analysis: Flow Dynamics Over Time

In developing a dynamic, prospective MFA model, as opposed to the static approach described in the previous chapter, the key distinction lies in analysing how material flows evolve over time, rather than capturing a single moment or period. With insights in flow dynamics over time, this creates the possibility to model material and GWP impacts towards the future and evaluate the outcomes of future strategies.

5.1 Methodology: Dynamic MFA & Modelling Concept

Product flows over time

To gain insights into how the flows, as presented in Chapter 4 behave over time, the first step involved visualizing the 'real-time' flows through actual data points from the y to y+4 period. Showing their progression over time, as illustrated in Figure 14.

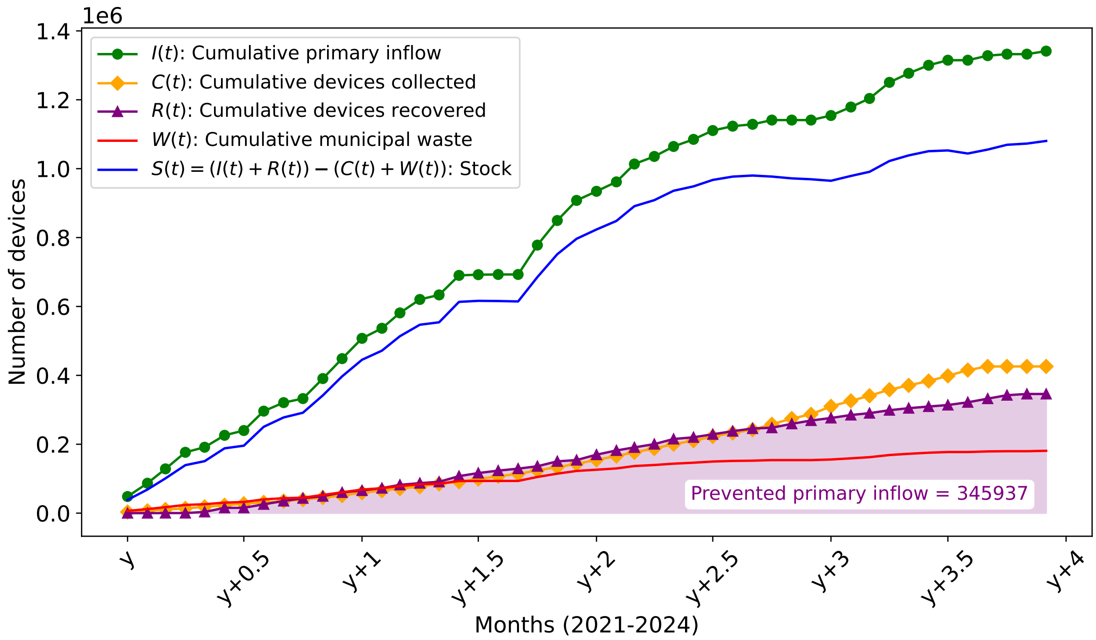


Figure 14: Cumulative flows and stock over the y to y+4 period. *Note: dots on lines indicate data points and straight lines calculations derived from data points.*

As shown in Figure 14, the *cumulative primary inflow* steadily increases over the y to y+4 period without any major disruptions. In the initial stages, the *cumulative devices collected* line rises only marginally. However, after some time, this line, along with the *cumulative devices recovered*, begins to show a more rapid increase. This pattern can be explained by the fact that most newly distributed devices do not require replacement in the early years, leading to initially low collection volumes and, consequently, a limited base for recovered inflow. As the number of collected devices increases over time, a greater share becomes available for reuse, resulting in a steeper rise in both cumulative collection and recovery figures.

The purple area beneath the *cumulative devices collected* line represents *prevented primary inflow*, based on the logic that each reused device displaces the need for a new one. Over the y to y+4 period, this equals 346 thousand devices that did not need to be manufactured.

Additionally, two lines in the Figure are based on calculations. The *municipal waste* stream is modelled similarly to the static MFA approach and is aligned with KPN's internal projections, representing 13% of the total outflow. The *stock* line is calculated by subtracting the cumulative monthly outflows (collected and waste) from the cumulative inflows (primary inflow and recovered).

Discontinuation Process

This section outlines the dynamics surrounding the discontinuation process provided by the senior commercial product manager ([redacted], personal communication, [redacted])[redacted] as shown in Figure 15.

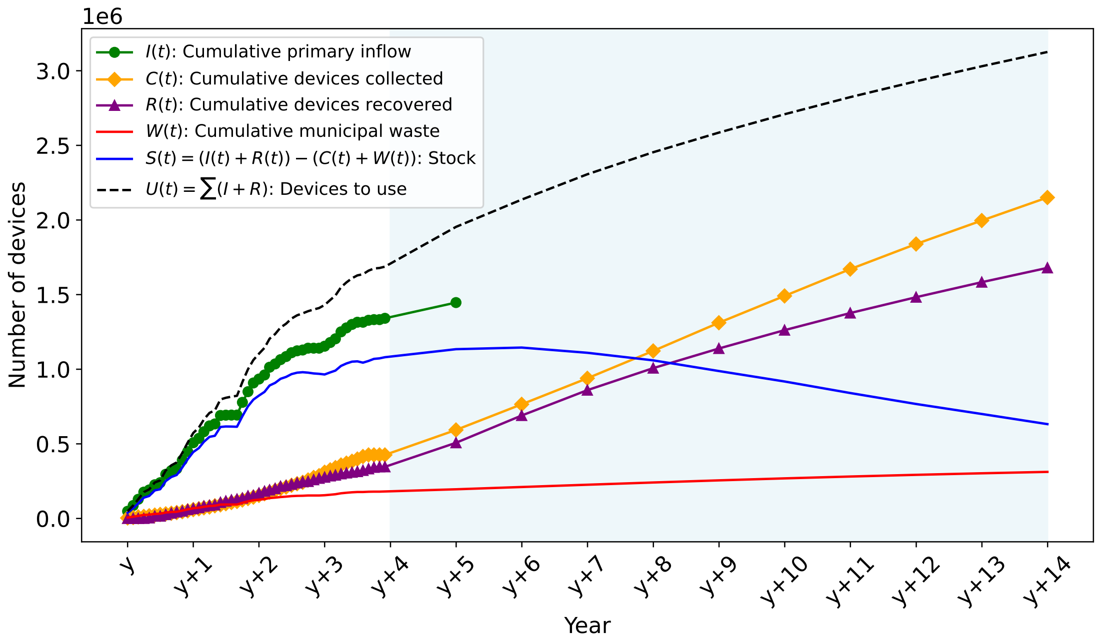


Figure 15: Cumulative flows and stock over the y to y+14 period. *Note: blue section after y+4 indicates data is projected, dots on lines indicate data points and straight lines calculations derived from data points.*

Figure 15 illustrates the discontinuation process for Product A, based on the projected cumulative flows and stock until the end of y+14. As shown, the stock at the end of this period is still expected to be approximately 0.6 million devices, reflecting the prolonged discontinuation timeline.

The *cumulative primary inflow* of Product A continues until the end of 2026, after which this inflow from the manufacturer stops and all devices supplied to consumers are taken from previously collected flows. Therefore the *cumulative devices collected* line is projected to keep increasing over the years, also when product A is gradually phased out as KPN strives to collect all devices themselves. The reason this line exceeds the stock is due to some devices being reused multiple times and thus being collected more than once.

The *cumulative devices recovered* line is projected to increase until approximately 2030, to maintain the devices in the install base (stock) at a consistent level. After 2030 the install base is gradually decreased which is done through supplying customers with a newer model in contrast to Product A. This is seen through the lesser increase of the *cumulative devices recovered* line from 2030 onward, which in turn affects the stock resulting in a decrease of the install base.

Lastly, there is the *devices to use* line, which illustrates the total amount of devices supplied to customers through a summation of the primary inflow and recovered devices. This shows how many devices have, in total, been supplied by KPN through primary inflow and reuse over the total plotted lifetime. The stock is expected to gradually decrease for around five more years, as previously mentioned Product A will have a longer in use time than its predecessors, from when no more than 20,000 should remain in the install base.

5.1.1 Dynamic MFA: goal, scope and basemodel

With the projected product flows of Product A in mind the following step was to design a dynamic MFA to assess the past (y to y+4) and future material flows, and the effect of future strategies. A model is defined as dynamic if the behaviour of a system over an interval of time is described (E. Müller et al., 2014). The value added by a dynamic MFA, is the possibility to identify the stocks which are in-use (or 'hibernating'), and visualise the synthesis between these parameters and in- and outflows over time (Graedel, 2019). The goal of the dynamic MFA model is similar to the static model, an additional parameter is the analysis of scenarios and an extension of the scope until y+14. The dynamic model also applies the transfer coefficients as defined in Chapter 4, Table 3.

To estimate future in- and outflows under varying circularity strategies, a stock-driven model was developed as a first step. The model was created by calculating each cohort based on yearly stock data. A stock-driven MFA modelling approach was applied, as for the y+4 to y+14 period only predicted stocks were available. To determine the inflow, the formula for a stock-driven model by Fishman (2023) was applied as shown in Equation 4.

$$\mathrm{inflow}(y) = \frac{\mathrm{stock}(y) - \sum_{t=y_0}^{y-1} [\mathrm{inflow}(t) \cdot \mathrm{sf}(y-t)]}{\mathrm{sf}(0)} \tag{4}$$

Equation 4 calculates the inflow, the amount of products or materials entering the system at time y, using three parameters:

1. $\mathbf{stock}(y)$**:** This represents the stock (inventory) of the product or material at time y, which refers to the amount of the product or material present in the system at that specific moment.
2. $\sum_{t=y_0}^{y-1} [\mathbf{inflow}(t) \cdot \mathbf{sf}(y-t)]$: This is the sum of all previous inflows from $t = y_0$ to $t = y-1$, where each inflow $\mathrm{inflow}(t)$ is multiplied by the survival curve $\mathrm{sf}(y-t)$. The survival curve accounts for the influence of the inflow at time t on the stock at time y. This term essentially describes how earlier inflows impact the current stock level.
3. $\mathbf{sf}(0)$**:** This is the storage factor at the initial point ($t = 0$), which serves as a normalization factor, ensuring the influence of the storage correction on the inflow is accounted for.

To calculate the inflow in a given year all previous inflows and their contributions to the stock up to that year must be accounted for. By summing past inflows, each weighted by the corresponding survival curve, the inflow at time y can be estimated. This approach enables an indirect calculation of inflow based solely on stock data over time.

Before introducing the stock-driven model for Product A, the survival curve is defined using the European Commission's WEEE Generated Calculation Tool (European Commission, 2024a). This tool provides parameters for a Weibull-type curve; commonly used for electronics due to its reflection of early product longevity and later-stage outflows (Sindhu and Atangana, 2021). The survival and outflow curves for Product A are shown in Figure 16.

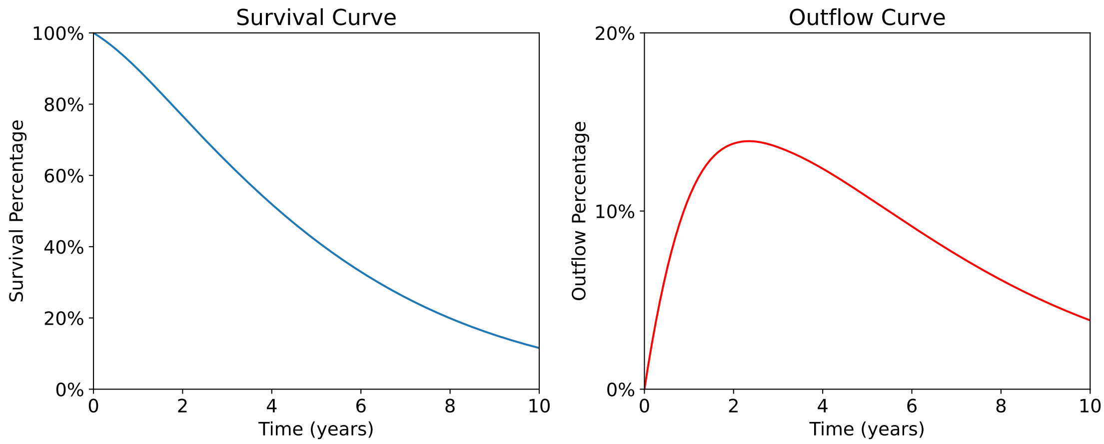


Figure 16: Survival- and outflow curve Product A. *Note: curve shape = 1.3 and curve scale = 5.535, outflow curved derived from general trend of the survival curve.*

To model the curves in Figure 16, the UNU-key 0301 was used, representing 'small IT equipment (e.g. routers, mice, keyboards, external devices and accessories)'. With 2020 as the reference year, the year Product A was launched at KPN, the tool returned an average lifetime of 5.68 years, a shape of 1.3, and a scale of 6.15. The scale of 6.15 is based on a products total lifetime, however, 10.0% of product A is also collected due to KPN customer switching providers which results in the adjusted scale of $6.15 \cdot 0.9 = 5.535$.

For the y to y+4 period, data on inflows, outflows, and total stock accumulation per year were well-documented by KPN. These data were presented and applied in the static MFA models discussed in Chapter 4. However, for the y+4 to y+14 period, both the availability and certainty of available data decreases. This is primarily because, rather than real-time records, future projections are used which inherently carry a higher degree of uncertainty.

Moreover, the projected data depends on scenarios that are not yet fully defined, particularly regarding the pace at which Product A will be phased out. To address this uncertainty, a midpoint scenario, considered the 'most likely', was applied. This scenario follows the trend previously illustrated in Figure 15. Notably, this data and therefore also the dynamic MFA model are based on yearly stock data, as accurate yearly inflow data could not be acquired for the y+4 to y+14 period.

With the actual stock data from y to y+4 and projected stocks from y+4 to y+14 in place, the dynamic MFA model for Product A, across the full y to y+14 period was developed. The output of the base model is presented in Figure 17.

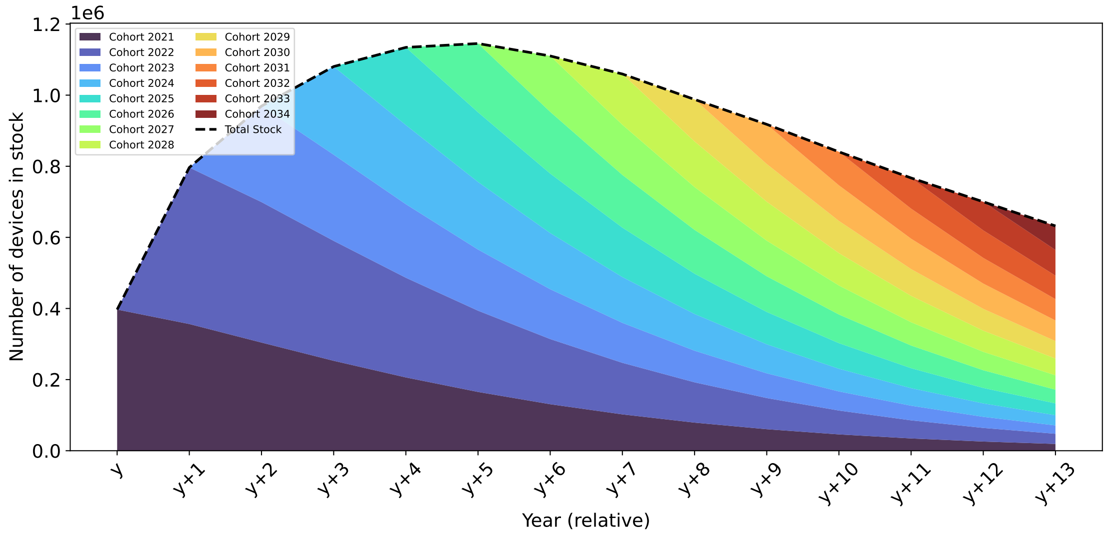


Figure 17: Dynamic MFA: yearly stock based on primary annual inflow.

In Figure 17, the yearly inflow of Product A is shown entering the total stock, with each inflow's lifetime defined as a cohort. Over time, devices introduced into the system are observed to largely remain in-stock during the initial years. After the average lifetime of approximately five years, outflows begin to increase. Notably, the period between approximately y to y+4 sees the highest inflow of devices, after which the yearly inflow stabilizes. The dataset begins at 0.4 million devices in year y, due to a substantial initial inflow in y-1, the year Product A was first introduced, for which detailed data is unavailable.

This model provides a preliminary insight into the behaviour of yearly cohorts over time. It illustrates how the total stock of Product A accumulates and highlights the approximate period during which newly introduced devices remain in use. It is important to note that, in contrast to the static MFA models presented in Chapter 4, this model uses average values. While this increases general applicability, it also reduces precision. Overall, the model is considered a realistic representation of the system's dynamics, although some finer details may be overlooked. Additionally, the current version does not yet include the effects of reuse and recycling, which are addressed in the following sections.

The effects of reuse on primary CRM inflows over time

As one of the primary circular impacts, identified in Chapter 4, was the potential impact of reuse on reducing the need for primary CRM inflows, the next step involved incorporating this parameter into the stock-driven MFA model. This is achieved by modifying the $inflow(t)$ term to include both the primary inflow ($inflow^{new}$) and the quantity of products reused from a previous year.

The reused quantity is calculated by applying the reuse rate (r) to the product outflow in year $(t-1)$. This reused portion is then added to the primary inflow for the following year (t). For example, if r = 80.0%, then 80.0% of the outflow from year $t-1$ re-enters the system as inflow in year t, while the remaining 20.0% must be supplied via primary inflow $inflow^{new}$. Since both reused and newly introduced products are subject to finite lifetimes, their contribution to the stock gradually declines over time. In this model a reuse percentage of 81.2% is used, reflecting the observed reuse rate of collected products during the y to y+4 period.

The effect of reuse on primary CRM inflows is thus integrated into the intrinsic formula in Equation 4, by adding the reused portion from the previous year as part of the total cohort for a given year. This adjusted approach is presented in Equation 5, while Equations 6 and 7 define the net addition to stock (NAS) and the predicted outflow.

$$\text{inflow}(y) = \frac{\text{stock}(y) - \sum_{t=y_0}^{y-1} \left[(\text{inflow}^{new}(t) + r \cdot \text{outflow}(t)) \cdot \text{sf}(y-t) \right]}{\text{sf}(0)} \tag{5}$$

$$NAS(y) = \text{stock}(y) - \text{stock}(y-1) \tag{6}$$

$$\text{outflow}(y) = \text{inflow}(y) - NAS(y) \tag{7}$$

When integrated into the model, the equations above result in a modified version of the yearly stocks visualization, as shown in Figure 18. This figure illustrates the addition of reuse per cohort, providing a visual representation of the dynamic behaviour of the system over time.

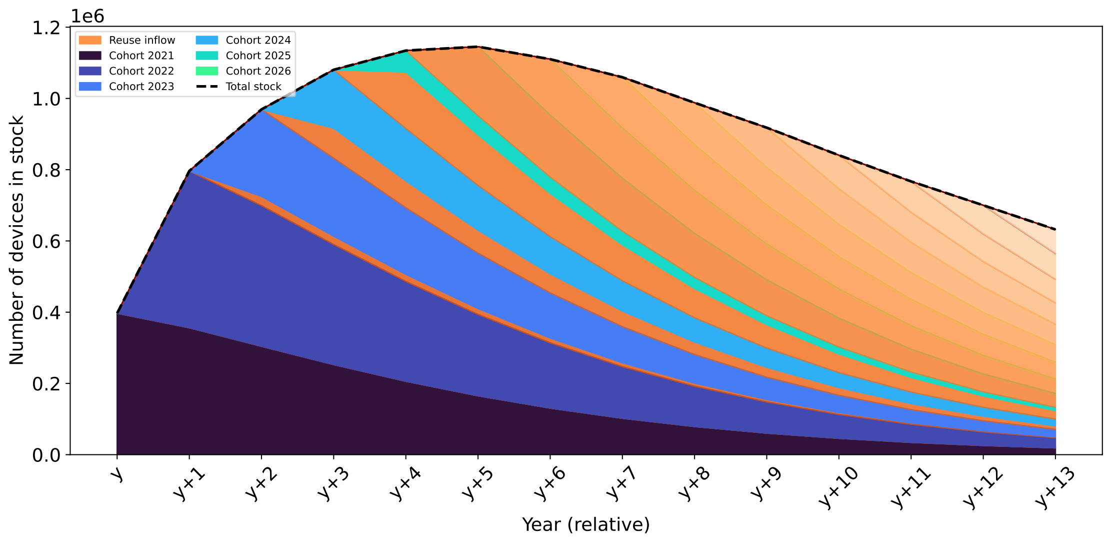


Figure 18: Dynamic MFA: yearly stock based on annual inflow from primary and reuse devices. *Note: reuse rate = 81.25%, cut-off year for primary inflow = 2026.*

The plot in Figure 18 illustrates how reused products behave within the system over time. In the initial years, most inflows consist of primary products, which is expected, as Product A is newly introduced to the market and no collected devices are yet available for reuse. Nevertheless, the model already shows a small inflow from reused products in 2022, which gradually increases. This trend reflects more devices reaching the expected lifetime of three years, as indicated by the survival curve in Figure 16.

The cut-off year for primary inflow was set to 2026, which is depicted in the model as the last cohort, requiring a marginal primary inflow that year. The marginal primary inflow is a result of the high reuse percentage of 81,2%; if this rate were lower, primary inflow in 2026 would likely account for a greater share. After 2026, primary inflow is deliberately stopped, with all incoming devices sourced from reuse. This scenario is only feasible because devices can be reused multiple times, otherwise, the orange-coloured segments representing reused cohorts could never exceed the size of the primary inflow cohorts.

Given that reuse is a central focus of this study, the plot is further refined: the cohorts shown in Figure 18 are restructured into a separate cohort matrix. This matrix represents the total quantity of materials reused, as illustrated in Figure 19.

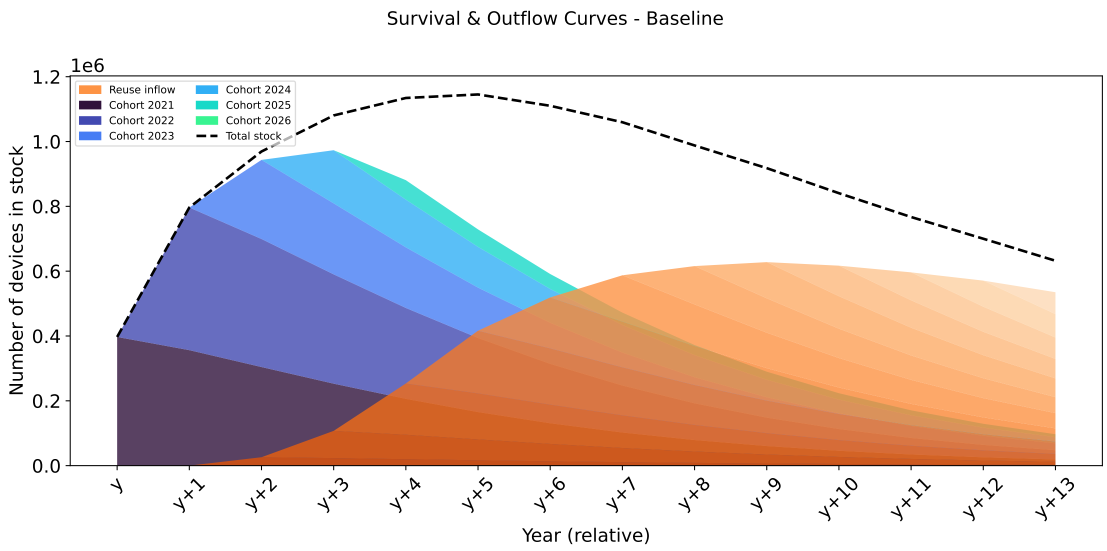


Figure 19: Dynamic MFA: yearly stock based on annual inflow with separate primary and reuse cohort matrices. *Note: reuse rate = 81.25%, cut-off year for primary inflow = 2026.*

The reuse cohorts are modeled as a separate cohort matrix, as shown in Figure 19, due to the significance of the product quantities represented in this section. This area encompasses all reused products and, following the logic of this study, reflects the number of devices that were prevented from being newly produced from primary materials.

Given the CRM composition of Product A, this matrix enables the calculation of the recovered quantity of CRMs, the GWP impact score avoided through reduced primary extraction, and possibly other implications. For this purpose, Equation 8 is used, which multiplies the total quantity of reused products by an impact variable (IV). This variable can represent CRM content, an environmental impact metric, or a another indicator.

$$\text{reuse impact}(y) = \sum_{t=y_0}^{y-1} [r \cdot \text{outflow(t - 1)}] \cdot IV \tag{8}$$

5.1.2 Material and prevented GWP impact of reuse

Whereas the prior figures 17, 18 and 19 visualized the overall dynamics of primary and reused stocks and flows for Product A, this section aims to translate those insights into quantitative outcomes.

The first measured effect concerns material reuse, specifically the quantity of primary-sourced CRMs that were avoided through product reuse.

As discussed previously, this study assumes that each reused product would have otherwise been newly produced, requiring its full CRM composition from primary sources (Cooper and Gutowski, 2017). In practice, this is more complex, as certain CRMs can be recovered through recycling and reintroduced via secondary streams. Nonetheless, since KPN currently does not knowingly apply recycled CRMs within its own operations (due to insufficient insights in downstream supply chains), and since the production locations are located in China making closed loop recycling highly unlikely, the chosen modelling approach remains valid within the scope of this research.

This results in Equations 9 and 10, where the reuse impact is determined by multiplying the total number of reused products by the material impact variable $IV_{(materials)}$, which reflects the CRM content per product.

$$\text{reuse impact}(y) = \sum_{t=y_0}^{y-1} [r \cdot \text{outflow(t - 1)}] \cdot IV_{(materials)} \tag{9}$$

$$IV_{(material)} = CRM\ content \tag{10}$$

Similarly to the material impact, the GWP impact of reuse is also assessed by modifying the base formula; quantifying the total prevented GWP through reuse by multiplying each material quantity by its GWP in kg CO_2-eq, as presented in Equation 11 and 12. Note that the prevented GWP is an indication based on the GWP associated with the material's primary production, due to data limitations further up- and downstream emissions are not included.

$$\text{reuse impact}(y) = \sum_{t=y_0}^{y-1} [r \cdot \text{outflow(t - 1)}] \cdot IV_{(\text{GWP prevented})} \tag{11}$$

$$IV_{(GWP\ \text{prevented})} = CRM\ content \cdot GWP \tag{12}$$

5.1.3 Material and prevented GWP impact of recycling

As visualized in Figure 12 from Chapter 4.2.2, every device in use eventually transitions to one of the three EoL processing routes: recycling, energy recovery, or landfill. While delaying this transition through reuse is considered beneficial, these scenarios remain unavoidable and, as shown in Figure 20, often represent the most significant sources of CRM loss.

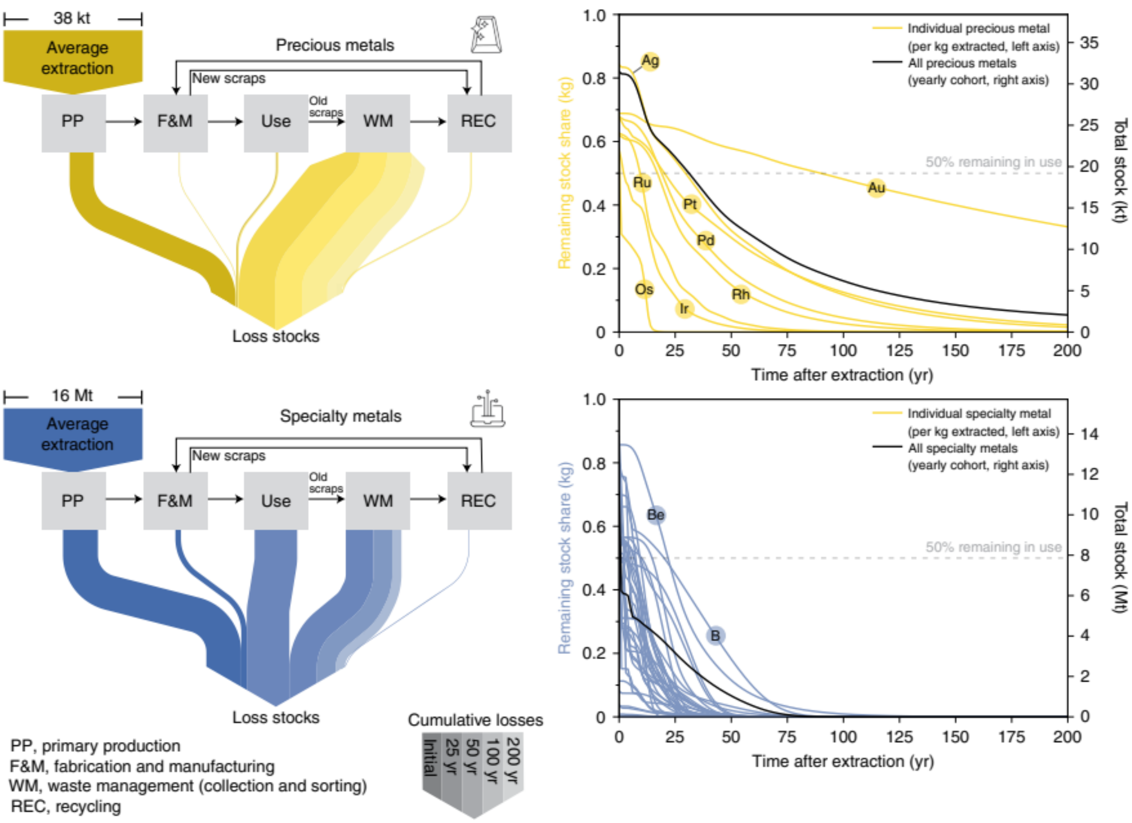


Figure 20: Predicted in-use stocks and losses of metals over two centuries for a yearly cohort of extracted metals. *Source: Charpentier Poncelet et al. (2022).*

The impact of waste management processes on CRM losses, as visualised in Figure 20, is based on findings by Charpentier Poncelet et al. (2022) concerning metal losses and lifetimes in the global economy. For both PMs and specialty metals, which include most CRMs as defined by the EC (Grohol and Veeh, 2023), most losses occur during waste management. Although this global data may not perfectly reflect the EU or Dutch context, CRM losses in waste handling are also a key concern regionally, as described by Campbell-Johnston et al. (2024), who emphasize the urgency of effective mitigation and recovery strategies.

In the Netherlands, 16.5 million kg of small IT and telecommunications equipment waste collected in 2022 alone, and with demand for electronics rising, this represents a significant waste stream (Eurostat, 2025).

In a TNO report, Campbell-Johnston et al. (2024), identified several materials for which enhanced WEEE recycling could be feasible and impactful. Antimony and PMs are categorized as recyclable materials with potential for increased recovery. Magnesium and gallium are seen as moderately important for meeting CRM Act benchmarks, while cerium is considered a low-priority element. Beryllium and bismuth were excluded due to their low presence in waste data, with tantalum and tungsten also excluded for unspecified reasons.

The assumed recycling percentages for KPN are 81.6% for aluminium, 14.0% for PMs, and 0% for the remainder of identified CRMs. Herein some deviations from the overall EU EoL-RIR values as shown in Table 2 can be identified. Figure 21 shows how the identified recycling rates for Product A relate to the EU's EoL-RIR per material.

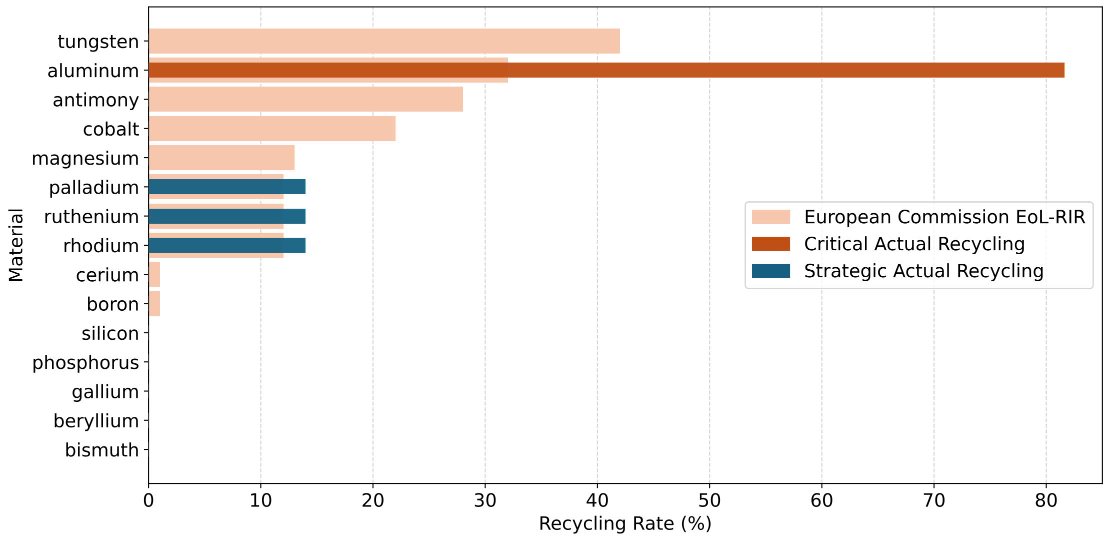


Figure 21: Potential recycling based on the EC's 2023 EoL-RIR compared to KPN's assumed recycling rates. *Source: Grohol and Veeh (2023).*

As shown in Figure 21, there is a discrepancy between the CRMs currently assumed to be recycled by KPN's partners and what could theoretically be recycled from an EU-wide perspective. Without further context, the graph suggests aluminium and PMs in Product A are recycled above the EU average and for other CRMs, recycling is likely not applied.

However, the EU rates should be interpreted with the overall application scale of each material, as opposed to the PCB in Product A, in mind. For example, tungsten, despite having the EU's highest EoL-RIR, is mainly used in tools like mill and cutting tools (33%), mining and construction tools (23%) or other wear tools (18%), where it can be easily separated for dedicated recycling. In electronics, where only 6% of tungsten is used, its minimal and often compound presence on PCBs makes recovery far more complex (Grohol and Veeh, 2023).

A similar logic applies to cobalt and magnesium. Cobalt is largely used in aviation superalloys (32%) (Akande et al., 2021), and magnesium in automotive (48%) and packaging sectors (23%) (Grohol and Veeh, 2023), where bulk recycling is more feasible than from electronic scrap.

There are two notable exceptions. First, aluminium in Product A is located in the heatsink (**Appendix C**), not the PCB, suggesting potential to raise recovery even further than the current 81.6% to possibly to 97.2% (Capuzzi and Timelli, 2018). Second, antimony, primarily used as a flame retardant (43%) in the PCB base, requires complex pyrolysis to recover, likely explaining its low recycling rate (Dupont et al., 2016; Grohol and Veeh, 2023). Nevertheless, EU data suggests some improvement may be possible.

With PM recycling aligning with EU averages, and elements like cerium and boron also showing minimal recovery across the EU, KPN and its downstream partners likely don't deviate much from broader trends, except in the case of aluminium.

EoL processing and recycling calculations

In the dynamic MFA model, the recycled amount of devices or materials is calculated by multiplying the relevant EoL destination rate – recycling (*MR*), energy recovery (*ER*) or landfill (*LF*) – by the number of products which flow out of each year's cohorts and are no longer eligible for reuse, as shown in Equation 13, 14 and 15. It is important to note that these formulas are applied separately to the collected product and municipal waste streams, as the shares for *MR*, *ER*, and *LF* differ between them, as detailed in the static MFA in Chapter 4. Additionally, Equation 16 includes recycling efficiency as an extra parameter to quantify the actual amount of material recovered from the total sent to recycling, unlike 14 and 15, which assume no recovery.

$$\text{recycling}(y) = \sum_{t=y_0}^{y-1} \left[MR \cdot (\text{outflow}(t-1) - \text{reuse}(t-1)) \cdot \eta_{\text{recycling}} \right] \tag{13}$$

$$\text{energy recovery}(y) = \sum_{t=y_0}^{y-1} \left[ER \cdot (\text{outflow}(t-1) - \text{reuse}(t-1)) \right] \tag{14}$$

$$\text{landfill}(y) = \sum_{t=y_0}^{y-1} \left[LF \cdot (\text{outflow}(t-1) - \text{reuse}(t-1)) \right] \tag{15}$$

For recycling, the impact variable (IV) is calculated similarly to those for reuse in Chapter 5.1.2 and 5.1.3. This is done by multiplying the total amount of recycled device by either the material quantity ($IV_{material}$) or the GWP per kg of the material ($IV_{\text{GWP prevented}}$) as shown in Equation 16.

$$\text{recycling impact}(y) = \sum_{t=y_0}^{y-1} \left[MR \cdot (\text{outflow}(t-1) - \text{reuse}(t-1)) \cdot \eta_{\text{recycling}} \right] \cdot IV_{\text{x}} \tag{16}$$

5.1.4 Overview of the Combined Dynamic MFA Model

The previous sections of this chapter described the modelling concept. Starting from the expected stock and covering reuse, recycling, and waste streams for the y to y+14 period. These were incorporated into a dynamic MFA model, building on the standard formula for stock-based MFA (Fishman, 2023). The model was extended in four ways: by introducing reuse as a variable, by adding recycling as an additional parameter and by adding the material and GWP impact as calculation steps. The purpose of this model is to evaluate how changes in key parameters, with emphasis on reuse and recycling as circular strategies used by KPN, affect material use and GWP impact scores.

This section presents the complete structure of the dynamic model used to generate the results shown in this chapter. As illustrated in Figure 22, the model builds on the core equation for dynamic stock-based MFA (Equation 4). This is expanded to include reuse, which is collected from prior years to partly substitute the primary inflow in subsequent years (Equation 5). In the final step, recycled quantities are derived from the outflow, defined as products no longer in use and unfit for reuse, and divided into recycling, energy recovery, and landfill fractions (Equation 13, 14, and 15). This is calculated separately for collected and municipal waste streams. Material and GWP impact are then determined by applying the relevant impact factors to both reused and recycled quantities (Equation 10 and 12). Together, these modelling steps and parameters form the combined dynamic MFA model for which the Python code and input data are available in **Appendix I**.

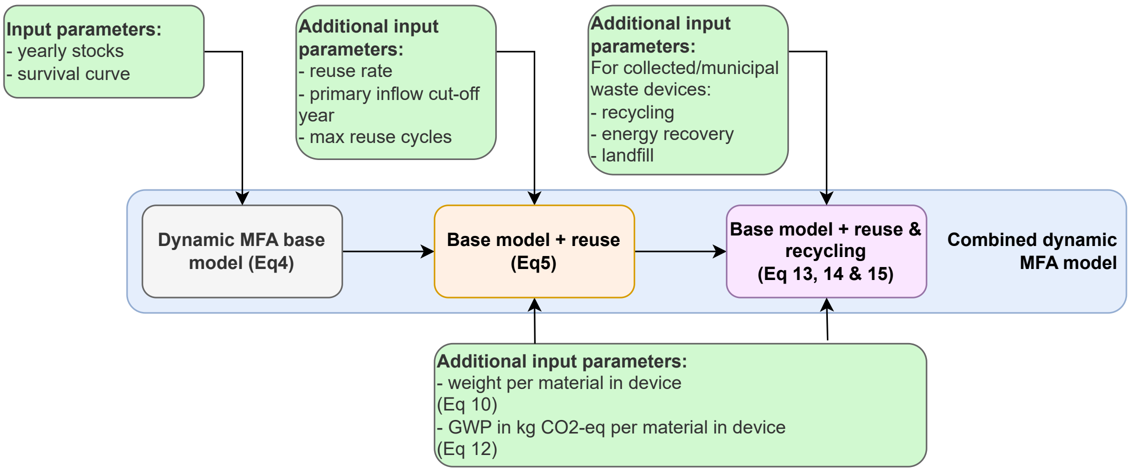


Figure 22: Combined dynamic MFA model: graphical representation.

5.1.5 Dynamic MFA model validation, uncertainty and sensitivity analysis

Similarly to the static model, the dynamic MFA is evaluated against its initial goal and scope, data quality, and the uncertainty of its results. The stepwise approach for addressing uncertainty in MFA, as described by Laner et al. (2014), is applied to this model as well in Chapter 5.4.

Unlike the static MFA in Chapter 4, which is descriptive, the dynamic MFA is exploratory in nature. According to Laner et al. (2014), this type of model requires more extensive validation. Therefore, uncertainty is assessed using a Monte Carlo Simulation (MCS), additionally a sensitivity analysis to further test the model's robustness is introduced as a fifth step.

5.2 Development of Modelling Scenarios

With Product A's flow dynamics over time established, the final methodological step is defining strategies to slow CRM waste flows based on the model output. Four strategies are proposed for KPN: three align with the circular economy principles introduced earlier: closing, narrowing, and slowing the loop (Månberger, 2023), while the fourth focusses on an additional solution, identified as a viable options during this study.

1. Closing the loop

This strategy focuses on enhancing recycling to retain CRMs within a circular system. To evaluate its impact, three recycling increase scenarios are modelled. As discussed by Grohol and Veeh (2023), antimony is used as flame retardant and could be recycled on EU average. Aluminium could also be recycled from the heatsink which is partly designed for disassembly (**Appendix C**).

In the second scenario, all CRM recycling rates below the EU average are increased to match it.

Though less feasible, since these CRMs are more efficiently recycled in other bulk applications, this scenario could illustrate future potential.

The third scenario models the effect of reaching the EU's 25.0% recycling target for 2030 (Office of the European Union, 2024). While also considered unlikely, it demonstrates potential material and GWP impacts if achieved.

2. Narrowing the loop

This strategy reduces CRM usage by designing products that require fewer materials or by limiting production of CRM-intensive goods. Two reduction scenarios are modelled. The first is based on Product A's CRM report (**Appendix B**), identifying non-critical alternatives for antimony and rhodium. Alternatives for other materials are indicated as well, however, these would also be CRMs and are therefore not included.

The second scenario models a general 10.0% material reduction to explore the potential impact of innovative design, though this is considered less realistic.

3. Slowing the loop

The last circular strategy as defined by Månberger (2023) aims to prolong the lifespan of products containing CRMs to reduce demand for new materials. The primary approach to assess the impact of this scenario is increased reuse. Currently 81.2% of Product A is reused, therefore, the impact of increased efficiency is measured by modelling a 10.0% increase.

As a second scenario, an expected lifetime extension of 10.0% for Product A is modelled, altering the Weibull curve shape from 5.535 to 6.15. Since this value is equal to the initial Weibull correction for churn, customers leaving KPN and returning their device, this scenario also shows the effect of a situation wherein customers would not need to switch modems when changing providers.

Earlier versions of Product A lasted approximately five to ten years. Newer versions benefit from software KPN can support indefinitely, potentially keeping devices in their install base longer. The impact of this scenario is measured through the same model adjustments as the two prior scenarios, since essentially the lifespan is also extended.

4. Reduced municipal waste

Currently, 12.7% of devices end up in municipal waste, which is the main stream leading to landfill or incineration instead of reuse or recycling. KPN could reduce this by e.g. introducing fines for non-returned devices, encouraging returns to their EoL manager. A 10.0% reduction of the municipal waste flow is modelled to assess the impact.

5.3 Results: Dynamic MFA Model

After running the model with the baseline parameters, it provided a total of 1.32 million reused- and 490 thousand recycled devices over the y to y+14 period. Additionally, the output indicated a total of 220 thousand devices to be sent for energy recovery and 11.7 thousand to landfill. Combined the total GWP was calculated to be $6.56 \cdot 10^6$ kg CO_2-eq.

Moreover, the model produced total material savings, amounting to 241 tonnes including- and 624 excluding aluminium. For prevented GWP, these values equated 83.5% ($5.47 \cdot 10^6$ kg CO_2-eq) of the total production's GWP including aluminium. Excluding aluminium this was 3.06% ($201 \cdot 10^3$ kg CO_2-eq).

Lastly, the model also provided the total prevented emissions value through the multiplication of all reused devices by the 12.5 kg CO_2 emissions per device, as outlined in Chapter 3.2.4. This resulted in an estimated $16.5 \cdot 10^6$ kg of CO_2 emissions avoided through reuse (based on KPN figures). Compared to the $5.47 \cdot 10^6$ kg CO_2-eq avoided through prevented primary material production, this implies that there are additional emissions in other production stages, unaccounted for in this study. However, due to differences in system boundaries and emission metrics (CO_2 vs CO_2-eq), these values should be interpreted with caution.

5.3.1 Prevented material and GWP impact of reuse

The amount of CRMs prevented from being primarily produced is found by applying Equation 9 to the baseline scenario, to quantify the prevented GWP, Equation 11 is similarly applied, with the results shown in Table 10.

This table quantifies the total weight of CRMs reused over the modelled period from y to y+14. Additionally, prevented GWP is expressed in kg CO_2-eq and as prevented percentage of total production; assuming devices would otherwise neither be reused nor recycled but instead newly produced from primary sources. Herein, reuse is responsible for 64.7% of prevented GWP.

Table 10: Dynamic MFA output: predicted kg of reused CRMs and prevented GWP in kg CO_2-eq. and percentage of prevented GWP compared to total production over y to y+14 period.

Material	kg reused	Prevented GWP (kg CO_2-eq.)	% of total GWP for production
aluminium	$1.85 \cdot 10^5$	$4.05 \cdot 10^6$	$6.17 \cdot 10^1$
palladium	$3.67 \cdot 10^{-1}$	$4.11 \cdot 10^3$	$6.27 \cdot 10^{-2}$
rhodium	2.20	$1.77 \cdot 10^5$	2.70
ruthenium	1.01	0.00	0.00
antimony	7.45	$1.71 \cdot 10^2$	$2.61 \cdot 10^{-3}$
beryllium	4.96	$3.41 \cdot 10^3$	$5.20 \cdot 10^{-2}$
bismuth	1.02	0.00	0.00
boron	2.02	5.79	$8.84 \cdot 10^{-5}$
cerium	$2.90 \cdot 10^{-5}$	$4.70 \cdot 10^{-4}$	$7.17 \cdot 10^{-9}$
cobalt	1.07	$4.82 \cdot 10^1$	$7.35 \cdot 10^{-4}$
gallium	$1.98 \cdot 10^{-2}$	3.39	$5.16 \cdot 10^{-5}$
magnesium	4.21	$1.16 \cdot 10^2$	$1.77 \cdot 10^{-3}$
phosphorus	$8.49 \cdot 10^{-1}$	3.96	$6.05 \cdot 10^{-5}$
silicon	$5.97 \cdot 10^2$	$6.44 \cdot 10^3$	$9.83 \cdot 10^{-2}$
tungsten	1.99	$1.11 \cdot 10^1$	$1.69 \cdot 10^{-4}$
Total	$1.86 \cdot 10^5$	$4.24 \cdot 10^6$	64.7

Parameters: curve shape = 1.3, curve scale = 5.535 years, reuse rate = 81.24%, primary inflow cut-off = 2026, max number of reuses = No., values rounded to three significant figures.

Material impact of reuse

When comparing the results in Table 10 to the reuse column for the y to y+4 period in the static SFA in Table 7 (Chapter 4.3.2), it becomes clear that all values have almost tripled. This outcome is expected, as despite a declining total stock, devices are reused multiple times, and from 2026 onwards, all primary inflows are halted and fully replaced by reused units.

This allows for a scenario wherein, a relatively efficient process such as reuse, delays the need for less-efficient processes such as primary material extraction, production or recycling. While these processes will never be avoided entirely, extending the period before they become necessary through more efficient methods could be, and will likely always remain, a viable approach.

Similar to the static MFA and SFA models, aluminium is reused the most by far, due to its abundance in Product A. This same logic is seen for all materials, with silicon also being reused in large quantities and alternatively, cerium still the least.

GWP impact of reuse

The results presented in Table 10 aim to provide a preliminary indication of the GWP impact scores that could potentially be prevented through reuse. However, in contrast to the material impact values shown in this table, the GWP values are subject to greater uncertainty. In addition to being based on data from Ecoinvent, which inherently involves a degree of generalisation and subjective method selection, these figures do not yet account for the GWP impact scores of the reuse process itself. They also assume that every reused product would otherwise have required the full production of a new device using primary materials.

This is based on the assumption that reused devices would otherwise be sourced from the manufacturer's primary production line in China, rendering it unlikely that such 'new' versions of Product A contain significant shares of recycled CRMs. Nonetheless, as these upstream processes lack transparency, particularly when tracing them back to a single device such as Product A, the 'prevented' GWP impact should be interpreted as an indication under average conditions.

5.3.2 Prevented material and GWP impact of recycling

To quantify the materials saved through recycling, Equation 16 is applied to the baseline scenario, resulting in the recycling and prevented GWP as shown in Table 11. This table only includes materials for which the recycling efficiency is higher than zero. The recycling processes are responsible for 18.9% of prevented GWP, if materials would otherwise be newly produced.

Table 11: Dynamic MFA output: predicted kg of recycled CRMs, prevented GWP in kg CO_2-eq. and percentage of prevented GWP compared to total production over y to y+14 period.

Material	kg recycled	Prevented GWP (kg CO_2-eq.)	% of total GWP for production
aluminium	$5.60 \cdot 10^4$	$1.23 \cdot 10^6$	$1.87 \cdot 10^1$
palladium	$1.91 \cdot 10^{-2}$	$2.14 \cdot 10^2$	$3.26 \cdot 10^{-3}$
rhodium	$1.14 \cdot 10^{-1}$	$9.19 \cdot 10^3$	$1.40 \cdot 10^{-1}$
ruthenium	$5.24 \cdot 10^{-2}$	0.00	0.00
Total	$5.60 \cdot 10^4$	$1.24 \cdot 10^6$	18.9

Parameters: curve shape = 1.3, curve scale = 5.535 years, reuse rate = 81.24%, primary inflow cut-off = 2026, max number of reuses = No., values rounded to three significant figures.

5.3.3 Scenario comparison results

To compare the impact of the strategies listed in Chapter 5.3, each scenario is modelled in the dynamic MFA model. Every individual strategy is represented by its effect on material and GWP savings relative to the baseline scenario as shown in Figure 23.

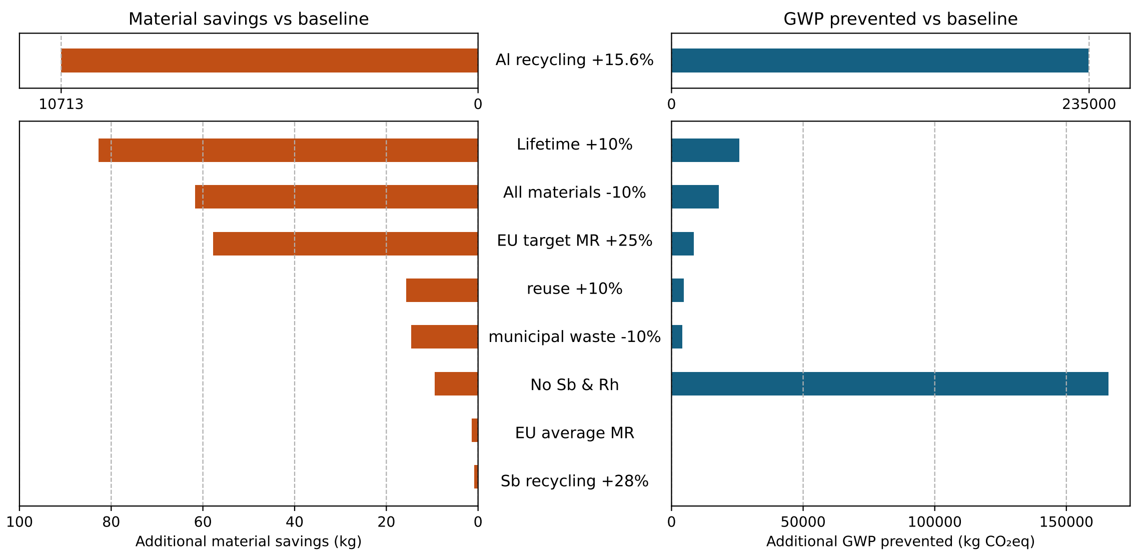


Figure 23: Comparison of different scenarios on material savings and GWP prevention. *Note: aluminium only included in Al recycling +15.6% scenario.*

The baseline scenario in Figure 23 corresponds to the 0-value on the x-axis in Figure 23, with the bars showing the impact of adjusted variables in relation to the baseline. Aluminium is only included in the *'Al recycling +15.6%'* scenario as this would otherwise render the other material's results incomparable. Furthermore, the baseline is defined by a set of parameters intended to replicate the actual dynamics of Product A as accurately as possible. Baseline parameters include an aluminium recycling rate of 81.6%, PM recycling rates of 14.0%, and 0.00% for the remaining CRMs. The reuse fraction is 81.2%, material quantities are specified in **Appendix B and C**, the Weibull curve uses the EC's parameters (shape of 1.3 and scale of 5.535), and municipal waste streams are modelled at 12.7% (European Commission, 2024a).

- **Al recycling 15.6%:** reflects the effect of recycling aluminium at highest possible rate. Since this material is used in a heatsink that can partially be dismantled, this level of recycling is considered feasible. Resulting in the highest impact on both material use and the environment.
- **Sb recycling 28.0%:** examines the same scenario for antimony. The 28.0% EU average recycling rate could partially apply to antimony also used as a flame retardant, suggesting some increase might be feasible (Campbell-Johnston et al., 2024). As shown in Figure 23, this results in a slight increase in material savings, with no visible effect on GWP prevention.
- **EU average MR:** (material recovery) models the effect of aligning all material recycling rates in Product A to the European EoL-RIR. While unlikely, since most of these rates rely on bulk recycling not yet viable for PCBs, it illustrates the limited impact of this strategy. The increase is only significant for four materials: antimony, tungsten, cobalt, and magnesium (as shown in Figure 21, all of which have relatively low GWP values in kg CO_2-eq.
- **EU target MR +25.0%:** is the first, non-aluminium, scenario to show a clearly measurable effect. As most CRMs in Product A currently have little to no recycling, raising all rates by 25.0% leads to a notable increase in material recovery.
- **No Sb & Rh:** shows the impact of removing these CRMs from Product A altogether. According to the CRM report **(Appendix B)**, both materials could be substituted by non-critical alternatives. This results in more material savings than *Sb recycling* or *EU average MR*, due to the efficiency of full exclusion. Recycling involves multiple stages of loss, whereas removing a material prevents 100% of the primary demand. With a GWP of $80.4 \cdot 10^3$ kg CO_2-eq per kilogram, removing rhodium results in a substantial GWP reduction.
- **All materials -10.0%:** applies a 10.0% material reduction across all CRMs. As expected, this yields a significant decrease in material use for the same reasons outlined above. However, the lower GWP effect compared to the previous scenario is mainly due to rhodium still being included for 90.0%, maintaining a high environmental burden.
- **Reuse +10.0%:** models an increase of devices reused. Although its relative impact is modest, it is a realistic and actionable short-term strategy for KPN. Given that current reuse already stands at 81.2%, it remains the largest contributor to overall impact reduction.
- **Lifetime +10.0%:** extends the average use period of Product A. Extending the devices life reduces the overall number of required units, limiting the need for additional production, reuse, and recycling. Although fewer devices can be reused, this also results in less inefficient streams, therefore, the net effect is a highly efficient system with reduced material loss.
- **Municipal waste -10.0%:** reduces the share of products entering this stream and redirects them to KPN's EoL processing. While this is the intended route, customer non-compliance remains an issue. A 10.0% reduction demonstrates a comparable impact to increased reuse, making it a promising parameter for KPN to influence.

From these scenarios the Al recycling +15.6%, reuse +10.0% and municipal waste -10.0% are perceived as implementable on the short term since they rely on available technology and lie within KPN's direct influence. Combined these stragies could reduce material use by an additional 10.7 tonnes and prevent GWP by an additional 3.89% ($265 \cdot 10^5$ kg CO_2-eq).

5.4 Results: Model Validation, Uncertainty and Sensitivity Analysis

5.4.1 1. Establishing the mathematical model

The equations, used to design the dynamic MFA, apply most transfer coefficients used in the static model. The rates for collected products, reuse, recycling and waste management (**Appendix E**) from the static MFA all remain applicable. Although these values now carry greater uncertainty, as they are generalized over the entire future period, this is considered inherent to prospective modelling, since future yearly percentages can never be estimated with full accuracy.

Two key variables are newly introduced: the survival curve, based on the EC's generalised lifetime for small IT and telecom equipment, and the primary inflow cut-off year, which sets the point at which all new production should rely solely on reused products. The survival curve, being a generalised estimate, is the main source of added uncertainty.

With these parameters, the dynamic MFA operates based on Equation 5, which uses annual stock data, the survival curve, and the reuse fraction as inputs. These determine when devices reach their end-of-life and enter downstream processes, where the remaining rates are applied to define the shares collected, reused, recycled, or disposed of through waste management.

5.4.2 2. Characterize data uncertainty

To define the uncertainty in the model's input data, four main variables are considered: yearly stock, reuse, recycling, and municipal waste. The primary inflow cut-off year is excluded, as it is a modelling assumption rather than a time-dependent source of uncertainty.

For yearly stock, an uncertainty margin of 10.0% is applied. This reflects deviations observed between predicted scenarios and actual stock data for comparable devices in KPN's portfolio ([redacted], personal communication, [redacted]).

The reuse fraction is assigned a higher uncertainty of 30.0%, as it depends on less predictable factors such as device malfunctions, customer behaviour, and the propagated uncertainty of the install base estimated under the stock variable.

Uncertainty in the survival curve is assessed for both its shape and scale parameters, with each set at 10.0%. Product A, being an internet modem for household use, is typically stored in stable conditions, making failures due to external factors relatively rare.

Finally, recycling rates are subject to 30.0% uncertainty. Like reuse, these rates are influenced by external variables, including process inefficiencies and price volatility affecting material recovery.

While the assignment of uncertainty values is a subjective measure, possibly resulting in expected outcomes, its value is argued to lie in testing whether these parameters show unusual behaviour or predict uncertainty in accordance with expectations.

5.4.3 3. Combine data and mathematical model

The third step is defined as inserting the data into the mathematical model, cross-checking and plausibility assessment. The correctness of variables, applied to the static MFA propagates to this model. To evaluate the model's projections, results are compared against actual stock trend predictions by Product A's senior product manager to assess feasibility, who indicated the output to be realistic ([redacted], personal communication, [redacted]).

To test the model's functioning, two randomly selected baseline outputs are manually verified through manual calculations. These are shown below using three significant digits for clarity, which may result in minor rounding deviations. When performed using the full values from **Appendix B**, the results align exactly with the model output.

- **Reuse of beryllium:** The model reports a total of **4.96 kg** of reused beryllium over the full y to y+14 period. This value can be verified by the following calculation:

Total reused devices:	$1.32 \cdot 10^6$
Mass per device:	$1.40 \cdot 10^{-1}$ kg
Total reused CRM mass:	$1.32 \cdot 10^6 \cdot 1.40 \cdot 10^{-1} = 1.85 \cdot 10^5$ kg
Beryllium content per device:	$3.76 \cdot 10^{-6}$ kg
Beryllium share in device mass:	$3.76 \cdot 10^{-6} / 1.40 \cdot 10^{-1} = 2.68 \cdot 10^{-5}$
Reused beryllium mass:	$1.85 \cdot 10^5 \cdot 2.68 \cdot 10^{-5} = \mathbf{4.96}$ **kg**

- **Recycling of rhodium:** The model reports a total of **0.114 kg** of recycled rhodium. This can be validated as follows:

Total recycled devices:	$4.91 \cdot 10^5$
Mass per device:	$1.40 \cdot 10^{-1}$ kg
Total recycled CRM mass:	$4.91 \cdot 10^5 \cdot 1.40 \cdot 10^{-1} = 6.87 \cdot 10^4$ kg
Rhodium content per device:	$1.67 \cdot 10^{-6}$ kg
Rhodium share in device mass:	$1.67 \cdot 10^{-6} / 1.40 \cdot 10^{-1} = 1.19 \cdot 10^{-5}$
Rhodium entering recycling:	$6.87 \cdot 10^4 \cdot 1.19 \cdot 10^{-5} = 0.819$ kg
Recycling efficiency (13.98%):	$0.819 \cdot 1.40 \cdot 10^{-1} = \mathbf{0.114}$ **kg**

5.4.4 4. Calculate the uncertainty

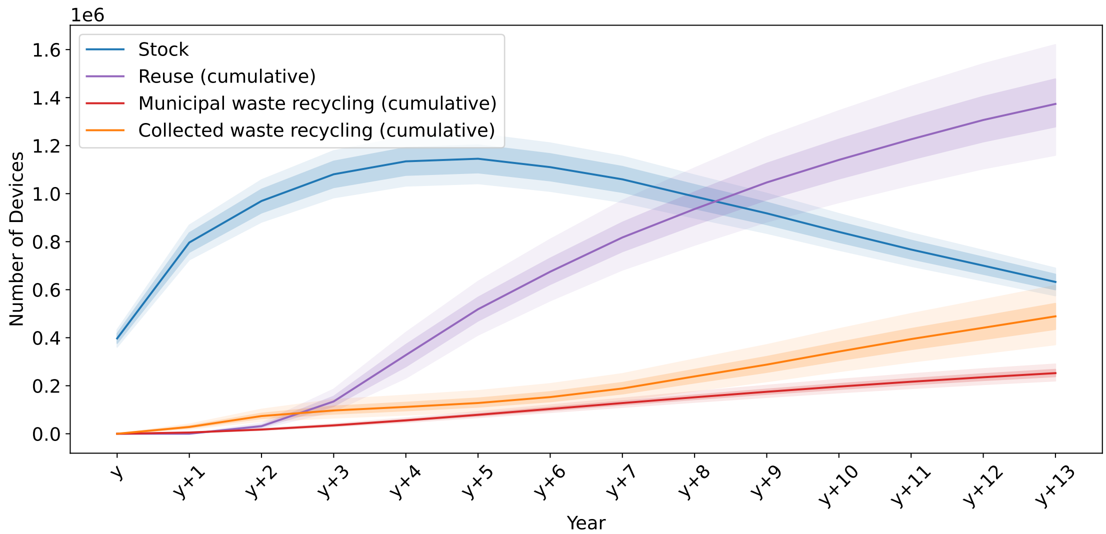


Figure 24: Monte Carlo Simulation $10.0 \cdot 10^3$ runs.

Figure 24 shows the uncertainty results based on the percentages defined in step 2. A MCS with 10 thousand runs was used to assess uncertainty for yearly stock and cumulative flows.

Figure 24 indicates moderate uncertainty for both stock and cumulative municipal waste recycling. For *stock*, this results from its basis in predetermined yearly values, influenced only by the 10.0% uncertainty defined in the MCS. While uncertainty increases slightly in the early years, it declines after 2026 as cohorts expire due to the finite lifetime imposed by the survival curve.

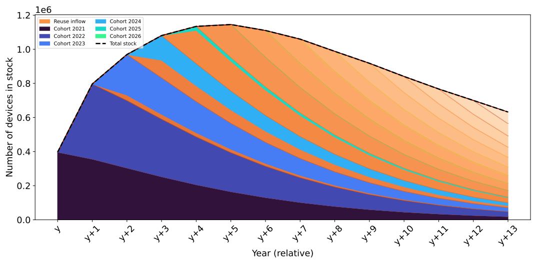
Municipal waste recycling also shows a relatively low and steady level of uncertainty, despite being modelled with a 30.0% margin. This is likely because it depends on use-phase outflows, calculated as a fixed percentage of total outflows, which follow the relatively stable survival curve.

Collected waste recycling shows slightly greater uncertainty, mainly due to its dependency on reuse. It includes products initially sent to reuse but deemed unsuitable for reuse or repair. This is reflected in the small rise in reuse until y+4, a period when most devices still come from primary inflows and reuse plays a limited role. As more devices flow out of the use-phase, and become available for reuse, the collected recycling line briefly flattens. This trend persists until stock levels decline and not all collected products are reusable, resulting in higher recycling volumes, further reinforced by more devices reaching the survival curve's end.

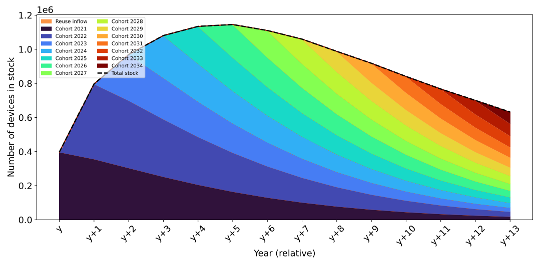
Lastly, the *reuse* flow shows the highest and most time-dependent uncertainty. While partly due to the assigned 30.0% uncertainty, the main driver is its self-reinforcing nature. As inflows decline, reused devices re-enter the reuse loop, sometimes multiple times. This interdependence increases uncertainty over time.

5.4.5 5. Sensitivity analysis and scenario development

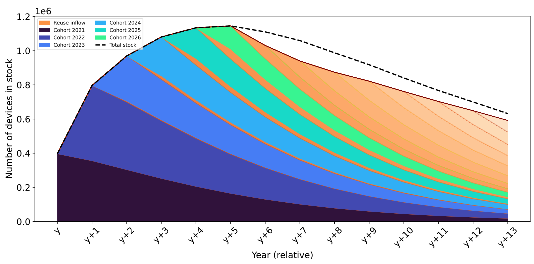
The final step for exploratory models, as defined by Laner et al. (2014), is the sensitivity analysis. This stage evaluates how variations in parameters affect model outputs and forms the foundation for scenario analysis. The dynamic MFA underwent these parameter adjustments and scenario testing in Chapter 5.3.3, where relatively moderate changes were applied to assess the model's behaviour. As a final validation, the model is tested with a set of more 'extreme' values to evaluate its robustness under less typical conditions as listed below and shown in Figure 25.



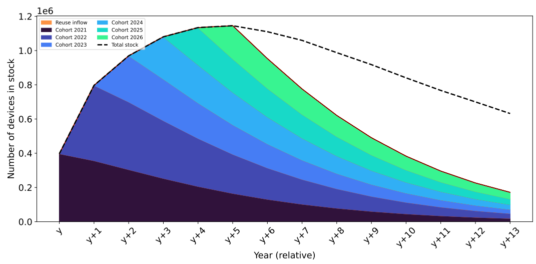
(a) reuse increased to 100%



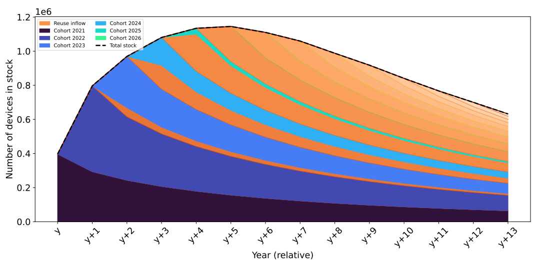
(b) reuse decreased to 0.00% & no primary inflow cut-off



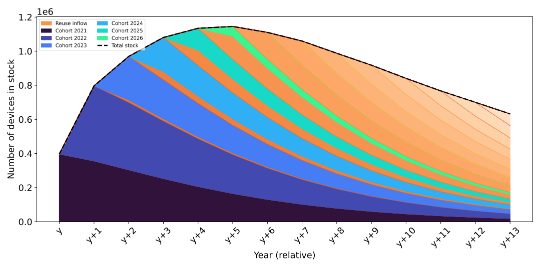
(c) reuse decreased to 20.0%



(d) reuse decreased to 0.00% & 2026 primary inflow cut-off



(e) lifetime increased by 10.0% (Weibull shape 0.700)



(f) municipal waste increased to 50.0%

Figure 25: Scenario results with extreme values, plotted as cohorts with nested reuse fractions.

a The **reuse 100%** scenario assumes that all collected devices, meaning all outflows excluding municipal waste, are suitable for reuse. In this case, the inflow from reused devices rises rapidly, making the primary inflow for 2026 nearly obsolete. Given that the baseline model already operated at a reuse rate of 81.2%, this increase is considered realistic.

b If **reuse is set to 0.00%**, and the primary inflow cut-off in 2026 is removed, the model depicts a scenario in which reuse plays no role. This produces the expected outcome where ongoing inflows supply the system, and reuse is removed entirely.

c When **reuse is reduced to 20.0%**, the model presents a valid but nuanced result. The dotted stock line reflects the annual quantity of devices required for customers. Under this scenario, with primary inflow stopping in 2026 and only 20.0% of devices reused, the system cannot meet demand. This is shown by a visible shortage in the model, represented by white space beneath the stock line, indicating insufficient supply.

d A similar outcome appears in the scenario with **0.00% reuse under the baseline conditions**. With no reuse and no primary inflow after 2026, the model again shows a supply shortage, visualized by the white space below the stock line.

e When the **Weibull shape parameter is reduced to 0.700**, it creates a distribution where most devices fail early, while those that survive tend to last much longer. This scenario would be unrealistic for modems, which are typically stored in stable environments and are not prone to early failures from external factors. Nonetheless, the model reflects this input correctly.

f Lastly, increasing **municipal waste to 50.0%** results in slightly lower reuse inflows compared to the baseline. This is realistic, as fewer devices are collected by KPN's EoL manager.

As illustrated in Figure 25, each adjustment has a different effect on the cohorts and thus the system's output. However. none show irregular results and are therefore argued as 'healthy' model dynamics.

Besides accurately visualising system dynamics, one sidenote is relevant to the modelling process. Prior to model adjustments, the *lifetime +10.0% scenario* produced an unexpected outcome. Increasing the Weibull scale from 5.535 to 6.15 (and thus the lifetime) initially resulted in negative values for material savings and GWP prevention, suggesting that a longer product lifetime would be undesirable.

This outcome results from how the model calculated prevented impact. Extending the Weibull scale to 6.15 lengthens the product use phase, reducing the number of devices entering reuse or recycling. As a result, the model records fewer prevented impacts compared to the baseline scenario, even though longer use actually delays the need for material input via reuse or recycling.

To address this discrepancy, the *lifetime +10.0% scenario* was modelled inversely. It illustrates the impact avoided through lifetime extension, with each longer-lasting device effectively delaying flows into reuse and recycling processes, thereby saving material indirectly.

6 Analysis & Implications

6.1 CRM Circularity in the Context of KPN

Whereas Chapters 3, 4, and 5 aimed to identify a relevant product, mapping current CRM flows, and assessing predicted flows and stocks over time, this chapter aims to integrate these findings into a coherent framework. It begins by analysing the results of both the static and dynamic MFA models, followed by an evaluation of the overall CRM circularity in KPN's EoL flows. In Chapter 6.2, the scope is broadened with an outlook on both KPN's internal processes and external dynamics.

6.1.1 Static MFA: current circular practices

The static MFA aimed to map current circular practices as accurately as possible. The method of analysing the supply chain and modelling flow dynamics in STAN, which generated insightful Sankey-style flowcharts, contributed significantly to understanding the system. Moreover, since the model was mostly based on well-maintained historical data, it is considered to offer a reliable representation of real-world conditions.

With the static MFA and SFA results processed, and uncertainty assessed, the extent to which KPN's EoL processes for Product A align with circular economy principles are evaluated. Since flows were first modelled at the product level and later linked to CRM composition. The results provided a detailed overview of the in- and outflows of Product A, one of KPN's most frequently supplied consumer products.

Two circular strategies were identified in the case study: reuse and recycling. Reuse emerged as the most impactful, creating a buffer that extends product lifetimes through minimal intervention. Using this strategy, KPN has prevented the need for 243 kg of CRMs (72.4 tonnes when including aluminium) that would have otherwise been sourced from primary production, noting that 233 kg of the reused quantity results from silicon.

Although the precise origin of CRMs is uncertain, Product A's manufacturing sites are located in China. While concrete numbers are limited, Ganguli and Cook (2018) discuss how China mainly uses primary REE in domestic production. Therefore, if the reused products were newly produced, it is likely they would have also required CRMs from primary extraction.

Besides reuse, KPN's downstream partners recycled a limited amount of material, mainly aluminium (23.2 tonnes) and precious metals (0.769 kg for palladium, rhodium, and ruthenium combined). Recovery efficiency for aluminium is substantially higher than EU averages, for PMs the recovery rate is in line with EU averages, and the remaining CRMs are not recovered at all.

Aside from reuse and limited recycling, no other circular strategies were identified in KPN's modelled EoL processes. KPN does indicate to advocate for practices such as lifetime extension, miniaturisation, or material substitution, however these impacts would occur at the manufacturing level upstream in the supply chain (KPN, 2024b).

Product A's EoL practices, particularly the focus on reuse, are seen to be consistent with those of similar products in KPN's portfolio, suggesting broader contributions to material and GWP impact score reduction at the company level. However, the direct contributions of this study are interpreted as limited to Product A until further use cases are examined.

6.1.2 Dynamic MFA: flow dynamics over time

The dynamic MFA was developed as an extension to the static MFA, enabling the same flow dynamics to be analysed over time. This methodology provided insight into stock build-up and outflow, as well as the impact of reuse and recycling strategies. It resulted in a functional model capable of assessing the use case of Product A under both the baseline and other scenarios. Moreover, the model structure is applicable to future use cases involving similar products.

The output of the dynamic MFA baseline scenario included graphical representations, illustrating expected product lifetimes and the impact of reuse on individual cohorts over time. The model also provided numerical data on reused and recycled quantities, accompanied by material and GWP impact metrics. These numerical results quantified the scaled impact of reuse and recycling with increased product volumes and longer time frames opposed to the static MFA. As a final application, the model served as a foundation for scenario analysis, enabling the assessment of system changes.

At the product level, the model indicated that, with a reuse rate of 81.2%, 1.32 million devices are reused. Multiplying the reuse by the total production and transport emissions per device resulted in 16.5 million kg of CO_2 emissions prevented through reuse. Furthermore, the model showed that 490 thousand devices are sent to recyclers, 220 thousand to energy recovery, and 11.7 thousand to landfill. Including aluminium, the baseline scenario resulted in 241 tonnes of material savings and 83.5% ($5.47 \cdot 10^6$ kg CO_2-eq) of prevented GWP, if these materials would otherwise be sourced from primary production. Excluding aluminium, due to its relatively large mass in Product A, the model shows a total of 624 kg in material savings and 3.06% ($201 \cdot 10^3$ kg CO_2-eq) of prevented impact.

These outcomes were largely expected. Since reuse and recycling already had some effect in the y to y+4 period and those parameters remained unchanged, their overall impact naturally increased over time as they were applied to more products. Beyond visualising these developments, the model's key contribution lies in its ability to assess scenario impacts relative to the baseline.

The scenario analysis showed the potential effect of several future scenarios. Some, such as 10.0% material reduction or reaching the EU's 25.0% recycling targets, were included mainly as references rather than realistic projections. Others, such as increasing reuse by 10.0% or reducing municipal waste by 10.0%, are more feasible and could contribute to material and GWP savings. The scenario with the highest impact was to increase aluminium recycling by 15.6%, a feasible option as the heatsinks should be partly designed for disassembly. Alternatively, a 10.0% increase in product lifetime should the highest impact on material use and prevented GWP. While this may be constrained by technical and especially commercial factors, it remains a potentially viable and highly impactful measure relative to the baseline scenario.

6.1.3 Overall circularity assessment

The impact of reuse and recycling

Building on the results presented in Chapters 3, 4, an and 5 this section evaluates the overall circularity of KPN's current EoL operations in the context of CRMs. As mentioned in the static MFA results, the main circular strategies identified were reuse and recycling. Herein reuse made the most significant impact as it was applied to all materials by reusing the entire product, and thus all CRMs within the product (excluding marginal replacements required during repair).

While effective, reuse should not be regarded as a complete solution to CRM dependency. Since every product that is reused, even when reused multiple times, will eventually reach a stage wherein it can no longer be supplied to a customer. Therefore, reuse acts as a buffer to slow primary CRM demand but could never resolve the issues surrounding it.

The second strategy applied in KPN's processes is recycling. The quantity of recycled materials is marginal compared to reuse, and recycling operations are limited to only aluminium and PMs. Furthermore, the model only accounts for a single recycling iteration. In practice, these materials could undergo multiple recycling cycles, potentially amplifying their overall impact (Schaubroeck et al., 2021). However, due to the uncertainty of downstream supply chain dynamics, the contribution of KPN's recycling partner is modelled as a one-time effect. The combined results of reuse, recycling and their respective prevented GWP values are shown in Figure 26.

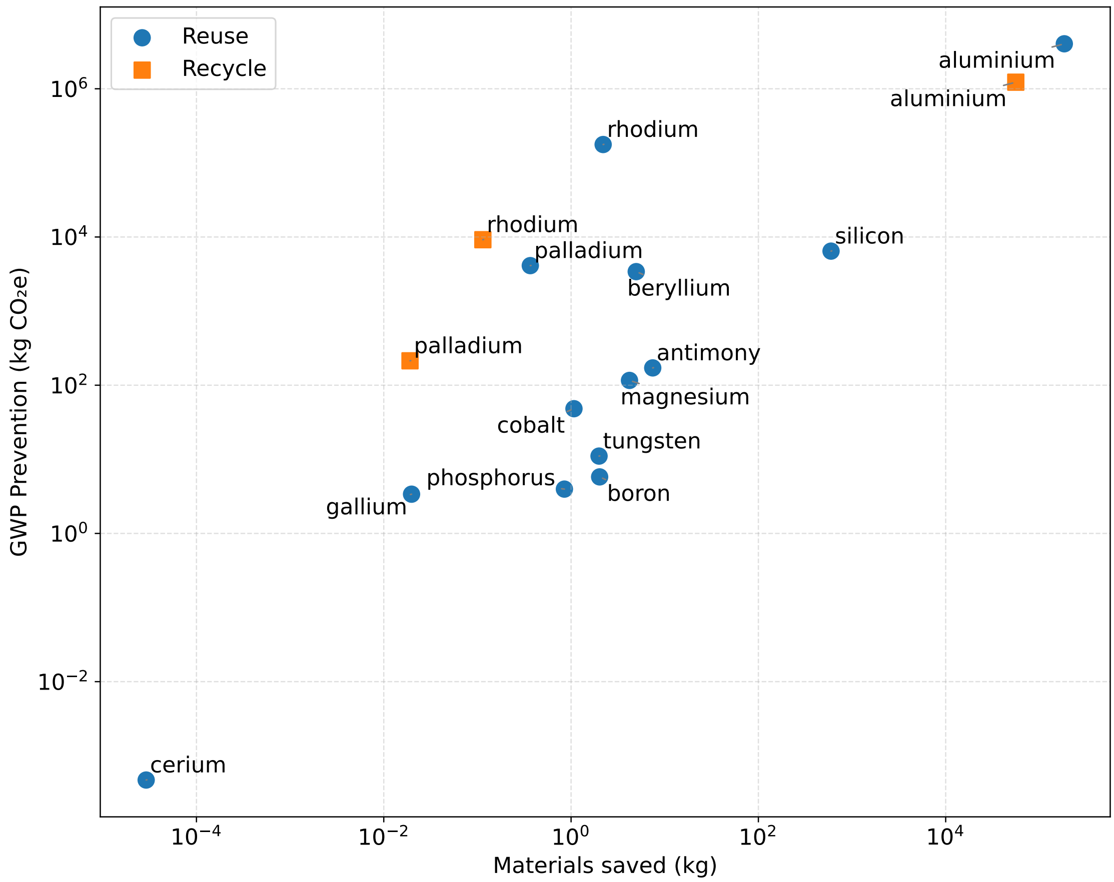


Figure 26: Scatterplot on quantity of materials reused and recycled on x-axis, quantity of GWP prevented on y-axis for the y to y+14 period.

Figure 26 shows the impact of reuse and recycling on material savings and GWP prevention. It effectively illustrates the current effect of KPN's applied circularity in the context of Product A.

The reuse material impact is dependent on the quantity of materials used in Product A, as the product is reused in its entirety. Herein aluminium is reused the most and cerium the least as these are the most and least occurring materials. Accordingly, aluminium shows the highest material impact, and cerium the lowest, reflecting their respective quantities in the device. In terms of GWP prevention, aluminium again has the highest impact, primarily due to its volume. Rhodium follows as the second highest despite its moderate presence in Product A, as a result of its high GWP impact score in primary production processes (Ecoinvent, 2019; Nuss and Ciuta, 2018).

A similar trend is observed for recycling: aluminium shows the greatest impact due to its abundance. Furthermore, rhodium recycling results in higher material and GWP savings than palladium due its used quantity and high GWP impact score.

However, these results only show the absolute values per material but do not account for material criticality as defined by Grohol and Veeh (2023). When material criticality is accounted for, saving one kg of aluminium would be less impactful than saving one kg of cerium, which is more critical in terms of EI and SR. Therefore, Figure 27 shows the relation between each materials position in terms of reuse in relation to its criticality. The reuse results are placed on the scatterplot by scaling them to the values between 0.80 and 1.00 which renders them similarly to their positioning in Figure 26. The criticality per material is the same as in Figure 6 from Chapter 3.2.2.

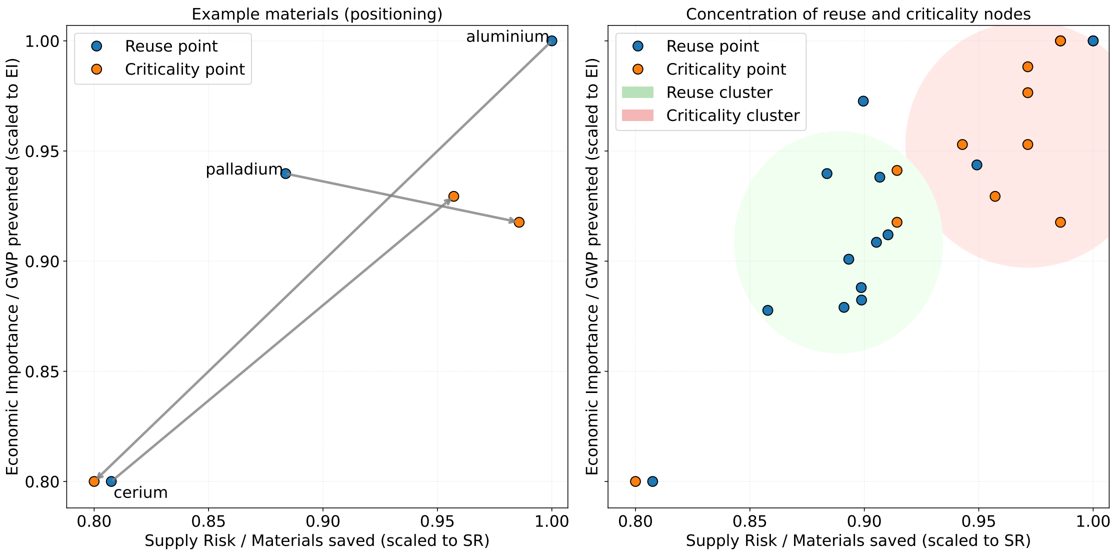


Figure 27: Scatterplot for comparing the reuse results over the y to y+14 period to material criticality as defined by the EC (Grohol and Veeh, 2023). *Note: lines for aluminium, cerium and palladium are plotted to show examples of positioning (left graph), green area indicates concentration of reuse nodes and red area concentration of criticality nodes (right graph).*

The left graph in Figure 27 visualizes how most of the material's reuse positioning differs from their criticality scores based on EI and SR. For aluminium for example, the absolute reuse results would place this material on the top-right of the scatterplot; indicating a substantial amount of this material could be saved through circular practices. However, this is only true when accounting for absolute values and without criticality in mind. The criticality score for aluminium places it on the bottom left of the scatterplot, the difference in positioning is indicated by the line connecting these nodes. As a result, saving aluminium could prevent a substantial amount of materials used and GWP, however, in terms of supplier resilience the impact would be more marginal. This claim is substantiated by aluminium's main application in the EU, which is primarily in construction, the automotive industry, transport equipment and packaging (Grohol and Veeh, 2023). Therefore, while applying circular practices in the telecom sector is also important, this material might not be as critical in this context as the other CRMs.

A similar difference in positioning is identified for cerium and palladium, which have a low reuse value in kg but score relatively high in terms of criticality. Mainly cerium is reused in low absolute kg's but scores high in terms of criticality on the EI and SR axes. Palladium has an average reuse weight and would also score higher on the SR axis but slightly lower on the EI axis.

Lastly, the graph on the right in Figure 27 shows green and red coloured sections. The green indicates a high concentration of reuse nodes and the red a high concentration of criticality nodes. In total this shows that, for most materials, the criticality scores are relatively higher than the absolute reuse values. However, it has to be noted that the reuse values are scaled, resulting in a comparison between scaled absolute values with indexed criticality rates and could therefore induce ambiguousness in the interpretation.

CRM circularity in the context of the Netherlands

To further contextualise the results, they are compared to total CRM quantities collected in WEEE, as presented in a TNO report by Campbell-Johnston et al. (2024). Using Dutch waste collection data for 2020, the report quantifies CRM content in WEEE products. The TNO annual CRM figures are multiplied by 13, matching the 13-year period applied in this study's model, and then compared against the reused CRM totals for Product A. These values are presented in Table 12.

Table 12: Predicted kg of reused CRM over y to y+14 period compared to material found in Dutch WEEE (2020 recovery scaled to 13 years), calculation in **Appendix J - Table 31**.

Material	kg reused	% of material in WEEE	Material	kg reused	% of material in WEEE
aluminum	$1.85 \cdot 10^5$	n.a.	cerium	$2.90 \cdot 10^{-5}$	$1.31 \cdot 10^{-5}$
palladium	$3.67 \cdot 10^{-1}$	$3.00 \cdot 10^{-2}$	cobalt	1.07	$1.01 \cdot 10^{-5}$
rhodium	2.20	8.46	gallium	$1.98 \cdot 10^{-2}$	$2.38 \cdot 10^{-3}$
ruthenium	1.01	n.a.	magnesium	4.21	$1.97 \cdot 10^{-3}$
antimony	7.45	$1.22 \cdot 10^{-2}$	phosphorus	$8.49 \cdot 10^{-1}$	n.a.
beryllium	4.96	1.74	silicon	$5.97 \cdot 10^2$	n.a.
bismuth	1.02	1.57	tungsten	1.99	$7.92 \cdot 10^{-3}$
boron	2.02	n.a.			

Parameters: curve shape = 1.3, curve scale = 5.535 years, reuse rate = 81.24%, primary inflow cut-off = 2026, max number of reuses = No., values rounded to three significant figures, calculations in Appendix J.

While the percentages in Table 12 may appear marginal, it is important to note, they represent the reuse impact of a single product, compared to the total assumed material occurrence in WEEE collection over a thirteen-year period. For instance, the 1.02 kg of reused bismuth equals 1.57% of this material's estimated occurrence in Dutch WEEE. This suggests that scaling reuse across more devices could make a substantial difference. For rhodium, the reused amount accounts for 8.46% of total rhodium found in Dutch WEEE. This could indicate that rhodium is overrepresented in this specific product, or it may reflect data limitations that result in an unrealistically high value.

Alternatively, the prevented GWP values for Product A can be contextualised by comparing them to the total emissions of the Dutch IT and communication sector, which emitted 156 million kg CO_2 in 2023 (CBS, 2023). With a modelled GWP prevention of 5.47 million kg CO_2-eq over 13 years, this results in an annual reduction of roughly 0.42 million kg CO_2-eq, or about 0.270% of the Dutch communication sector's yearly emissions through reuse. If compared to the total production emissions of 16.5 million kg CO_2, as determined by KPN, this percentage increases to 0.814%.

Although this quantity is marginal, it illustrates the potential of scaling. If all products listed in **Appendix A** were included, assuming similar weights, the emissions reduction could reach roughly 1.63%. Furthermore, if such strategies were adopted across all Dutch IT and telecom providers or even to other electronics, the national impact could be considerable. Additionally, from the scenario analysis the, *Al recycling +15.6%* scenario showed potential for an additional GWP prevention of 3.58% ($235 \cdot 10^3$ kg CO_2-eq). Therefore, if these results are scaled to more devices and circular practices are applied, this could result in notable impacts on a larger scale.

While mainly dependent on KPN's future goals and directories, this study suggests a set of approaches which could possibly be implemented on the short term: aluminium recycling +15.6%, municipal waste -10% and reuse +10%. While further research into the actual feasibility of these strategies would need to be studies, these are expected to lie within KPN's reach. Alternatively, the remainder of scenarios, as shown in Figure 23, are included as indicative or long-term possibilities.

To provide insights into the effect of short-term scenarios per material, in contrast to the current quantity of reused materials and prevented GWP per material, Figure 28 and 29 show the compared impacts. Herein both figures show that the impact of current reuse by KPN, and the impact of short term scenarios, are quite close to each other. If all the short-term scenarios; increasing aluminium recycling, increasing reuse and reducing municipal waste, would be implemented this could result in an additional 3.89% of GWP savings (calculated as total production emissions of $6.56 \cdot 10^6$ kg CO_2-eq divided by $265 \cdot 10^5$ kg CO_2-eq of additional GWP savings). This would increase the total prevented GWP over Product A's production from 83.5% to 87.4%. While this impact is marginal, the short term scenarios could be feasible and might therefore show some potential for KPN.

Additionally, for materials which are reused in high quantities compared to identified amounts in Dutch WEEE a detailed graph is shown to the right. This shows that for beryllium, bismuth and rhodium, the reused quantity by KPN could be substantial compared to total Dutch waste streams.

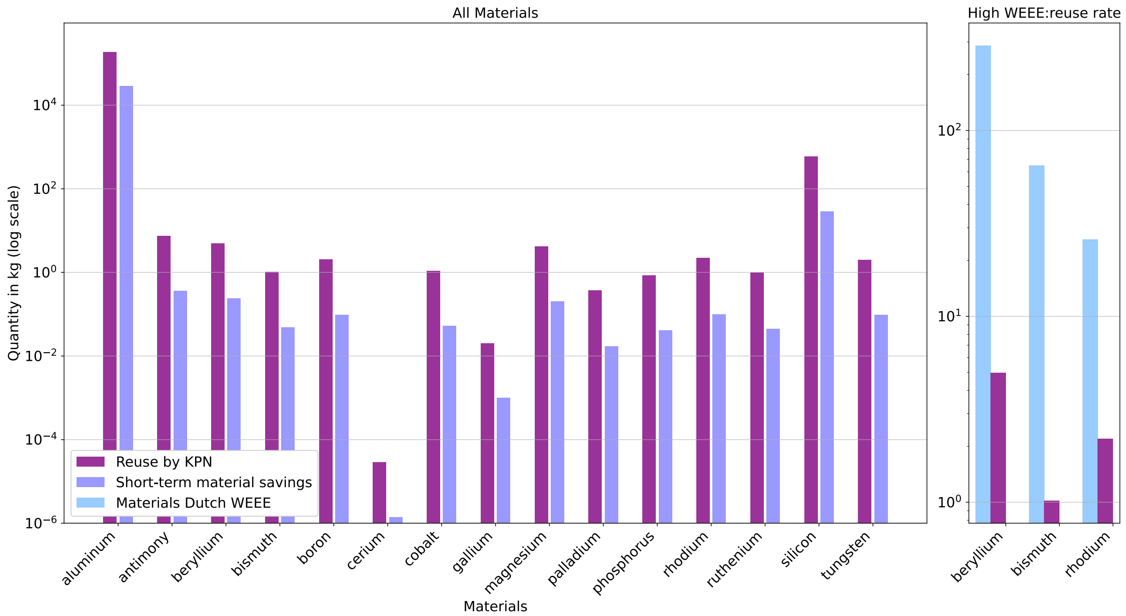


Figure 28: Bar chart comparing reused materials and short term scenario's material savings (aluminium recycling +15.6%, municipal waste -10% and reuse +10%) for the y to y+14 period. Detail chart on the right compares the amount of CRMs found in Dutch WEEE to KPN reused materials for three highest relatively reused materials based on Campbell-Johnston et al. (2024). *Note: 0-values indicate missing data, calculations in* ***Appendix J - Table 32***.

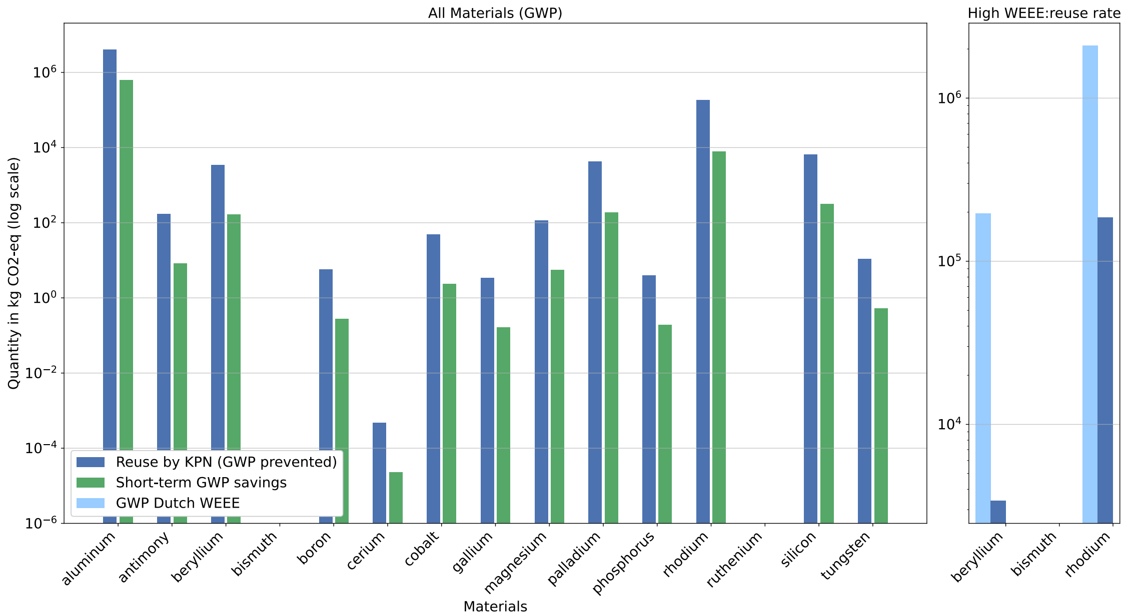


Figure 29: Bar chart comparing prevented GWP for reused materials and short term scenario's GWP savings (aluminium recycling +15.6%, municipal waste -10% and reuse +10%) for the y to y+14 period. Detail chart on the right compares the GWP for CRMs found in Dutch WEEE to KPN reuse GWP prevention for three highest relatively reused materials based on Campbell-Johnston et al. (2024). *Note: 0-values indicate missing data, calculations in* ***Appendix J - Table 33***.

KPN's positioning on the R-ladder

As discussed in Chapter 2.1.2, this study identifies some circular strategies applied by KPN in the R-ladder framework (Potting et al., 2017). As shown in Figure 30, reuse and repair form a direct link with the distribution chain, which functions similarly in KPN's EoL chain. These are relatively efficient processes which require minimal interventions and are therefore high in terms of circularity. Recycling, while difficult to avoid, scores low on the R-ladder as materials are often lost in the process and need to be remelted which requires high amounts of energy (Gheewala, 2024).

Moreover, KPN's recycling is open-loop, resulting in the materials flowing to unknown secondary production lines which is often less efficient than closed-loop recycling. Lastly, some materials are sent for energy recovery. This process is defined as the least desirable circular strategy since none of the materials are recovered but rather used as a last-means of energy generation.

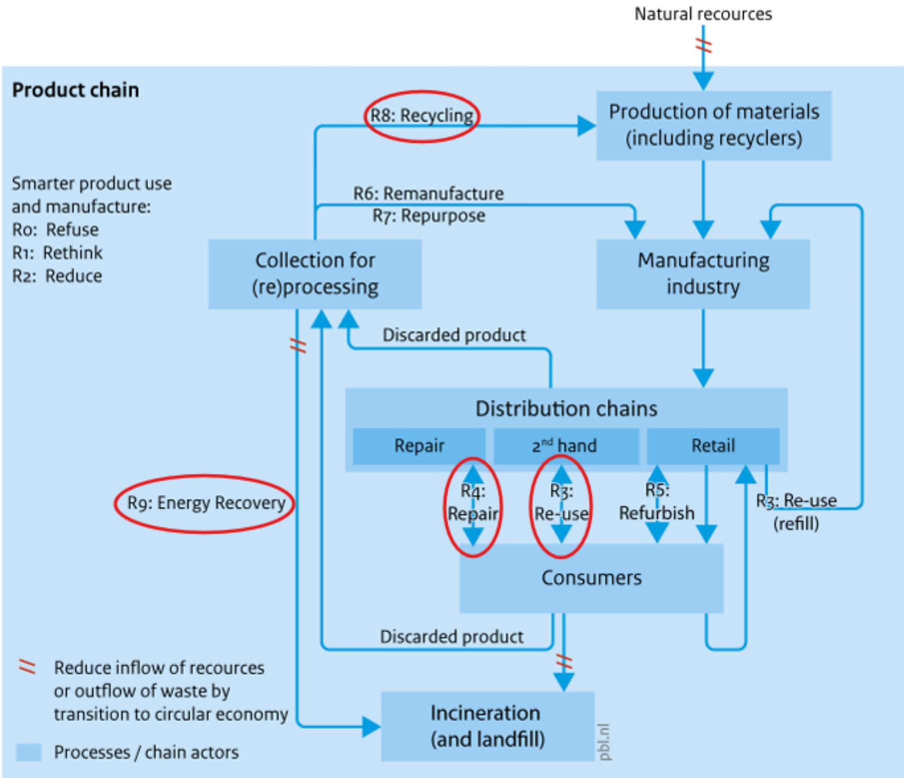


Figure 30: Circular strategies on the R-ladder and the role of actors in the product chain, *note: red circles indicate KPN's strategies, KPN recycling is open loop, source: Potting et al. (2017).*

Possible implications for other electronics

Overall, reuse and repair show the most potential as supply chain strategies KPN applies to increase circularity, while energy recovery should be avoided and recycling delayed as long as possible. Herein, important factors to effectively implement reuse are Product A's low risk use phase (i.e. modems mostly do not get damaged as they are stored away) and continued KPN ownership.

In a broader context, certain products such as other telecom devices, but possibly also TVs, computers or household appliances, could benefit from similar circular strategies. For products which are more prone to get damaged, such as smartphones, mainly customer awareness is likely a key factor; incentivizing people to handle these devices with care and return them to the right collection points for efficient redistribution or processing.

However, since these strategies can still only delay the need for repurposing, remanufacturing and recycling as shown in Figure 30, increasing the effectiveness of these strategies is also key for electronics in general. Additionally, the top three circular strategies, refuse, rethink and refocus, could provide high impacts as was also seen in the scenario modelling output for reduced materials.

6.2 Outlook on Future Circular Possibilities and Processes

To broaden the scope of this study, this chapter includes an outlook on identified Strengths, Weaknesses, Opportunities and Threats for KPN according to the SWOT framework (Leigh, 2010). As mentioned in Chapter 1, KPN strives to reach net-zero emissions in the value chain by 2040 (KPN, 2023). Therefore, this chapter outlines future possibilities which aid in reaching this goal, for Product A and other devices within KPN's upstream supply chain.

6.2.1 Outlook on internal factors for CRM circularity

Within KPN's scope, several strategies can be derived from this study's findings to improve the circularity of EoL CRM flows. Reuse is already implemented effectively, and while increasing this could provide further benefits, greater impact may also be achieved through additional strategies. This section discusses internal strengths: KPN's core competencies and short-term actionable strategies, and weaknesses: immediate hurdles and less functional aspects in current operations.

Strengths

KPN already benefits from established collection and reuse processes, which not only help reduce material and GWP but also contribute to cost savings, the efficiency of these processes is a solid foundation that can be expanded further. A short term opportunity for improvement, expected to be achievable, is increasing recycling rates for aluminium heatsinks in Product A. The ability to recover pure aluminium parts that can be efficiently recycled presents a high potential for impact, as up to 97.2% could be recovered (Capuzzi and Timelli, 2018). If these recycling rate for aluminium are met, this would result in an additional 10.7 tonnes of materials saved and 3.58% ($235 \cdot 10^3$ kg CO_2-eq) of additional GWP prevented. This recycling potential indicates strengths in material recovery, within the short-term reach of KPN.

Another achievable strategy for KPN is to reduce the amount of devices ending up in municipal waste flows. These product flows can not be reused and mostly divert products to less efficient waste streams. This could be achieved by introducing a fine for customers who do not return their modem as required to KPN's EoL manager, which is currently under discussion (KPN, 2024b).

Other strengths would be to expand on the wider array of circular economy perspectives. Perhaps motivating suppliers to design their products for easier repair, longer lifetimes or with reduced CRM quantities (Ferro and Bonollo, 2019a).

Weaknesses

Despite the potential for increased aluminium recycling, other CRMs, present challenges in terms of recovery. These materials are often not recycled due to the lack of economic incentive. Since many businesses focus on economic profit, materials that do not provide immediate financial returns are often not recycled (Karali and Shah, 2022). As a result, KPN's recycling initiatives may be limited in their ability to address the full list of CRMs. This poses a weakness, as the company can hardly control the recycling of CRMs that are economically less viable.

Additionally, KPN's dependency on upstream suppliers also complicates the implementation of circular approaches. KPN, as a service provider, can only exert limited influence on suppliers to design products with CRM circularity in mind (Viale et al., 2022). This reliance makes it challenging for KPN to take a strong stance on improving CRM circularity across its supply chain.

6.2.2 Outlook on external factors for CRM circularity

Besides processes within the scope of KPN, the world around it, likely far more than KPN itself, influences the dynamics discussed in this study. Therefore this section steps away from the Ceteris Paribus principle and discusses the external opportunities: KPN's future directories for positive impact, and threats: societal or governmental developments with negative impacts.

Opportunities

A major opportunity for KPN lies in the broader political and regulatory landscape. National or European policies could provide further motivation to enhance reuse efforts, either for KPN or other telecom providers. Currently, reuse is driven partly by economic considerations, as it offers cost savings alongside environmental benefits (Hischier and Böni, 2021). However, if economic incentives for reuse decrease, it is uncertain whether this process would remain viable. Therefore, political action could increase the reuse incentive. Soft measures, such as subsidies for devices reused multiple times, or harder measures, such as taxes on non-reused products, could create a framework that enhances the economic viability of reuse (Milios, 2021). Perhaps by introducing scales that increase the economic gains or restrictions based on the iterations of product reuse.

Additionally, recycling emerges as the most realistic and impactful strategy for KPN's CRM circularity. However, this is often hindered by the lack of economic incentive to recycle many CRMs (Karali and Shah, 2022). A shift in perspective induced by national or European policy could aid in improving CRM recycling rates and thus KPN in overcoming this barrier (Karali and Shah, 2022). If CRMs were valued more in terms of their supply risks and environmental costs, this could drive up their prices and, consequently, the economic incentive for recycling.

Moreover, the scenario analysis showed an increased lifetime of 10.0%, or similarly adjusting the Weibull shape for the 10.0% of customers leaving KPN each year, as the second most impactful measure. These customers return their modem because they are switching from providers, not because it ceased functioning. As discussed by Deng et al. (2017), shared telecom infrastructure could reduce the collaborative consumption of materials and energy. If KPN would engage in a collaboration with other telecom providers and introduce a joint modem, on which different providers can run their individual software, this would halt the outflow of devices by 10.0%.

Lastly, certain CRMs such as palladium, platinum, gold, and silver have reached a level of economic importance where they are traded on international markets under ISO 4217 currency codes (European Commission, 2015). If this level of economic importance were applied to other CRMs, perhaps by valuation based on criticality end environmental impact, it could provide a significant increase to their recovery. This could not only incentivize recyclers to recover these materials efficiently but also encourage manufacturers to design products with reduced CRM quantities or facilitate easier dismantling for material recovery. If this shift would take place, the advice would be to focus primarily on the reduced use of rhodium as this scores high on SR and EI indexes and accounts for the highest GWP (Ecoinvent, 2019).

Threats

Despite these opportunities, KPN faces several external threats. The economic barriers to recycling are particularly apparent, as most CRMs lack sufficient economic incentives for businesses to invest in their recovery (Karali and Shah, 2022). Without a substantial shift in the economic valuation of CRMs, this barrier could persist, limiting the scale of KPN's recycling initiatives.

Another significant threat lies in the lack of industry-wide adoption of circular practices. While KPN may advance its own recycling and reuse strategies, the actions (or lack thereof) of other telecom providers could undermine its efforts (Sgroi, 2022). If competitors fail to embrace circularity to the same extent, KPN could face a competitive disadvantage, particularly if such companies continue to profit from linear business models that do not prioritize CRM recovery.

Achieving sector-wide collaboration remains a substantial challenge. The proposal for a joint modem is likely to encounter resistance due to the different economic, marketing and possibly even legal obstructions of telecom providers.

Finally, perhaps the most worrisome external dynamic is that of geopolitical dynamics. Due to the dependency of countries on certain CRMs, geopolitical tensions could induce sudden CRM supply disruptions (Dou et al., 2023), resulting in even greater challenges which would not be controllable by KPN. In such a scenario KPN would rather be dependent on national policy.

6.2.3 Current and Future CRM Circularity in the Context of KPN

SWOT analysis on the value chain

All in all, KPN has achieved the highest impact on CRM circularity through reuse and to some extent through recycling. To enhance this impact further, several internal opportunities remain, such as increased recycling for aluminium and other CRMs, reducing municipal waste streams, and engaging with suppliers to address CRM use in product design.

These dynamics are also influenced by national, European, and global developments, including: CRM pricing, supply and demand risks, and economic incentives. Such factors could be influenced by assigning value to CRMs based on supply uncertainties and their environmental impact. Figure 31 presents a simplified overview of Product A's downstream value chain, combined with the respective internal and external factors as identified within the SWOT framework.

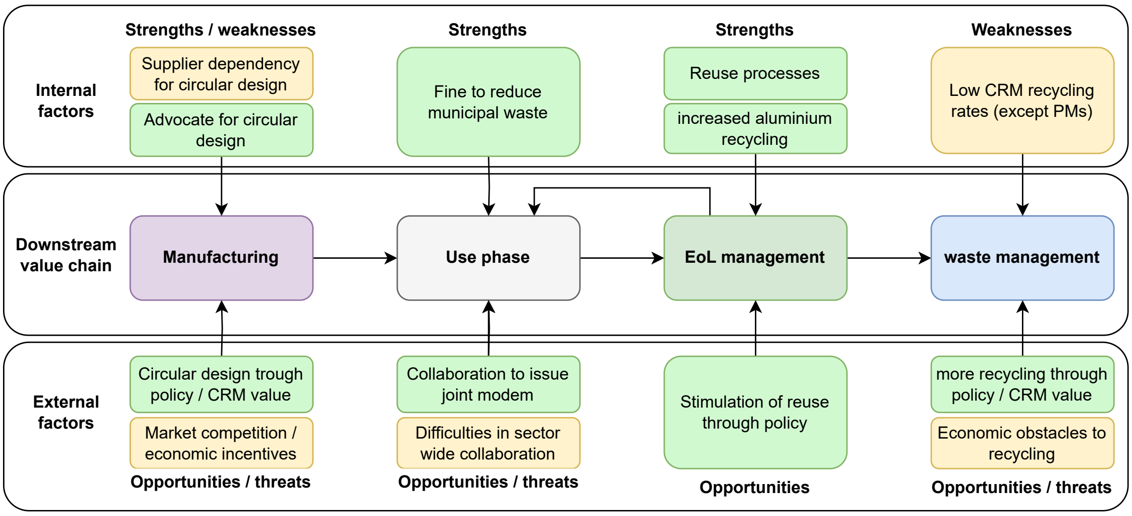


Figure 31: Strengths, weaknesses, opportunities and threats (SWOT) factors identified for the key steps in KPN's downstream value chain, *Note: yellow = weakness / threat and green = strength / opportunity.*

As visualized in Figure 31, some of the external factors are opposites of the internal factors for KPN, which characterizes the current dynamics around CRMs. Suppliers do not yet prioritise efficient manufacturing through design strategies that enable lifetime extension, easy repair, or reduced CRM use. Consequently, KPN's role is limited to advocating for such improvements. Similar dynamics apply to lifetime extension (via joint modems), stronger reuse incentives, and enhanced CRM recycling.

However, three areas where internal and external dynamics are more aligned are the reduction of municipal waste. further increased reuse and the recycling of aluminium. These are identified as both realistic and impactful strategies to improve circularity in the short term.

All in all, the SWOT analysis projected onto Product A's downstream value chain, as shown in Figure 31, highlights areas where KPN is already performing well and where further improvements, internally or externally, are possible. This study does not attempt to quantify the exact improvements needed to achieve net-zero emissions in the value chain by 2040, as the use case for Product A alone lacks the necessary impact.

Nevertheless, the identified strengths and opportunities may serve as a qualitative roadmap toward that long-term objective. KPN could attempt to focus on implementing short term strategies such as aluminium recycling and municipal waste reduction while simultaneously designing an awareness programme with upstream suppliers and downstream waste processors. Herein KPN could use its position as a large telecom provider and try to incentivise its partners to reduce the sector's impact as a whole.

Key points of focus

While reuse shows potential, and will likely remain a beneficial strategy, this study also identifies some points of improvement. Herein, the use case for product A does not yet show sufficient headway to reach the targets as listed in the CRMA. Most importantly within this study's context, the CRMA lists a benchmark for 2030 wherein 25.0% of strategic raw materials should be coming from recycled flows within the EU (European Union, 2024). Herein, KPN's recycling rates for all materials in Product A would need a substantial increase to meet this target. PM recycling, for which economic incentives are likely the main driving force, should be almost doubled (Xia and Ghahreman, 2024). And, expected to be even more difficult are the other strategic raw materials, which are currently not recycled. For the CRMs (non-strategic), aluminium, antimony, cerium, phosphorus and beryllium, the CRMA indicates the expected consumption should be moderated (Grohol and Veeh, 2023). The difficulty in this situation lies partly in KPN's limited influence on their downstream recycler's processing capabilities. Therefore, increasing such rates would likely be largely dependent on incentives through policy and regulations.

Besides circular strategies such as reuse and recycling, the R-ladder lists refuse, rethink and reduce as the most effective approaches (Potting et al., 2017). KPN indicated to have made some headway in reducing the size of devices such as Product A and their PCB. While a clear overview of this measure's effect on actual CRM use is unavailable this could indicate a step in the right direction. However, herein there is also room for improvement to limit the amount of necessary CRMs. The refuse step on the R-ladder (R0) is difficult to obtain and would require radical non-CRM intensive technological developments or a shift in public paradigm. The rethink (R1) step might offer some possibilities, as was proposed in this chapter through initiating a joint modem or telecom infrastructure in general (Deng et al., 2017). However, this would also require far-going changes with respect to current dynamics in market competition. The most effective and achievable impact could likely be made through further incentivizing upstream manufacturers to design products with minimal CRMs and which are build for reuse and repair processes.

6.3 Website: dynamic modelling tool for future CRM assessments

The direct application of this study, and its value for KPN, lies in providing a comprehensive overview of where circular strategies are already applied, and how these could evolve in future strategies based on both quantitative modelling and qualitative SWOT analysis. However, the true potential for impact can only be realised by scaling this approach to additional products, which may be the most relevant long-term application for KPN.

Therefore, the final step in this research focused on expanding the applicability of reuse and recycling strategies beyond the initial scope. During informal interviews regarding the dynamic modelling results, KPN experts expressed interest in applying the model to future projects. A key barrier identified was the reliance on Python as an intermediary between Excel-based input and output, which limited accessibility.

To overcome this, a website was developed as the final output of this study, integrating the dynamic MFA model into a user-friendly platform. Functionally identical to the model discussed in Chapter 5, this version offers easily accessible input fields and buttons. An adjusted version of the code provided in **Appendix I** runs in the background, generating results based on user-defined parameters. The output includes graphs for stock and reuse, total material and GWP savings, and a summary table per material. A download function allows users to export the results directly to Excel for further analysis.

To access the website click this **LINK** (username and password required). A manual on the website's functioning is included in **Appendix K**.

A second KPN partner expressed interest in assessing the potential impact of reuse for their own device (Product B). This served as a test case for the website tool and produced realistic, workable output. Resulting in conversations between KPN, EoL manager A, and Product B's supplier regarding future possibilities for this device's EoL management, indicating the practical applicability of the model.

6.3.1 Employee considerations for website tool

The website tool was presented to and assessed by two KPN employees: an energy and environment strategist, and the Senior Commercial Product Manager of Product A. Each received a brief explanation of the tool's functionality and limitations, followed by a demonstration of the input parameters and output fields.

The energy and environment strategist responded positively, suggesting that the tool could prove useful for future assessments concerning critical raw material use and environmental impact but also to increase awareness. A key limitation identified during this study was the lack of CRM data, which prevented a broader analysis across multiple products. KPN is currently requesting more of this information from suppliers, and the strategist expressed interest in using the tool once more comprehensive data becomes available. One suggestion for improvement was the inclusion of an option to input the GWP, or other measures for environmental impact, of the reuse and recycling processes themselves. This would allow users to assess net-prevented environmental impact, rather than only the gross benefits from avoided primary production.

The second employee, the Senior Commercial Product Manager of Product A, showed interest in the tool and indicated to see its potential for future use. However, this individual also mentioned that current expectations within KPN do not yet allow him to apply this tool in his day-to-day work. These expectations are mainly based on commercial incentives, meaning that material and environmental impacts are not yet included as part of the decision-making process. Nevertheless, the employee noted that if KPN were to incorporate these parameters in the future, the website could provide a functional tool for such assessments.

7 Discussion & Conclusion

7.1 Discussion

As the results presented in this study are not without uncertainty, Table 13 provides a summarized overview of all identified uncertainties, their context within the study, implications and, if applied, ways in which these uncertainties were attempted to be reduced. Below this table, each uncertainty is elaborated more extensively.

Table 13: Overview of uncertainties, context, implications, and mitigation measures in the study.

Uncertainty	Context within study	Implications	Uncertainty reduction strategy
Subjectivity inherent to MFA modelling (Laner and Rechberger, 2016).	Static and dynamic MFA models.	Could result in differently designed models when reproduced.	Attempted to prevent uncertainty through directly copying KPN's systems and expert reviews.
Geographic and political CRM dynamics (Schicho and Espinoza, 2024).	Characterization of material criticality.	Could shift the study's outcomes if material criticality shifts.	Attempted to avoid by designing a generally applicable model and website tool.
Selection of LCIA method and impact category.	GWP calculations.	The LCIA method or impact category selection could shift GWP impacts.	LCIA method selected based on the ILCD framework and climate change as a pressing environmental issue (Jang et al., 2022; Joint Research Centre, 2010).
Data uncertainty.	Primary input for static and dynamic MFA models.	Uncertainty in the input data propagates through the models and therefore affects output data.	Application of a stepwise procedure for addressing uncertainty in MFA (Laner et al., 2014). No mitigation applied for incomplete CRM report.
Systematic perspective of MFA modelling.	Static and dynamic MFA models.	By applying a systems perspective, broader dynamics and social aspects could have been excluded (Nilsson, 2019).	Ceteris paribus: results can only be viewed as a modelling output wherein all else remains unchanged.
Single stakeholder research.	Study conducted in collaboration with solely KPN.	Research could unintentionally be constrained by KPN's objective or subjective (legal) obligations (Clarke and Davison, 2020).	Scientific approach and fact-based research; however, unintentional constraints cannot be ruled out.
Use of average predicted values.	Dynamic MFA model.	Average rates (e.g. reuse, recycling etc.) neglect precise yearly dynamics.	Difficult to avoid, especially when modelling future projections. Best available KPN data was used.

Uncertainty	Context within study	Implications	Uncertainty reduction strategy
Exclusion of repair in dynamic MFA.	Dynamic MFA model.	Excludes the repair of devices which would require additional CRM inputs.	Could not be mitigated as data on specific CRM repairs was unavailable.
Gross GWP calculation.	Dynamic MFA model.	Excluding GWP impact scores (e.g. transport, reuse) results in inconclusive findings (Ligthart and Ansems, 2012).	Total emissions calculation based on KPN data; however, this lacks material-specific detail and reuse GWP.
Definition on when a product is reused.	Reuse terminology.	Ambiguousness between interpretation of reuse or e.g. extended use.	Applied definition on reuse and reuse impact by Cooper and Gutowski (2017).
Singular recycling impact calculation.	Dynamic MFA model.	The potential impact of multiple recycling iterations is unaccounted for (Schaubroeck et al., 2021).	No mitigation applied due to unavailable data.
Results interpretation (scaling).	Overall results.	Scaling is necessary to identify if current circular practices are substantial in a wider context or not.	Rough calculations comparing the results to the Dutch telecom sector's emissions and materials found in WEEE.
Results interpretation (environmental targets).	Overall results.	Upstream GWP reduction cannot be attributed to Dutch climate targets (IPCC, 2019).	Upstream GWP reduction can be attributed to KPN's (scope 3) climate targets (KPN, 2023).

The methodology, wherein static and dynamic modelling was applied to describe and create future scenario projections, comes with some inherent uncertainties. These models interpret physical dynamics from a controlled setting and naturally exclude external influences. Hence, models, such as the ones used in this study, are almost never complete. These models were designed to deepen the understanding of KPN's circularity regarding EoL CRM flows. However, defining a goal and system boundary with accompanying parameters to assess these dynamics comes with a degree of subjectivity (Laner and Rechberger, 2016). Moreover, these parameters reflect only a limited subset compared to all possible impact variables in a real-world scenario.

The criticality of materials is subject to time, geographic positioning and local shortages (Schicho and Espinoza, 2024). Therefore, influences in seemingly unrelated sectors could render this study's findings inaccurate. For example, geopolitical shifts could affect CRM criticality or changes in tax regulations might impact reuse profitability, thereby altering reuse rates and resulting in a deviation from the modelled expectations (Dou et al., 2023; Milios, 2021). Also the GWP per material is influenced by assumptions related to the choice of an impact assessment method. This research applies the CML v4.8 (2016) LCIA method, as recommended within the ILCD framework by the EC, due to its compatibility with CRM-focused sustainability evaluations (Joint Research Centre, 2010). Nevertheless, it is acknowledged that alternative LCIA methods could be applied, potentially resulting in varying impact outcomes.

Moreover, climate change was selected as a metric for the environmental impact calculation due to its positioning as one of the more pressing environmental issues and impact categories (Abdurahman Mume et al., 2024; Jang et al., 2022). However, this selection could also be approached differently; if one would seek to assess the effects of CRM use on biodiversity or acidification the impact scores per material might be different, as well as the relation between materials. Therefore, an assessment of all impact categories would be a valuable addition.

For the static MFA and SFA models, limitations are mostly tied to specific data used as a basis. While some data is reliable, such as yearly inflow, outflow, and reused devices due to barcode scanning, other sources are more uncertain. This applies particularly to municipal waste flows, based on expected averages, and the PM and aluminium recovery rates, derived from a 2019 report by KPN's former recycling partner (**Appendix E**). Although this uncertainty is considered in the model, it remains a significant limitation. Another data limitation lies in the CRM report (**Appendix B**), which was written in 2020 when the EC used an earlier CRM list. Therefore, materials now defined as critical but not included at that time could be excluded from this study. This report also identified 83.0% of the material composition of Product A. Although, the missing components where not expected to be mainly CRMs, this is also a significant limitation to this study's results.

Another limitation of static MFA is its systematic perspective. It captures only what is defined within the goal, scope, and boundaries, possibly neglecting other relevant factors. Aspects such as supply chain errors, logistic delays or human context are excluded, reducing the model's reflection of real-world complexity (Nilsson, 2019). Moreover, framing the case study using KPN's internal procedures introduces a narrowed perspective, which may overlook broader CRM dynamics beyond the company's operational scope. As discussed by Clarke and Davison (2020), single-stakeholder research can be constrained by the legal obligations of that stakeholder to prioritize economic interests. While not objectively noticed, these obligations could occasionally conflict with the environmental and social objectives this study sought to address.

The limitations, in terms of data sources, identified for the static MFA propagate into the dynamic model as well. Since the CRM report, material quantities and transfer coefficients (**Appendix B, C and E**) used for the static model also formed a basis for processing rates in the dynamic MFA, this results in similar uncertainties.

Moreover, dynamic MFA comes with additional uncertainties, wherein the main uncertainty lies in the use of average predicted values. This model uses rates such as 81.2% reuse and 13.0% municipal waste. These values are based on averages over the y to y+4 period but could vary from year to year. Predicting yearly values with high certainty is difficult, making averaged inputs a necessary limitation. However, with this approach the current version of the model only takes one average per parameter. Therefore, the y to y+4 period for which yearly and monthly data is available can not be modelled separately from the y+4 to y+14 period for which an average would be a more acceptable approach.

Additionally, the dynamic model does not include the repair parameter which is included in the static model. Due to limited data availability, on which CRMs are repaired, this variable was excluded. To increase the model's completeness, about 3.67% (6.14% of collected products is sent to repair from which 59.7% requires CRM replacements) of reused products should reflect CRM replacements, slightly reducing the output on material and GWP savings from reuse.

In practice, the amount of GWP saved would also be subject to further calculations for which data was not available. Currently, only the GWP from primary material production was considered. Full impact calculations would include emissions from processing, transport, and production, as well as those from reuse and recycling (Ligthart and Ansems, 2012). Although, an indication of total emissions was supplied by KPN, this lacked material specific values. Additionally, while emissions of the reuse process itself are likely marginal, they are not negligible and would need to be subtracted from the primary production emissions to calculate net-prevented emissions.

While extended impacts are modelled for reuse in this study, they are not included for recycling due to limited data availability, representing another limitation in the dynamic MFA. The model considers recycling as a single iteration of material and GWP savings. In reality, recycling could have an extended impact, as these materials could be recycled multiple times. To achieve this the iterative process-by-process methodology by Schaubroeck et al. (2021) in combination with LCA could be applied. However, to analyse this would require deeper downstream data insights.

Reflecting on the results, this study's outcomes alone are not interpreted as substantial on a company or national level. Reuse and recycling reduces material uptake and GWP, but the 0.814% reduction in kg CO_2 is marginal on its own (CBS, 2023). Scaling this study's approach across more KPN products, or similar telecom applications, could render substantial impact. However, this proved difficult as collected product-specific CRM-data could often not yet be provided by KPN's suppliers. Nevertheless, in its essence reuse could function as a buffer for most electrical devices directed to the correct EoL management or waste streams.

This view is supported in an article by Cooper and Gutowski (2017), which indicate reuse could save the energy and other impacts of primary production, if the product would otherwise become waste. However, they also state that reuse does not automatically lead to environmental benefits. For such benefits to occur, reused products must substitute newly manufactured ones. While this is often the case for KPN's modems, where reuse is based on forecasted demand, in other contexts, reuse may lead to surplus products, potentially resulting in negative environmental outcomes. Overall, the definition by Cooper and Gutowski (2017), provides a framework within this study's context, however, different visions on reuse could also deviate from this framework and therefore interpret the effect of reuse from other perspectives.

Lastly, interpreting reductions in environmental impact comes with another consideration. As KPN reports emissions under the GHG protocol, emissions from extraction, production, reuse, and recycling fall under scope three, defined as indirect supply chain emissions (KPN, 2023). In terms of company reporting the effect of production, reuse and recycling would thus count towards KPN's emissions reduction. However, this emission reduction would not be allocated to Dutch environmental targets but rather the upstream supplier's country (IPCC, 2019).

Nevertheless, with these considerations in mind, the static model contributes to both KPN and the scientific literature by offering insights into CRM flows within the context of widely distributed telecom devices. It also identifies reuse and recycling as key circular strategies currently applied. The dynamic model builds upon these results by providing temporal insights into these flows and evaluating the upstream material and GWP prevention impacts of downstream processes. These findings offer a foundation for future research to address the challenges outlined in this section and to support the development of more comprehensive circular solutions at a broader scale.

7.2 Reflection on Methodology

During the process of writing this thesis, the methodological framework was occasionally adjusted, as the iterative steps of data collection, modelling, and feedback integration led to new insights and corresponding adjustments. Nevertheless, the main outline of the original proposal remained largely applicable.

The most significant change occurred in the first subquestion, which initially aimed to define a broader subset of KPN products based on CRM quantity assessments. Although suppliers were contacted even before the start of this research, CRM data proved difficult to obtain. As a result, product selection was based on the most supplied products containing a PCB. While this was a functional alternative, the initial approach, if CRM data becomes available in future studies, is recommended as more suitable. Additionally, the original intention was to define the 'most' critical products by comparing their EoL-RIR. However, due to data limitations and the realization that EoL-RIR is a less suitable indicator of criticality than the EC's metrics of EI and SR, EoL-RIR was used solely as a characterization tool.

In the current study only the GWP is applied as indicator for the impact category of climate change. While this choice was substantiated through literature, in reflection it would have been feasible to account for the other impact categories (e.g. acidification, eutrophication or biodiversity) as well if included from the beginning. At a later stage this became a time consuming addition to fully integrate and was therefore kept outside of the scope.

The static and dynamic MFA modelling stage was an iterative process but mainly in line with the proposed outline. The dynamic MFA, in particular, benefitted from additional time in the planning phase, which enabled the inclusion of extra parameters. While the initial goal was to assess the impact of circular strategies on CRM flows, the final model also incorporated GWP calculations as a key output. The website tool, developed to support KPN in future applications, was an additional parameter as well.

The creation of this tool also reflects a broader shift from the initial methodology. Initially, the study was expected to be a stand-alone case study, using Python for modelling. However, feedback from KPN employees revealed a lack of Python expertise among the individuals who would use the model, which led to the development of the website tool as a more accessible solution. While the website tool was found to be a means of bridging this gap, a goal of designing a usable end-product should have been included from the beginning.

A similar reflection applies to the inclusion of Chapter 6, which extends the results to a broader context and explores managerial implications for KPN. While this direction was suggested in the research question, it was not explicitly included in the methodological framework. Its addition is therefore recommended as a valuable component for similar future projects.

All in all, the methodology provided a sufficient framework to include the necessary elements within this thesis. Due to a swift start there was some spare time throughout the process which helped with including the necessary components. However, if some delays would have presented themselves this could have been more difficult. Therefore, while challenging, the main suggestion would be to clearly think of where you want to end and incorporate this more extensively in the methodology. However it was also important to embrace changes along the way as predicting the exact path would not have been not possible.

7.3 Conclusions and Recommendations

7.3.1 Conclusions

As telecommunication technology becomes increasingly embedded in modern society, it leads to a growing dependence, both for individuals and for the Dutch communications sector, on a stable supply of CRM containing products. Devices used for formal tasks, informal conversations, and everyday activities require CRMs for their production and repairs. However, these materials are often sourced from politically unstable regions or areas with low levels of governance. As a result, the continuity of the Dutch communications sector, and the systems that rely on it, depends to some extent on sensitive political relationships. Moreover, the extraction of primary CRMs causes substantial environmental harm, making continued procurement of such materials inherently unsustainable.

To gain a deeper understanding of CRM flows in telecommunication products, KPN provided the possibility to analyse their product supply chain. This study used an IE perspective with a systems-based approach to identify the impact of KPN's operations on CRM extraction and its associated environmental consequences. This led to a case study of a widely distributed household internet modem (Product A), with a primary inflow of 1.34 million devices from y to y+4. Fifteen CRMs were identified in this product and primarily located on the PCB, only aluminium was used in a different section as a heatsink and therefore a dominant factor in terms of weight. Through both static (bookkeeping) and dynamic MFA modelling, the product and material flows were assessed in relation to circular economy principles, leading to the central research question: *"To what extent can circular practices, regarding CRMs in KPN's products, be identified and potentially further developed to slow primary CRM demand?"*.

Static MFA modelling identified two circular practices in KPN's downstream supply chain: reuse, the most widely and effectively applied, and recycling, which is effective to a marginal extent. With a reuse rate of 81.2%, the static model estimated a total of 243 kg of CRM reuse (excluding aluminium) and 72.4 tonnes when aluminium is included over the y to y+4 period. Recycling amounted to 23.2 tonnes (81.6% recycling rate) of aluminium, 0.0769 kg (14.0% recycling rate) of PMs, and no recovery for the remaining CRMs in Product A. In addition to these figures, the static MFA delivered detailed insights into CRM flow behaviour within KPN's downstream processes, including Sankey-style flowcharts via STAN software and full overviews of CRM flows per device and at the total production level. As such, the model offered a descriptive baseline of the current system, something not yet established within KPN.

To project these results over time, the dynamic MFA method was applied to design a prospective model, covering the y to y+14 period, until the final year for which KPN had install base projections for Product A. The base MFA formula was adapted to capture the influence of reuse and recycling, expressed in material savings, prevented GWP (kg CO_2-eq) and percentage GWP reduction compared to the total production's impact score. This led to a working Python model and accessible website tool to assess KPN's circular impact under the baseline and alternative scenarios.

For reuse and recycling combined, the model showed potential material savings of 624 kg without, and 241 tonnes with aluminium. For the total production's GWP impact, prevented GWP was calculated at 3.06% without, and 83.6% with aluminium. Of the 83.6%, reuse prevented 64.7% of the GWP impact score. Open-loop recycling had a lower impact compared to reuse: saving 56.0 tonnes of CRMs which prevents 18.9% of GWP.

Overall, the prevented GWP for primary CRM production, through reuse an recycling, represents a reduction of roughly 0.270% in emissions of the Dutch communications sector. A modest outcome individually, but potentially meaningful when scaled across all KPN devices and other telecom providers. When compared to the total production and transport emissions per device, including other materials besides CRMs as calculated by KPN, the total emission reduction through reuse could amount to 0.814% of emissions in the Dutch communications sector.

The summarized answer to the first part of the research question is therefore, that KPN currently applies the circular practices of reuse and recycling, which align with the circular economy principles of closing and slowing the loop and are positioned as R3 and R8 on the R-ladder. Herein, reuse is applied effectively, however, recycling only shows substantial recovery for aluminium whereas the other CRM's recycling rates are only half of the EU 2030 targets or non-existent; indicating a challenge within the limited time remaining. Additionally, preventing GWP was mainly achieved through aluminium reuse and recycling.

The second part of the research question, which focused on how CRM demand could be further slowed, was explored through dynamic scenario modelling and SWOT analysis. The most impactful strategies identified included increasing aluminium recycling to 97.2%, extending device lifetime by 10.0%, reducing material usage by 10.0%, or reaching EU-projected CRM recycling rates of 25.0%. Replacing high-impact CRMs like antimony and rhodium also showed potential, with rhodium in particular contributing to GWP.

However, several of these scenarios, especially material reduction and EU-level recycling, are considered unrealistic on the short term due to their complex integration on the PCB. A 10.0% lifetime extension, potentially achieved via a sector-wide joint modem, could significantly reduce returns but would require fundamental shifts in competitive dynamics, likely only achievable through policy intervention. However, if managed, this could result in substantial impacts and be considered to fall under rethink (R1) on the R-ladder. Similarly, changes in material design or CRM recycling, would likely only be achievable through political incentives as we well.

To answer the second part of the research question: the most realistic and impactful actions for KPN involve increasing aluminium recycling, further increasing reuse, and reducing municipal waste flows. These measures combined could increase material savings and GWP prevention by roughly 3.89% to a total of 87.4% of Product A's production impact. This number is marginal and therefore the main recommendation is to maintain the reuse practices and in parallel advocate for other measures among suppliers, recycling partners, and regulatory bodies, to refuse (R0), rethink (R1) and reduce (R2). Herein, rhodium could be a material of focus due to its high criticality score and GWP impact score. Although, also this could prove difficult as KPN's influence on these dynamics is likely marginal and would be primarily dependent on policy and regulations.

All in all, this study presents its results based on a single use case for an internet modem. For solely this device, the results indicate some potential impact through reuse, while recycling would still need to be greatly increased to meet the EU's 2030 targets of 25.0%. However, to identify any company- or nationwide impact, or lack thereof, this study's single use case should be scaled to company or country wide CRM flows. Only when this modelling approach would be applied to a wide array of similar devices, can the impact of reuse, potential impact of increased recycling and other measures such as those on the R-ladder be placed within the context of company or nationwide circular practices.

While not quantitively substantiated, reuse could be a potential strategy for electronics in general. If devices are returned in a functional state, they could be effectively redistributed to new owners with low material and GWP impacts. However, it also showed recycling for CRMs on PCBs is far from reaching the CRMA 2030 benchmarks. Policy and regulations should motivate companies as well as consumers to increase focus on these issues. Herein, well designated collection points, monetary recycling or lifetime expansion incentives could aid in these processes.

Overall, given the current level of recycling efficiency for Product A, reuse remains the most consistently beneficial strategy. Regardless of which materials are considered critical, reuse delays the need for primary extraction and thereby slows both material depletion and environmental harm. While further research would be required to substantiate these claims, the outcomes of this study provide an indication that reuse could be underexplored in scientific literature, seeing its potential to slow CRM demand in a world wherein recycling often does not yet meet its required efficiency.

7.3.2 Recommendations

To elaborate on the findings presented in this study, several limitations and valuable additions could be addressed. Herein, the key recommendation is to scale up this study's approach to evaluate whether a company-wide or even national impact on material use and environmental performance can be identified. The model could be adapted to explore national CRM flows over time and the effects of increased reuse in the electronics sector. This would depend on collecting more CRM-specific data; one of the greatest challenges in this research. Such data could be used not only with the website tool but also in broader assessments on CRM use and circularity.

Additionally, the main request from KPN employees for the website tool was to further develop the net-effect on GWP. This would require collecting data on emissions across the entire upstream supply chain, as well as emissions from the reuse process and downstream waste management. By subtracting the GWP or overall environmental impact of the reuse process from that of primary production and integrating this into the tool, its accuracy could be significantly improved.

Although complex to integrate into a functional tool for KPN, a valuable addition would be an LCA study on Product A. A cradle-to-cradle or cradle-to-grave LCA would inherently require full environmental data and could serve both as a stand-alone analysis and to improve the website tool's GWP (or other impact) calculations. Herein the approach by Ligthart and Ansems (2012) to include recycling in LCA and the process-by-process approach by Schaubroeck et al. (2021) to include the extended impact of recycling would increase the completeness of these calculations.

Alternatively, while the current model applies two impact variables, material and prevented GWP, it is structured to accommodate others. For instance, financial impact could be added to assess cost savings or losses under different reuse and recycling scenarios. If a study could indicate significant cost-savings through reuse, this might result in KPN, other companies or political and regulatory bodies to apply or incentivise for reuse on a broader scale as suggested by Cooper and Gutowski (2017). This could also align the results from this study with the financial risks surrounding material criticality as defined by KPN (2024b). Additionally, besides GWP, other impact categories such as acidification or human toxicity could be applied.

Another suggestion for improvement is a comparative case study. If similar data could be collected for a comparable device from another telecom provider, this could offer valuable insight into each provider's relative strengths and weaknesses.

In addition to expanding the model, the limitations discussed in Chapter 7.1 would need to be addressed. These include a deeper analysis of the data sources to verify their accuracy and long-term applicability. During this study, an attempt was made to have Product A analysed by TNO to assess its CRM composition, and information was requested from KPN's recycling partners; both without success. Gaining these insights would improve the model's reliability. These data points could be further improved as suggested by Nilsson (2019), by substantiation through insights from operators and employees working in production, reuse and recycling facilities to gain qualitative insights into their perception of these processes.

Additionally, in terms of improving the dynamic model, several parameters are recommended for future versions: the inclusion of CRM flows for repaired products, a net-prevented GWP calculation and the impact of multiple recycling cycles such as suggested by Schaubroeck et al. (2021). All of these are technically implementable in the model, with data availability being the main limitation

In the short term, the proposed actions for Product A, and likely also applicable to similar products, are to prioritize aluminium recycling, increase reuse further (enhanced by modular design), and reduce municipal waste flows. In the longer term, KPN will likely rely on external factors but should continue advocating for policy and procedural change, encouraging suppliers to adopt circular design strategies. Similar collaboration with competitors could also be explored, seeking sector-wide solutions for environmental harm reduction.

Besides KPN, this study's results could also be elaborated upon through further scientific research. The model, or a modified version thereof could be used to assess large-scale CRM flows within the Netherlands, the EU or even on a global level and compared to the effect of e.g. proposed policy measures, which would increase reuse or recycling. Since the topic of CRMs is subject to an ongoing academic and political debate, such future visions might be valuable in structuring these discussions.

A final recommendation, for KPN as well as for scientific literature, is to keep seeking for innovative solutions within the CRM-context. While this study adopted an approach to suggest circularity and implemented this into a modelling framework, there is a wide array of other available and perhaps not-yet available perspectives on this issue. Therefore, the final suggestion is to apply these results if perceived as valuable but also look beyond this study for the best suited approach.

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Appendix

Appendix A - Product Selection

Table 14 shows the total inflows associated with different product categories KPN offers in the business-to-consumer market. Internet, which consists of modems, is seen to be responsible for the highest share in terms of total kg of weight (highlighted green).

Table 14: Product group: total inflow quantities y+4

Source	Non-virgin Renewable weight (kg)	Virgin Renewable weight (kg)	Non-virgin Non-renewable weight (kg)	Virgin Non-renewable weight (kg)	Total weight (kg)
TV 1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
TV 2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Internet 1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Internet 2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Digitenne 1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Digitenne 2	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Telephony 1	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Modified from KPN dashboard on yearly circular flow quantities, green highlight is to indicate highest total quantity, TV = set top boxes, Internet = modems and ONT (Optical Network Terminal to translate fibre optic signals to digital), digitenne = wireless TV connection box, telephony = fixed telephone.

Table 15 shows how product A is responsible for the highest total quantity of inflow weight within the internet product group (highlighted green). This product group consists of other inter modems (Products E and F) and ONT (Optical Network Terminal) boxes, which translate fibre optic signals to digital signal which can be read by modems and routers (Product B, C and D).

Table 15: Product specific: total inflow quantities y+4

Product group	Product type	Product name	Inflow quantity (nr. of pieces)	Weight per product (kg)	Inflow weight (kg)
Internet	ONT	[redacted]	[redacted]	[redacted]	[redacted]
Internet	ONT	[redacted]	[redacted]	[redacted]	[redacted]
Internet	Modem	[redacted]	[redacted]	[redacted]	[redacted]
Internet	ONT	[redacted]	[redacted]	[redacted]	[redacted]
Internet	Modem	[redacted]	[redacted]	[redacted]	[redacted]
Internet	Modem	[redacted]	[redacted]	[redacted]	[redacted]

Modified from KPN dashboard on yearly circular flow quantities, green highlight is to indicate highest total quantity, product names have been modified, ONT = Optical Network Terminal to translate fibre optic signals to digital.

Appendix B - CRM Quantities

Molar mass calculations

** Removed in line with NDA agreements. Please contact author if further insights are required.*

Table 16: Calculation of totals for compound materials in Product A

Material	Calculated molar mass	Pure material	Total
antimony	[redacted]	[redacted] · [redacted]	[redacted] · [redacted]
bismuth	[redacted] · [redacted]	[redacted] · [redacted]	[redacted] · [redacted]
boron	[redacted] · [redacted]	[redacted]	[redacted] · [redacted]
cobalt	[redacted] · [redacted]	[redacted] · [redacted]	[redacted] · [redacted]
magnesium	[redacted]	[redacted]	[redacted] · [redacted]
phosphorus	[redacted] · [redacted]	[redacted] · [redacted]	[redacted] · [redacted]
silicon	[redacted] · [redacted]	[redacted] · [redacted]	[redacted] · [redacted]
ruthenium	[redacted] · [redacted]	[redacted]	[redacted] · [redacted]

Only materials for which a molar mass was calculated included in table, other values in table 17

Table 17: CRM quantities and supply index product A

Aton symbol	English element name	Type	EU CRM list 2023	Level of criticallity	SI(EI)	SI(SR)	Weight (gr.) of materials in product A	Compound material	kg. of total primary inflow y+1 to y+4
Al	aluminum	material	Yes	critical	0.82	0.86	[redacted].[redacted]	[redacted]	[redacted].[redacted]
Sb	antimony	material	Yes	critical	0.92	0.94	[redacted].[redacted]	[redacted]	[redacted]
Be	beryllium	material	Yes	critical	0.99	0.99	[redacted].[redacted]	[redacted]	[redacted]
Bi	bismuth	material	Yes	strategic	0.95	0.92	[redacted].[redacted]	[redacted]	[redacted]
B	boron	material	Yes	strategic	0.99	0.99	[redacted].[redacted]	[redacted]	[redacted]
Ce	cerium	LREE	Yes	critical	0.93	0.97	[redacted].[redacted]	[redacted]	[redacted].[redacted]
Co	cobalt	material	Yes	strategic	0.97	0.98	[redacted].[redacted]	[redacted]	[redacted]
Ga	gallium	material	Yes	strategic	0.98	0.98	[redacted].[redacted]	[redacted]	[redacted].[redacted]
Mg	magnesium	material	Yes	strategic	0.94	0.94	[redacted].[redacted]	[redacted]	[redacted]
Pd	palladium	PGM	Yes	strategic	0.92	0.99	[redacted].[redacted]	[redacted]	[redacted].[redacted]
P	phosphorus	material	Yes	critical	0.95	0.98	[redacted].[redacted]	[redacted]	[redacted].[redacted]
Rh	rhodium	PGM	Yes	strategic	0.99	1	[redacted].[redacted]	[redacted]	[redacted]
Ru	ruthenium	PGM	Yes	strategic	0.94	0.94	[redacted].[redacted]	[redacted]	[redacted]
Si	silicon	material	Yes	strategic	0.99	0.99	[redacted].[redacted]	[redacted]	[redacted].[redacted]
W	tungsten	material	Yes	strategic	0.95	0.96	[redacted].[redacted]	[redacted]	[redacted]
Ba	barium	-	No	-	-	-	[redacted].[redacted]	[redacted]	[redacted].[redacted]
In	indium	-	No	-	-	-	[redacted].[redacted]	[redacted]	[redacted].[redacted]

*kg. of total primary inflow is calculated based on the material weight * the quantity of primary product inflow of 1,341,296 during the y to y+4 period. For non-compound materials, values are directly taken from Manufacturer A report, for compound materials molar mass calculations included in table 16*

Table 18: Potential environmental impact calculations for product A

Atomi Symbol	English Element Name	Environme Impact (GWP)	Ecoinvent Dataset	LCIA Method	Total GWP	GWP unit of Measurement
Al	aluminum	$2.19 \cdot 10^{1}$	market for aluminium alloy, AlLi (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Sb	antimony	$2.30 \cdot 10^{1}$	market for antimony (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Be	beryllium	$6.87 \cdot 10^{2}$	market for beryllium (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Bi	bismuth	$0.00 \cdot 10^{0}$	-	-	[redacted] · [redacted]	kg CO2-Eq
B	boron	$2.87 \cdot 10^{0}$	market for trimethyl borate (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Ce	cerium	$1.62 \cdot 10^{1}$	market for cerium oxide (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Co	cobalt	$4.49 \cdot 10^{1}$	market for cobalt (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Ga	gallium	$1.71 \cdot 10^{2}$	market for gallium, semiconductor-grade (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Mg	magnesium	$2.76 \cdot 10^{1}$	market for magnesium (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Pd	palladium	$1.12 \cdot 10^{4}$	market for palladium (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
P	phosphorus	$4.67 \cdot 10^{0}$	market for phosphorus trichloride (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Rh	rhodium	$8.04 \cdot 10^{4}$	market for rhodium (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
Ru	ruthenium	$0.00 \cdot 10^{0}$	-	-	[redacted] · [redacted]	kg CO2-Eq
Si	silicon	$1.08 \cdot 10^{1}$	market for silicon, metallurgical grade (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq
W	tungsten	$5.56 \cdot 10^{0}$	market for tungsten concentrate (GLO)	CML v4.8 2016	[redacted] · [redacted]	kg CO2-Eq

Appendix C - Product A1: Components

Table 19: Product A1: component breakdown

Material	Material source	% of material source specified	Material weight (g)	Designed for disassembly
ABS	[redacted]	[redacted]	[redacted]	[redacted]
ABS	[redacted]	[redacted]	[redacted]	[redacted]
Aluminium	[redacted]	[redacted]	[redacted]	[redacted]
Aluminium	[redacted]	[redacted]	[redacted]	[redacted]
Brass	[redacted]	[redacted]	[redacted]	[redacted]
Cable	[redacted]	[redacted]	[redacted]	[redacted]
DC 12V plug	[redacted]	[redacted]	[redacted]	[redacted]
PC	[redacted]	[redacted]	[redacted]	[redacted]
PC-ABS	[redacted]	[redacted]	[redacted]	[redacted]
PCBA	[redacted]	[redacted]	[redacted]	[redacted]
PP	[redacted]	[redacted]	[redacted]	[redacted]
Rubber	[redacted]	[redacted]	[redacted]	[redacted]
Silicon Rubber	[redacted]	[redacted]	[redacted]	[redacted]
Steel	[redacted]	[redacted]	[redacted]	[redacted]

Total weight: 0.861 g, aluminium is the only CRM identified in the component breakdown and found in the heatsink which is partly designed for disassembly according to the data source for this component level data.

Appendix D - Extensive Flowchart EoL Manager A

** Removed in line with NDA agreements. Please contact author if further insights are required.*

Appendix E - Static MFA / SFA: Transfer Coefficient Calculations

This appendix provides an overview of how the transfer coefficients, as used in the static (and also partly in the dynamic) MFA and SFA models are deducted from KPN's datasets. First the logic behind the transfer coefficient's calculations is explained, resulting in the values used in the model. These values are shown in Table 20, the data these calculations is based on is presented in Tables 21, 22, 23, 24, 25, 26, 27.

Transfer coefficient calculation logic

This paragraph refers to the transfer coefficients presented below in Table 20.

- The TC's in P12 (aggregated collection and sorting) are calculated as 0% and 100% as this process functions as a means of directing the industrial- and municipal waste streams to their respective EoL processes - recycling, energy recovery and landfill. If these three EoL processess would have been modelled two times, one set of three for industrial and a second set of three for municipal waste, P12 would be obsolete. However, to maintain model clarity, as three more processes would have cluttered the model, the approach to use aggregated EoL processes was applied.
  Herein, 100% of industrial waste to energy recovery goes to energy recovery whilst 0% of this flow goes to recycling, the same goes for municipal waste to energy recovery and vice versa for the recycling processes.
- In P9 (collection and sorting industrial) the amount of industrial waste flowing to either recycling (70%) or energy recovery (30%) provides the TC. This is based on the downstream recycling report PCBs (Table 25).
- In P10 (collection and sortin municipal) the amount of municipal waste flowing to either recycling (64.16%), energy recovery (31.2%) or landfill (4.64%) provides the TC. This is based on a calculation of the averages values based on the municipal recycling report (Table 26).
- In P13 (quality assessment) the amount of devices that is recovered (reused) is calculated as: Total recovered inflow (Table 23) / total collected products (Table 22) = 81.24%. The amount of devices sent for repair is calculated as: sum of percentages for 'assumed CRM loss = Yes' in Table 24 (6.14%). The devices flowing from P13 to waste products is calculated as 100% - (percentage reuse + percentage to repair) = 12.62%. Lastly, in P13, all products flowing in from repair go to reuse. Therefore this inflow is divided as 100% to reuse an 0% back to repair and waste.
- In P5 the amount of recovered PMs is calculated based on a downstream recycler's report as shown in Table 27 (0.08%). For Al this is shown in Table 28 (3.53%).
- In P14 there is a distinction between products that don't require CRM replacements (40.27%) and those that do (59.73%), values are calculated as shown in Table 24. Also, 100% of the replacement CRMs are used for repairs and 0% of these CRMs are immediately discarded.
- In P1 the percentage of collected products is calculated as: total collected products (Table 22) / total primary inflow (Table 21) = 31.75%. The percentage of products defined as non-return waste products is based on the calculated average as shown in Table 26 (12.68%). Lastly, the products flowing to the use phase is based calculated as: 100% - (total collected products + non-return waste products) = 55.58%.

Besides the above listed TCs, all uncertainty values for the TCs used in P9, P10 and P5 are based on the calculated standard deviation through Equation 17, based on the mean and individual values as shown in Table 26.

$$\sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n}} \tag{17}$$

Table 20: Processes and transfer coefficients

Process	Process name	In->Out	TC	± TC	TC (calculated)	± TC (calculated)
P12	Aggregated collection and sorting	F20 -> F5	100.00%		100.00%	
P12	Aggregated collection and sorting	F20 -> F6	0.00%		0.00%	
P12	Aggregated collection and sorting	F21 -> F5	0.00%		0.00%	
P12	Aggregated collection and sorting	F21 -> F6	100.00%		100.00%	
P12	Aggregated collection and sorting	F22 -> F5	100.00%		100.00%	
P12	Aggregated collection and sorting	F22 -> F6	0.00%		0.00%	
P12	Aggregated collection and sorting	F23 -> F5	0.00%		0.00%	
P12	Aggregated collection and sorting	F23 -> F6	100.00%		100.00%	
P9	Collection and sorting industrial	∑ -> F20	70.00%		70.00%	
P9	Collection and sorting industrial	∑ -> F21		30.00%		0.000%
P10	Collection and sorting municipal	∑ -> F22	64.16%	0.086%	64.16%	0.059%
P10	Collection and sorting municipal	∑ -> F23	31.20%	0.083%	31.20%	0.059%
P10	Collection and sorting municipal	∑ -> F8	4.64%	0.007%	4.64%	0.007%
P13	Quality assessment	F2 -> F13	81.24%		81.24%	
P13	Quality assessment	F2 -> F26	6.14%		6.14%	
P13	Quality assessment	F2 -> F4	12.62%		12.62%	
P13	Quality assessment	F27 -> F13	100.00%		100.00%	
P13	Quality assessment	F27 -> F26	0.00%		0.00%	
P13	Quality assessment	F27 -> F4	0.00%		0.00%	
P5 (1)	Recycling	∑ -> F15	0.08%		0.08%	
P5 (1)	Recycling	∑ -> F17		99.92%		0.000%
P14	Repair	F25 -> F24	0.00%		0.00%	
P14	Repair	F25 -> F27	100.00%		100.00%	
P14	Repair	F26 -> F24	59.73%		59.73%	
P14	Repair	F26 -> F27	40.27%		40.27%	
P1	Use phase	∑ -> F16		55.57%		0.039%
P1	Use phase	∑ -> F19	12.68%	0.039%	12.68%	0.039%
P1	Use phase	∑ -> F2	31.75%		31.75%	

Layer = Goods for all processes.

Datasets used for transfer coefficient calculations

Table 21: Yearly primary inflow - product A

Year	Incl aluminium	excl aluminium
y+4	28,122.65 kg	94.65 kg
y+3	32,758.25 kg	110.25 kg
y+2	64,527.57 kg	217.17 kg
y+1	63,007.09 kg	212.05 kg
Total	188,415.56 kg	634.12 kg

Table 22: Yearly collected products - product A

Year	Incl aluminium	Excl aluminium
y+4	19,529.37 kg	65.73 kg
y+3	20,199.84 kg	67.98 kg
y+2	12,942.74 kg	43.56 kg
y+1	7,143.32 kg	24.04 kg
Total	59,815.27 kg	201.31 kg

Table 23: Yearly recovered inflow (reused) - product A

Year	Excl aluminium	Exclaluminium
y+4	10,825.53 kg	36.43 kg
y+3	16,131.05 kg	54.29 kg
y+2	13,214.13 kg	44.47 kg
Y+1	8,424.01 kg	28.35 kg
Total	48,594.73 kg	163.55 kg

Table 24: Sent for repair - product A with CRM loss assumptions

Testcode - Omschrijving	# Testing	Assumed CRM loss	% Of total
24	345615	No	93.86%
23	3708	Yes	1.01%
22	3122	Yes	0.85%
21	2955	No	0.80%
20	2683	No	0.73%
19	1323	Yes	0.36%
18	1308	No	0.36%
17	1140	Yes	0.31%
16	1067	No	0.29%
15	1042	No	0.28%
14	978	Yes	0.27%
13	906	Yes	0.25%
12	572	Yes	0.16%
11	524	Yes	0.14%
10	341	Yes	0.09%
9	304	Yes	0.08%
8	212	Yes	0.06%
7	181	Yes	0.05%
6	91	Yes	0.02%
5	79	Yes	0.02%
4	29	No	0.01%
3	15	No	0.00%
2	11	Yes	0.00%
1	4	Yes	0.00%
Total	**368210**		

based on total tested product A in y to y+4 period

Percentage to repair: 6.14%

Total yes (assumed discarded CRMs): 3.67% (59.73% out of 100%)

Total no (assumed CRM recovery): 2.47% (40.27% out of 100%)

Check 100%: 3.67 + 2.47 = 6.14% and 59.73 + 40.27 = 100.00%

Table 25: Downstream recycling report PCBs

	Recycling	ER	LF
WEEELABEX y+1	70%	30%	0%
WEEELABEX y+2	70%	30%	0%
WEEELABEX y+3	70%	30%	0%
WEEELABEX y=+4	70%	30%	0%
Average	70%	30%	0%

Table 26: Municipal recycling report

	Non return total	Recycling	ER	LF
y+4	10.30%	58.57%	36.26%	5.17%
y+3	10.30%	58.57%	36.26%	5.17%
y+2	11.61%	62.80%	33.41%	3.79%
y+1	18.50%	76.72%	18.84%	4.44%
Average	12.68%	64.16%	31.20%	4.64%

Table 27: PM recovered

Description	PM recovered	PM in PCB	PM recovered from total waste
Printed circuit board	0.002573%	0.06%	0.0000015%
Printed circuit board	0.0016875%	0.06%	0.0000010%
Printed circuit board	0.0397673%	0.06%	0.0000239%
Printed circuit board	0.0446195%	0.06%	0.0000268%
Printed circuit board	0.0126792%	0.06%	0.0000076%
Printed circuit board	0.0215712%	0.06%	0.0000129%
Printed circuit board	0.002542%	0.06%	0.0000015%
Printed circuit board	0.0103723%	0.06%	0.0000062%
Printed circuit board from dismantling	13.8419726%	0.08%	0.0110736%
Total PM recovered	13.98%		

CRM in total production of product A (- Al) = 634
PM in total production of product A = 3.63 kg
PMs in product A's PCB = 0.00573 kg (in total y+1 to y+4 production)
% of PM recovery in PCB 0.08009% (in total y+1 to y+4 production)

Table 28: Al recovered

Description	Al recovered
Elektronisch afval / E-waste y-1	81.6%

Appendix F - Static MFA: flows and processes

Flows and flow values for static MFA y+1 to y+4 period

Short symbol	Name	From	To	Mass flow (calculated)	± Mass flow (calculated)
F27	Repaired	P14,Repair	P13,Quality assessment	17.089 kg/a	0 kg/a
F26	Sent for repair	P13,Quality assessment	P14,Repair	17.108 kg/a	0 kg/a
F25	Replacement CRMs	Inflow	P14,Repair	10.2 kg/a	10.2 kg/a
F24	Discarded CRMs	P14,Repair	Outflow	10.218 kg/a	0 kg/a
F23	Municipal waste to energy recovery	P10,Collection and sorting municipal	P12,Aggregated collection and sorting	34.718 kg/a	0.126 kg/a
F22	Municipal waste to recycling	P10,Collection and sorting municipal	P12,Aggregated collection and sorting	71.394 kg/a	0.229 kg/a
F21	Industrial waste to energy recovery	P9,Collection and sorting industrial	P12,Aggregated collection and sorting	10.549 kg/a	0 kg/a
F20	Industrial waste to recycling	P9,Collection and sorting industrial	P12,Aggregated collection and sorting	24.614 kg/a	0 kg/a
F19	Non-return waste products	P1,Use phase	P10,Collection and sorting municipal	0.111 t/a	0.342 kg/a
F18	Waste (flyash / slug)	P6 (1),Energy recovery	Outflow	45.267 kg/a	0.126 kg/a
F17	Non-recovered CRMs	P5 (1),Recycling	Outflow	95.931 kg/a	0.229 kg/a
F16	In use products	P1,Use phase	P8,In use stock	487.663 kg/a	0.342 kg/a
F15	Precious metal recovery	P5 (1),Recycling	Outflow	0.077 kg/a	0.00018 kg/a
F14	CRM use	Inflow	P1,Use phase	634.12 kg/a	634.12 kg/a
F13	Reuse products	P13,Quality assessment	P1,Use phase	243.446 kg/a	0 kg/a
F8	Landfilled	P10,Collection and sorting municipal	P11,Landfill	5.163 kg/a	0.018 kg/a
F6	Waste to incineration+	P12,Aggregated collection and sorting	P6 (1),Energy recovery	45.267 kg/a	0.126 kg/a
F5	Waste to recycling	P12,Aggregated collection and sorting	P5 (1),Recycling	96.008 kg/a	0.229 kg/a
F4	Waste products	P13,Quality assessment	P9,Collection and sorting industrial	35.163 kg/a	0 kg/a
F2	Collected products	P1,Use phase	P13,Quality assessment	278.627 kg/a	0 kg/a

Table 29: Processes and stock accumulation for static MFA y+1 to y+4 period

Short symbol	Name	Stock	Sub system	Mass flow (calculated)	± Mass flow (calculated)
P1	Use phase	FALSE	FALSE		
P2	EoL management	FALSE	TRUE		
P4	Collection and sorting (Industrial/ municipal)	FALSE	TRUE		
P5	Recycling	FALSE	FALSE		
P6	Energy recovery	FALSE	FALSE		
P11	Landfill	TRUE	FALSE	5.163 kg/a	0.018 kg/a
P8	In use stock	TRUE	FALSE	487.663 kg/a	0.342 kg/a
P9	Collection and sorting industrial	FALSE	FALSE		
P10	Collection and sorting municipal	FALSE	FALSE		
P12	Aggregated collection and sorting	FALSE	FALSE		
P13	Quality assessment	FALSE	FALSE		
P14	Repair	FALSE	FALSE		

Appendix G - Static MFA: Discontinuation Subsystems

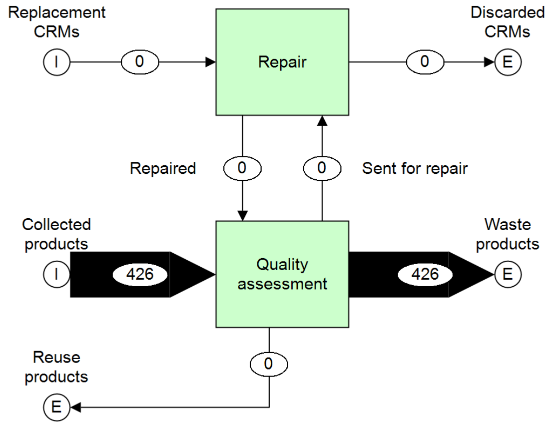


Figure 32: Sub-system of EoL supply partner in static MFA model of CRM flows in product A1: discontinuation. *Note: values in kg, green processes are within- and blue and grey are outside KPN's scope, aluminium not included*

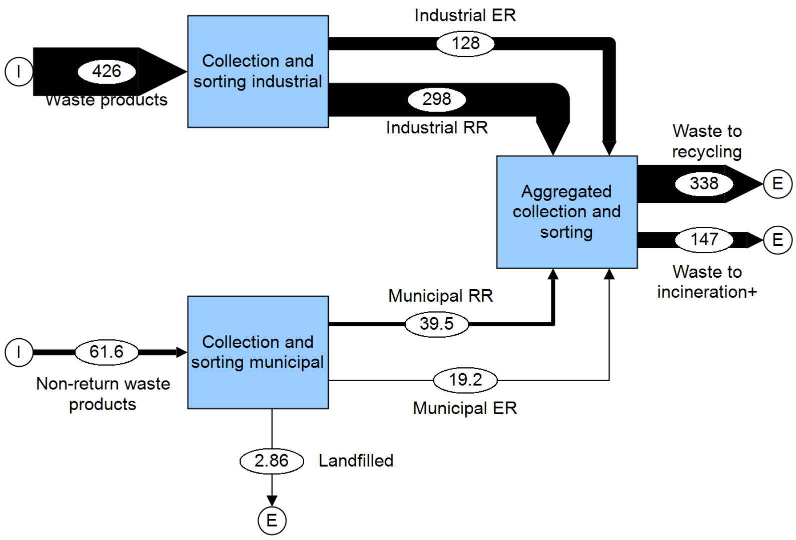


Figure 33: Sub-system of waste management (industrial & municipal) in static MFA model of CRM flows in product A1: discontinuation. *Note: values in kg, green processes are within- and blue and grey are outside KPN's scope, aluminium not included*

Appendix H - SFA Models

1. SFA model for Aluminium

The recycling rate for aluminium is modelled at 32%

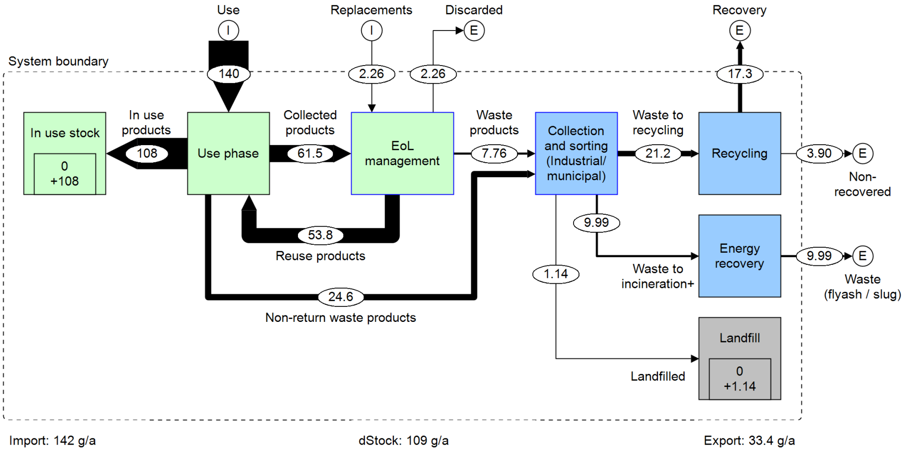


Figure 34: Static MFA model of Al flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

2. SFA models for platinum group metals

The recycling rate for platinum group metals is modelled at 12%

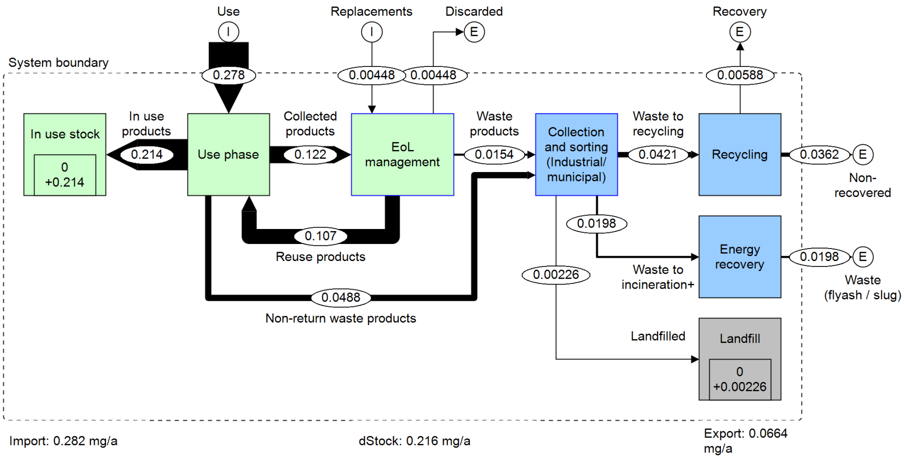


Figure 35: Static MFA model of Pd flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

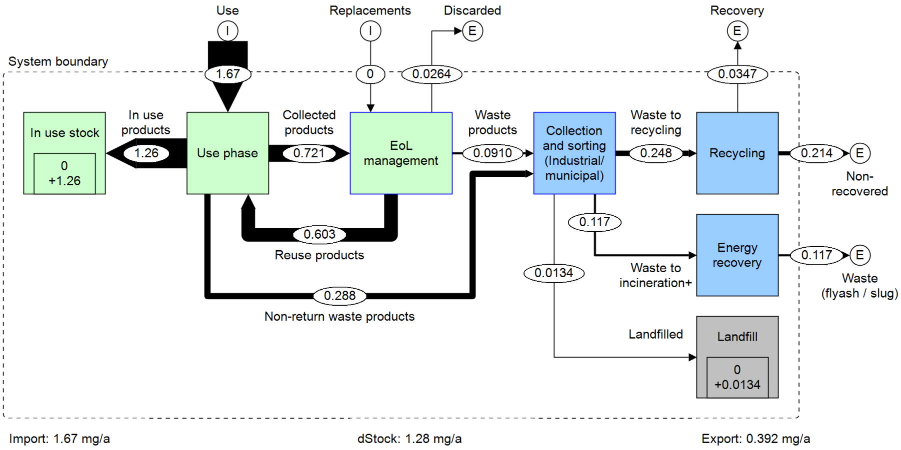


Figure 36: Static MFA model of Rh flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

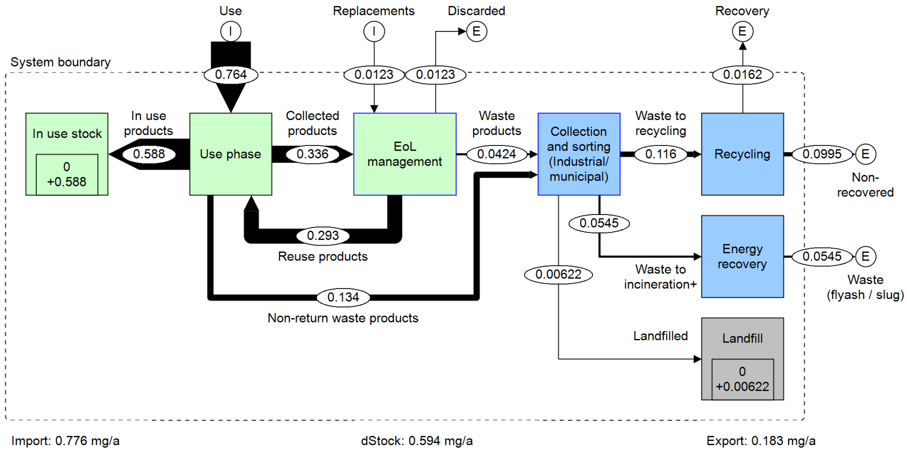


Figure 37: Static MFA model of Ru flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

3. SFA models for other CRMs

The recycling rate for non-aluminium and non-platinum group metals is modelled at 0%. EoL-RIR indicates higher percentages for some materials, however, no indications where found to suggest that these materials in KPN's modems are recycled.

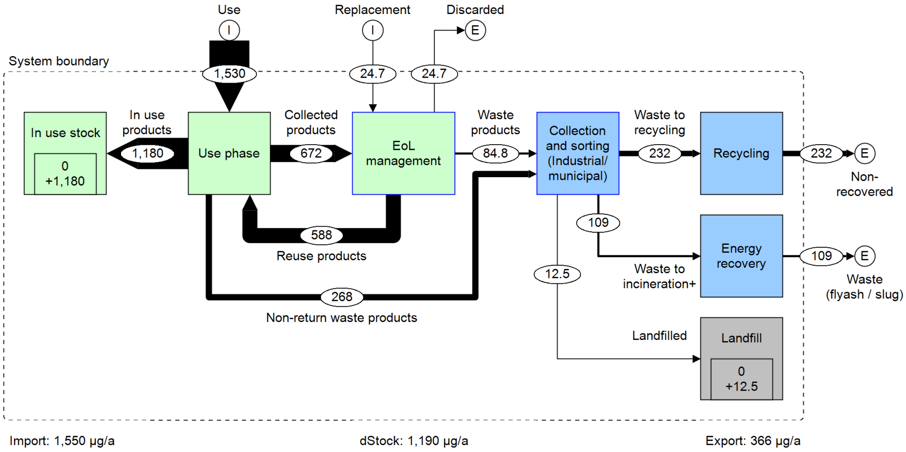


Figure 38: Static MFA model of B flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

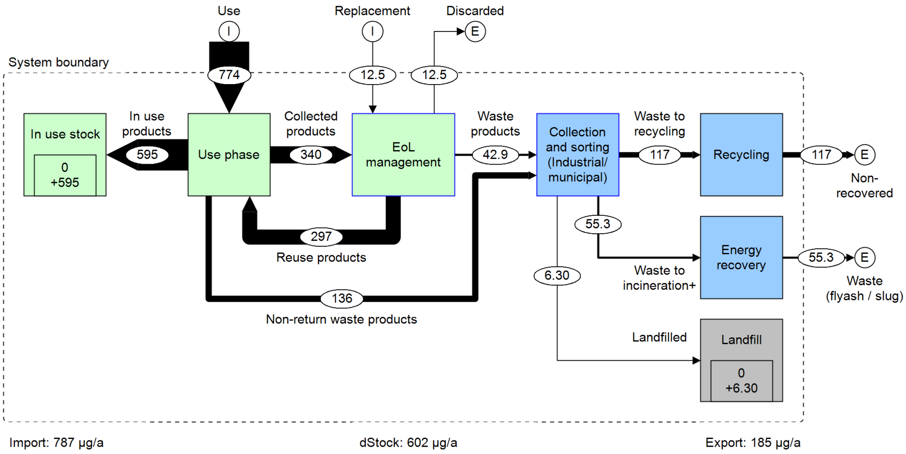


Figure 39: Static MFA model of Bi flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

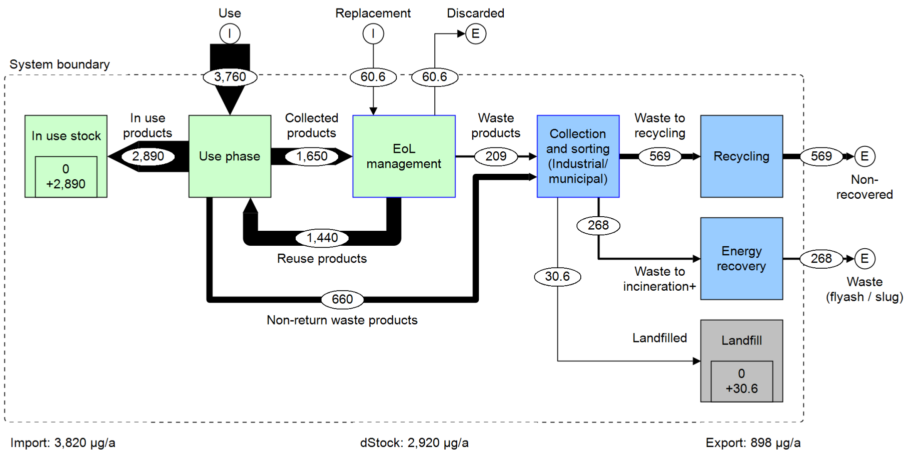


Figure 40: Static MFA model of Be flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

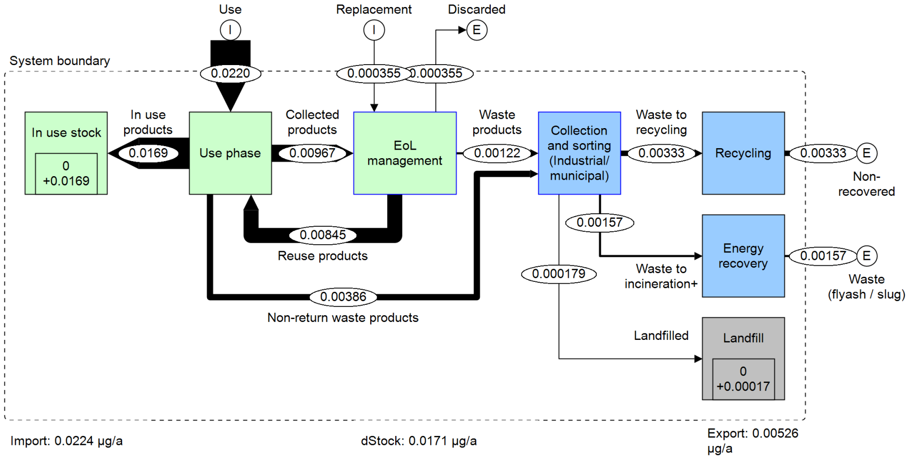


Figure 41: Static MFA model of Ce flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

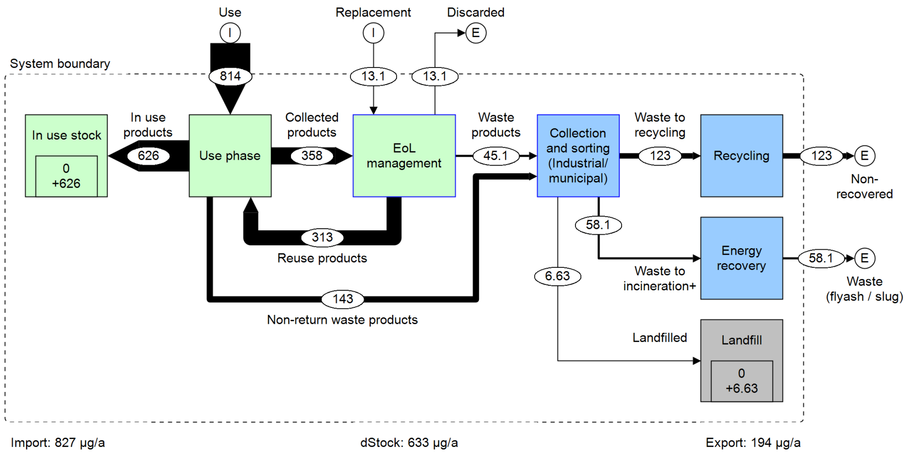


Figure 42: Static MFA model of Co flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

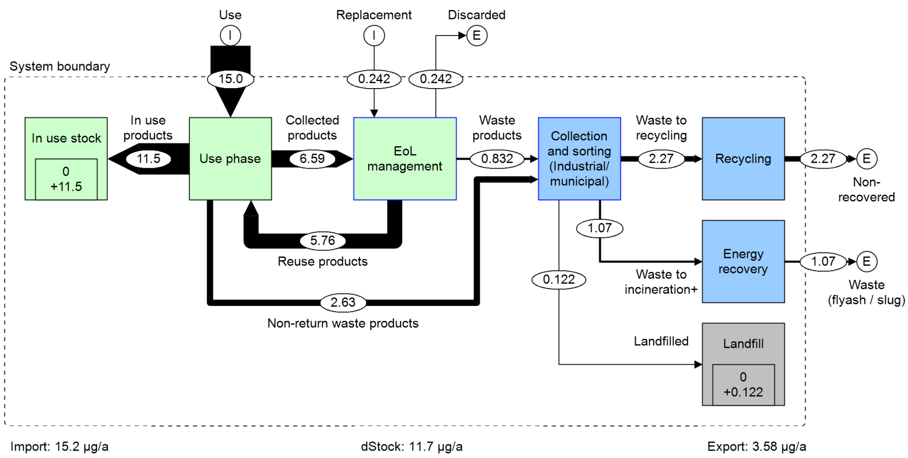


Figure 43: Static MFA model of Ga flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

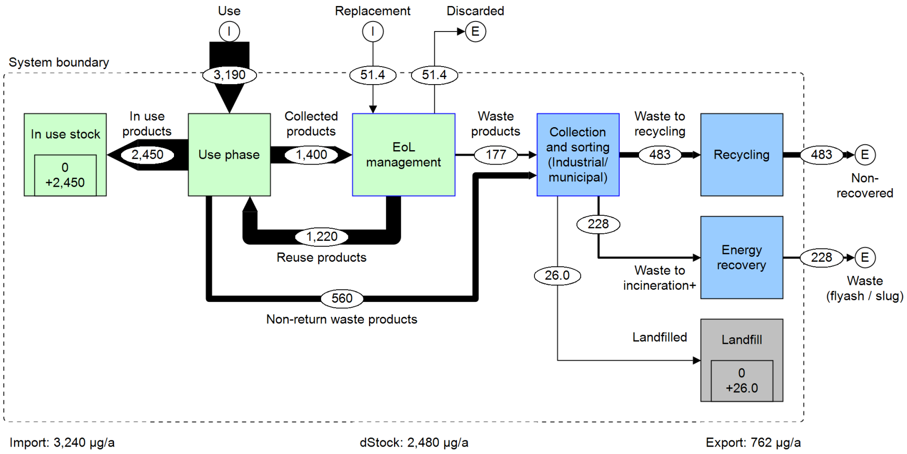


Figure 44: Static MFA model of Mg flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

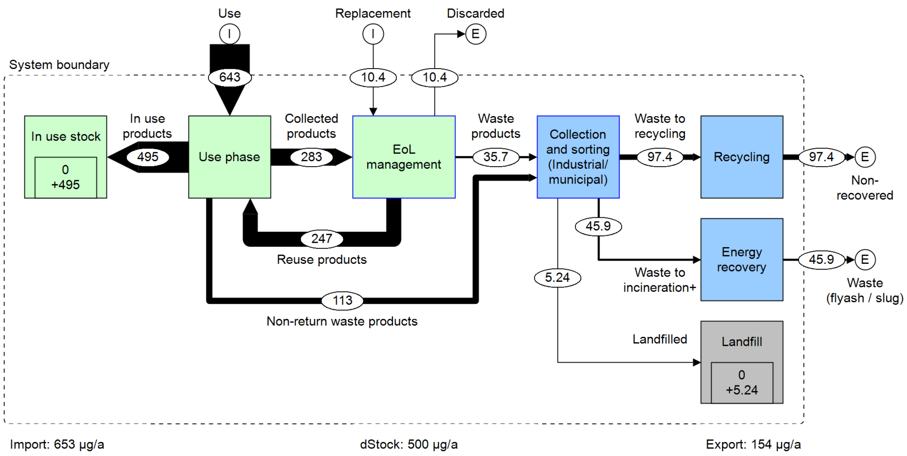


Figure 45: Static MFA model of P flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

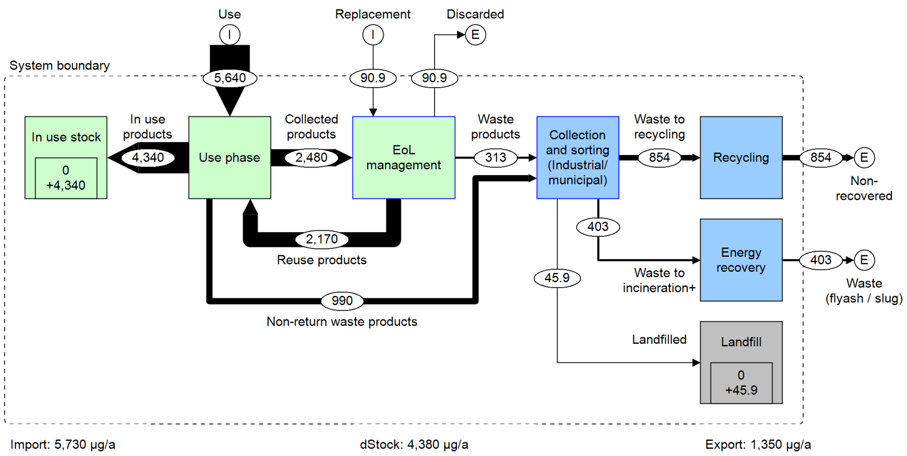


Figure 46: Static MFA model of Sb flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

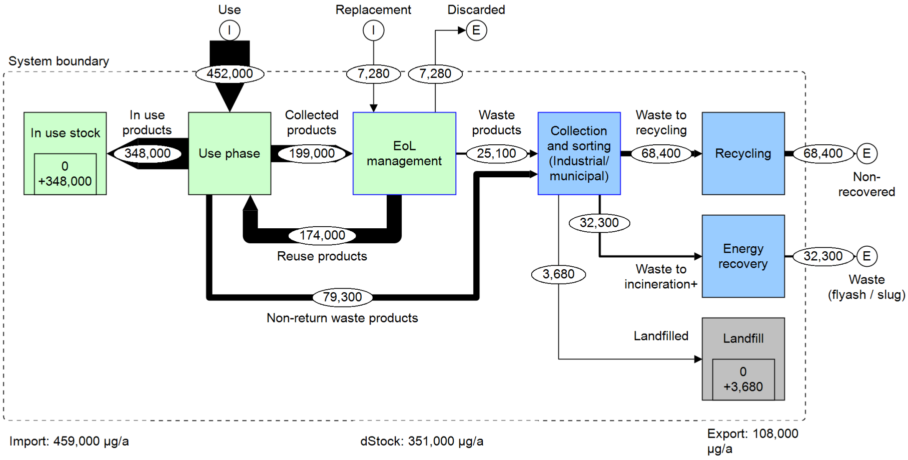


Figure 47: Static MFA model of Si flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

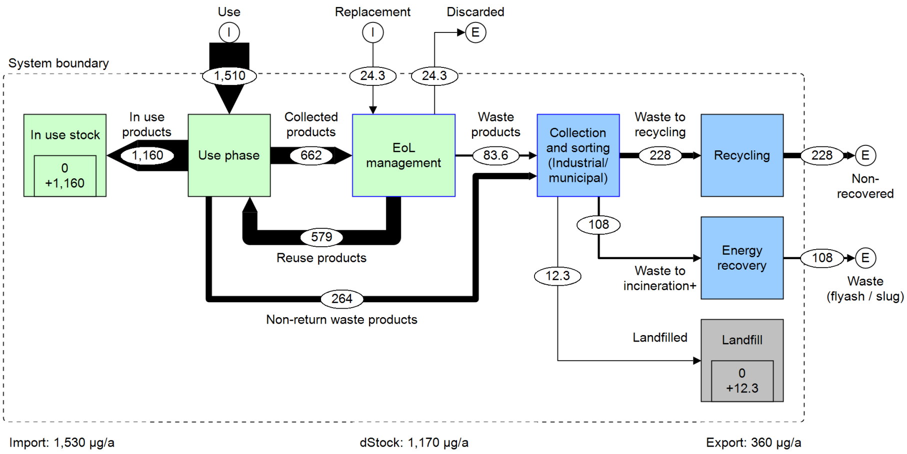


Figure 48: Static MFA model of W flows in product A. *Note: values in g, green processes are within- and blue and grey are outside KPN's scope*

Appendix I - Code for Dynamic MFA Model

```
# %% Load packages

import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import matplotlib.ticker as ticker
from scipy.interpolate import make_interp_spline
from datetime import datetime
import os
import copy

# %% Loading the data from excel

data_path = "C:/Users/kuste515/Downloads/Python/data/PY_code_and_data"
inflow_file = "ProductA_datafile.xlsx"

# creat a folder for plots in current directory
save_dir = 'dynamic_MFA_plots'
os.makedirs(save_dir, exist_ok=True)

# %% Define model as function

# Function is later used to call baseline and alternative scenarios independently
def dynamic_MFA(configurable_variable):
    scenario_name = configurable_variable.get("scenario_name", "Baseline Scenario") # dynamic name per scenario
    show_plots = configurable_variable.get("show_plots", True) # plots shown / not shown per scenario

# %% Configurable variables baseline scenario (DON'T ADJUST HERE --> ADJUST IN SCENARIOS BELOW)

    # True / False options to select survival curve type / include max reuse cycles / include primary inflow cut-off year
    use_normal_or_weibull = configurable_variable.get("use_normal_or_weibull", True) # True = Weibull / False = normal distr.

    use_max_reuse_cycles = configurable_variable.get("use_max_reuse_cycles", False) # True = include max reuse cycles
    max_reuse_cycles = configurable_variable.get("max_reuse_cycles", 3) if use_max_reuse_cycles else float('inf')

    use_primary_cutoff = configurable_variable.get("use_primary_cutoff", True) # True = include primary inflow cut-off year
    primary_inflow_cutoff_year = configurable_variable.get("primary_inflow_cutoff_year", 2026) if use_primary_cutoff else float('inf')

    # numerical options for adjustable paramaters - set to baseline scenario
    reuse_fraction = configurable_variable.get("reuse_fraction", 0.8124)
    collected_recycling_rate = configurable_variable.get("collected_recycling_rate", 0.7)
```

```python
    collected_energy_recovery_rate = configurable_variable.get("collected_energy_recovery_rate", 0.3)
    collected_landfill_rate = configurable_variable.get("collected_landfill_rate", 0.0)
    mun_waste_recycling_rate = configurable_variable.get("mun_waste_recycling_rate", 0.6416)
    mun_waste_energy_recovery_rate = configurable_variable.get("mun_waste_energy_recovery_rate", 0.3120)
    mun_waste_landfill_rate = configurable_variable.get("mun_waste_landfill_rate", 0.0464)
    mun_waste_share = configurable_variable.get("mun_waste_share", 0.1268)
    collected_share = 1 - mun_waste_share
    recycling_efficiencies = configurable_variable.get("recycling_efficiencies", {
    "aluminium": 0.816,
    "antimony": 0.0,
    "beryllium": 0.0,
    "bismuth": 0.0,
    "boron": 0.0,
    "cerium": 0.00,
    "cobalt": 0.0,
    "gallium": 0.0,
    "magnesium": 0.0,
    "palladium": 0.1398,
    "phosphorus": 0.,
    "rhodium": 0.1398,
    "ruthenium": 0.1398,
    "silicon": 0.0,
    "tungsten": 0.0
    })

# %% Load data from excel tab and define timesteps

    inflow_path = os.path.join(data_path, inflow_file)
    modem_inflow = pd.read_excel(inflow_path, sheet_name="ProductA_stock")
    time_max = modem_inflow.shape[0]
    timesteps = np.arange(time_max)

# %% Different survival curves Weibull / normal distribution - set to baseline values

    if use_normal_or_weibull:
        weibull_shape = configurable_variable.get("weibull_shape", 1.3)
        weibull_scale = configurable_variable.get("weibull_scale", 5.535)
        curve_surv = stats.weibull_min.sf(timesteps, weibull_shape, 0, weibull_scale)
    else:
        lifetime = configurable_variable.get("lifetime", 3)
        standard_dev = configurable_variable.get("standard_dev", 1.5)
        curve_surv = stats.norm.sf(timesteps, loc=lifetime, scale=standard_dev)

# %% Creating the survival matrix, first with placeholder zeros and then populated with shifted curves

    curve_surv_matrix = pd.DataFrame(0.0, index=timesteps, columns=timesteps)
    for t in timesteps:
        curve_surv_matrix.loc[t:, t] = curve_surv[:time_max - t]

# %% Plot survival and outflow curves
```

```
    # when show_plots is on, print the scenario name
    if show_plots:
        print(f"\n=== Scenario: {scenario_name} ===")

    # defining the survival curve as percentages
    surv_pct = curve_surv * 100
    outflow = -np.diff(curve_surv, prepend=curve_surv[0]) # calculate yaerly outflow as difference on t and t-1
    outflow_pct = (outflow / outflow.sum()) * 100 # define outflow curve as percentages
    outflow_pct[0] = 0 # no outflow in first year, therefore 0

    smooth = np.linspace(timesteps.min(), timesteps.max(), 300) # smooth line (aesthetics)
    y1 = make_interp_spline(timesteps, surv_pct)(smooth)
    y2 = make_interp_spline(timesteps, outflow_pct)(smooth)

    # plot both curves in one plot with two subplots
    if show_plots:
        fig, axs = plt.subplots(1, 2, figsize=(12, 5))
        axs[0].plot(smooth, y1)
        axs[0].set(xlim=(0, 10), ylim=(0, 100), title='Survival Curve', xlabel='Time (years)', ylabel='Survival Percentage')
        axs[0].set_yticks(np.arange(0, 110, 20))
        axs[0].set_yticklabels([f'{i}%' for i in range(0, 110, 20)])

        max_y2 = np.max(y2)
        tick_step = 10
        y2_limit = np.ceil(max_y2 / tick_step) * tick_step
        axs[1].plot(smooth, y2, color='red')
        axs[1].set(xlim=(0, 10), ylim=(0, y2_limit), title='Outflow Curve', xlabel='Time (years)', ylabel='Outflow Percentage')
        axs[1].set_yticks(np.arange(0, y2_limit + tick_step, tick_step))
        axs[1].set_yticklabels([f'{int(i)}%' for i in np.arange(0, y2_limit + tick_step, tick_step)])

        plt.tight_layout(rect=[0, 0.03, 1, 0.95])
        plt.savefig(os.path.join(save_dir, f'survival_curve_{scenario_name}.pdf'), format='pdf')
        plt.show()

# %% Inflow calculation

    modem_inflow["inflow"] = np.nan # initialise inflow as an empty column
    modem_surv_matrix = pd.DataFrame(0.0, index=timesteps, columns=timesteps) # create a matrix for the calculated survival per year / cohort
    for t in timesteps: # calculate inflow per year to match calculated stock with actual stock
        modem_inflow.loc[t, 'inflow'] = (modem_inflow.loc[t, 'stock'] - modem_surv_matrix.loc[t].sum()) / curve_surv_matrix.loc[t, t]
        modem_surv_matrix.loc[:, t] = curve_surv_matrix.loc[:, t] * modem_inflow.loc[t, 'inflow']

    # Stock delta and outflow
    modem_inflow['nas'] = np.diff(modem_inflow['stock'], prepend=0)
    modem_inflow['outflow'] = modem_inflow['inflow'] - modem_inflow['nas']
    modem_inflow['expansion'] = np.where(modem_inflow['nas'] < 0, 0, modem_inflow['nas'])
```

```python
    modem_inflow['maintenance'] = modem_inflow['inflow'] - modem_inflow['expansion']

    # Plot stackplot with stacked area per cohort
    x = modem_inflow["year"].values
    y = modem_surv_matrix.T.values
    cmap = plt.get_cmap("turbo", len(x))
    colors = [cmap(i) for i in range(len(x))]
    if show_plots:
        plt.figure(figsize=(12, 6))
        plt.stackplot(x, y, labels=[f'Cohort {y}' for y in x], colors=colors, alpha=0.85)
        plt.plot(x, modem_inflow["stock"], 'k--', linewidth=2, label='Total Stock')
        #plt.title(f"Build up of total stock per cohort - {scenario_name}")
        plt.xlabel("Year")
        plt.ylabel("Number of devices in stock")
        plt.legend(loc='upper left', fontsize=8, ncol=2)
        plt.xticks(x, rotation=45)
        plt.tight_layout()
        plt.savefig(os.path.join(save_dir, 'stock_per_cohort.pdf'), format='pdf')
        plt.show()

# %% Reuse and new inflow calculation

    # defininng outflow and dividing it over outflow to collected (to EoL manager) and to municipal waste
    outflow = modem_inflow['outflow']
    mun_waste_outflow = mun_waste_share * outflow
    collected = collected_share * outflow

    # matrices to track reuse
    reuse_count_matrix = pd.DataFrame(0, index=timesteps, columns=timesteps) # how often a device is reuse
    reuse_surv_matrix = pd.DataFrame(0.0, index=timesteps, columns=timesteps) # survival of reused devices
    new_surv_matrix = pd.DataFrame(0.0, index=timesteps, columns=timesteps) # survival of new devices
    reuse_inflow, new_inflow = [], [] # lists for total reused and new inflow

    # 1. look for devices from earlier years fit for reuse
    # 2. define reused quantity based on inflow-requirements
    # 3. inflow-requirements which can not be met by reuse are supplied from primary inflow
    for t in modem_inflow.index:
        inflow_need = modem_inflow.loc[t, "inflow"] # extract required inflow for year = t
        eligible = [ # determine for every previous year (s < t) how much devices from cohort s are available in year t
            (s, reuse_fraction * collected[s] * curve_surv_matrix.loc[t, s]) # quantity = reusable part of outflow times surv curv
            for s in range(t)
            if reuse_count_matrix.loc[t, s] < max_reuse_cycles] # only if max reuse cycles is not exceeded

        # define the reused amount, limited to what is necessary
        reuse_amt = min(inflow_need, sum(p[1] for p in eligible))
        reuse_used = 0 # 0 as starting point for reused devices
```

```python
        for s, potential in eligible: # loop through potential reuse cohorts
            if reuse_used >= reuse_amt: break # stop the loop when reuse-requirement is reached
            portion = min(potential, reuse_amt - reuse_used) # determine the amount of devices from cohort s effectively reused
            reuse_used += portion # add reused quantity to total reuse
            reuse_count_matrix.loc[t:, s] += 1 # track the reuse of devices from t untill end of the simulation
            reuse_surv_matrix.loc[:, t] += portion * curve_surv_matrix.loc[:, t] # add the survival of reused devices to the reuse surv matrix

        # determine the amount of devices which have to be newly fabricated (primary inflow after reuse), onlu if years is within cut-off
        new_amt = inflow_need - reuse_used if modem_inflow.loc[t, "year"] <= primary_inflow_cutoff_year else 0
        new_surv_matrix.loc[:, t] = new_amt * curve_surv_matrix.loc[:, t] # add newly produced devices to a survival matrix
        reuse_inflow.append(reuse_used)
        new_inflow.append(new_amt)

    # add lists of reuse and ne inflow as columns in the dataframe
    modem_inflow["reuse_inflow"] = reuse_inflow
    modem_inflow["new_inflow"] = new_inflow

# %% Plot reuse nested in cohorts and as seperate cohort matrix

    cohort_years = modem_inflow["year"].values # retrieve cohort years as a numpy array
    n = len(cohort_years) # determine the number of cohorts
    cmap = plt.get_cmap("turbo", n)
    colors = [cmap(i) for i in range(n)]
    reuse_base = plt.get_cmap("Oranges_r")
    reuse_colors = [reuse_base(i) for i in np.linspace(0.2, 0.8, n)]

    if show_plots:
        # plot the cohort matrix wiht reuse as a fraction of individual cohorts
        plt.figure(figsize=(12, 6))
        bottom = np.zeros_like(x, dtype=float)
        for i, year in enumerate(cohort_years): # loop through every index and year of cohorts
            y_reuse = reuse_surv_matrix.iloc[:, i].values # retrieve reused quantity per cohort
            y_new = new_surv_matrix.iloc[:, i].values # retrieve primary inflow per cohort
            plt.fill_between(x, bottom, bottom + y_reuse, color=reuse_colors[i], alpha=0.8)
            bottom += y_reuse
            plt.fill_between(x, bottom, bottom + y_new, color=colors[i])
            bottom += y_new

        plt.plot(x, modem_inflow["stock"], color='black', linewidth=2, linestyle='--', label='Total Stock')
        valid_indices = [i for i, yr in enumerate(cohort_years) if yr <= primary_inflow_cutoff_year]
        reuse_patch = mpatches.Patch(color=reuse_colors[n // 2], label='Reuse inflow')
        new_patches = [mpatches.Patch(color=colors[i], label=f'Cohort {cohort_years[i]}') for i in valid_indices]
```

```python
        stock_line = plt.Line2D([0], [0], color='black', linestyle='--', linewidth=2, label='Total stock')

        plt.legend(handles=[reuse_patch] + new_patches + [stock_line], loc='upper left', fontsize=8, ncol=2, framealpha=0.7)
        #plt.title(f"Build up of total stock per cohort - reuse within cohorts - {scenario_name}")
        plt.xlabel("Year")
        plt.ylabel("Number of devices in stock")
        plt.xticks(x, rotation=45)
        plt.ylim(bottom=0)
        plt.tight_layout()
        plt.savefig(os.path.join(save_dir, 'stock_per_cohort_reuse_percohort.pdf'), format='pdf')
        plt.show()

        # plot a second graph with reuse as a seperate cohort matrix
        plt.figure(figsize=(12, 6))
        fig.suptitle(f"Survival & Outflow Curves - {scenario_name}", fontsize=14)
        plt.stackplot(x, new_surv_matrix.T.values, colors=colors, alpha=0.8)
        plt.stackplot(x, reuse_surv_matrix.T.values, colors=reuse_colors, alpha=0.8)
        plt.plot(x, modem_inflow["stock"], color='black', linewidth=2, linestyle='--', label='Total Stock')

        plt.legend(handles=[reuse_patch] + new_patches + [stock_line], loc='upper left', fontsize=8, ncol=2, framealpha=0.7)
        #plt.title(f"Build up of total stock per cohort - reuse as separate survival matrix - {scenario_name}")
        plt.xlabel("Year")
        plt.ylabel("Number of devices in stock")
        plt.xticks(ticks=x, rotation=45)
        plt.ylim(bottom=0)
        plt.tight_layout()
        plt.savefig(os.path.join(save_dir, 'stock_per_cohort_seperate_matrix.pdf'), format='pdf')
        plt.show()

# %% EoL destinations --> outflow for which reuse is not applicable (municipal waste or unfit for ruese)

    # calculate what remains after reuse (clipped to prevent negative values)
    non_reuse_collected = (collected - modem_inflow["reuse_inflow"]).clip(lower=0)
    eol_from_non_reuse = non_reuse_collected # EoL devices from waste after reuse
    eol_from_mun_waste = mun_waste_outflow # EoL device from municipal waste

    # apply predefined recycling, energy recovery and landfill percentages to EoL flows
    modem_inflow['recycled'] = (eol_from_non_reuse * collected_recycling_rate + eol_from_mun_waste * mun_waste_recycling_rate)
    modem_inflow['energy_recovery'] = (eol_from_non_reuse * collected_energy_recovery_rate + eol_from_mun_waste * mun_waste_energy_recovery_rate)
```

```python
    modem_inflow['landfill'] = (eol_from_non_reuse * collected_landfill_rate + eol_from_mun_waste * mun_waste_landfill_rate)

# %% Total Material Flows

    # define the total amount of devices in reuse, recycling, energy recovery and landfill streams
    reuse_total = modem_inflow['reuse_inflow'].sum()
    recycled_total = modem_inflow['recycled'].sum()
    er_total = modem_inflow['energy_recovery'].sum()
    lf_total = modem_inflow['landfill'].sum()

# %% Material / environmental impact calculation

    # use the total device flows above to multiply by the impact factors (material / environmental)
    # load the second tab in the excel to acces the materials and GWP per material
    material_df = pd.read_excel(inflow_file, sheet_name="ProductA_materials")
    material_df = material_df[['materials', '#_materials_per_product', 'GWP_materials_per_kg']].dropna()

    # save the results for reuse, recycling and savings through material reduction
    reuse_results, recycle_results, avoided_results = [], [], []
    total_avoided_kg = 0
    total_avoided_gwp = 0

    # material multupliers added specifically for material reduction scenarios (can be commented out for baseline model)
    material_multipliers = configurable_variable.get("material_use_multiplier", {})

    # specific for -10% for all materials scenario (can be commented out for baseline model)
    if material_multipliers == "all_minus_10pct":
        material_multipliers = {mat.lower(): 0.9 for mat in material_df['materials']}

    # for every material:
    # 1. calculate kg + GWP for reuse
    # 2. same for recycling when a recycling efficieny is avaialable (=/= 0)
    # 3. calculate the prevented material use and GWP through reuse and recycling
    for _, r in material_df.iterrows(): # loop through all materials in the material_df table
        material = r['materials'].lower() # extract material name and set to lowercase
        multiplier = material_multipliers.get(material, 1.0) # use material multiplier for material reduction if applicable
        kg_per_device = (r['#_materials_per_product'] / 1000) * multiplier # calculate kg per device (mass in excel is in gr)
        reuse_kg = reuse_total * kg_per_device # calculate the total amount of material reused
        reuse_gwp = reuse_kg * r['GWP_materials_per_kg'] # calculate the prevented GWP
        reuse_results.append((r['materials'], reuse_kg, reuse_gwp)) # add reuse results to list
```

```python

        # when a recycling efficieny is included apply followig section, skip otherwise
        if material in recycling_efficiencies:
            efficiency = recycling_efficiencies[material] # extract efficiency from predefined efficiencies
            recycled_devices = (
                eol_from_non_reuse * collected_recycling_rate * efficiency +
                eol_from_mun_waste * mun_waste_recycling_rate * efficiency
            ).sum() # calculate total number of devices to recycling from non-reuse collected and municipal waste
            recycle_kg = recycled_devices * kg_per_device # calculate the total amount of material recycled
            recycle_gwp = recycle_kg * r['GWP_materials_per_kg'] # calculate the prevented GWP
            recycle_results.append((r['materials'], recycle_kg, recycle_gwp)) # add recycling results to list

        # calculation of saved materials / GWP through reduced material use
        baseline_kg_per_device = r['#_materials_per_product'] / 1000 # define standard weight in kg
        avoided_kg = (1 - multiplier) * modem_inflow["inflow"].sum() * baseline_kg_per_device # define saved material per year
        avoided_gwp = avoided_kg * r['GWP_materials_per_kg'] # calculate prevented GWP from saved material
        total_avoided_kg += avoided_kg # add to total material savings
        total_avoided_gwp += avoided_gwp # add to total GWP savings
        avoided_results.append((r['materials'], avoided_kg, avoided_gwp))

    # calculation for total environmental output based on 12.51 kg CO2 per device
    reuse_times_factor = reuse_total * 12.51

# %% Print results to console

    # Calculate average and total GWP values
    gwp_per_device_exact = 0
    for _, row in material_df.iterrows():
        kg_per_device = row['#_materials_per_product'] / 1000  # gram naar kg
        gwp_per_device_exact += kg_per_device * row['GWP_materials_per_kg']

    # Calculate total GWP for all EoL streams
    total_devices_all_flows = reuse_total + recycled_total + er_total + lf_total
    total_gwp_all_flows_exact = total_devices_all_flows * gwp_per_device_exact

    # Calculate GWP prevention for reuse and recycling based on total GWP for Product A
    total_gwp_reuse = sum(gwp for _, _, gwp in reuse_results)
    total_gwp_recycling = sum(gwp for _, _, gwp in recycle_results)
    perc_reuse_gwp = (total_gwp_reuse / total_gwp_all_flows_exact * 100) if total_gwp_all_flows_exact else 0
    perc_recycling_gwp = (total_gwp_recycling / total_gwp_all_flows_exact * 100) if total_gwp_all_flows_exact else 0

    if show_plots:
        print(f"\n=== Total Material Flows ({scenario_name}) ===")
        print(f"Reused:           {reuse_total:,.2f} devices")
```

```python
        print(f"Recycled:          {recycled_total:,.2f} devices")
        print(f"Energy Recovery:   {er_total:,.2f} devices")
        print(f"Landfilled:        {lf_total:,.2f} devices")
        print(f"Reuse * 12.51:     {reuse_times_factor:,.2f} kg CO2 (based on KPN calculation)")
        print(f"\n=== Material Savings & GWP Reduction ({scenario_name}) ===")
        print("\nREUSE:")
        for mat, kg, gwp in reuse_results:
            perc_total_gwp = (gwp / total_gwp_all_flows_exact * 100) if total_gwp_all_flows_exact else 0
            print(f"  {mat:<12} {kg:10,.2f} kg   |  GWP saved: {gwp:10,.2f} kgCO2e   |  {perc_total_gwp:6.2f}% of total GWP saved")

        print("\nRECYCLING (selected materials):")
        for mat, kg, gwp in recycle_results:
            perc_total_gwp = (gwp / total_gwp_all_flows_exact * 100) if total_gwp_all_flows_exact else 0
            print(f"  {mat:<12} {kg:10,.2f} kg   |  GWP saved: {gwp:10,.2f} kgCO2e   |  {perc_total_gwp:6.2f}% of total GWP saved")

    # calculate the total amount of material savings and prevented GWP with and without aluminium
    total_kg_with_al = sum(kg for *_, kg, _ in reuse_results + recycle_results)
    total_kg_without_al = sum(kg for mat, kg, _ in reuse_results + recycle_results if mat.lower() != 'aluminium')
    total_gwp_with_al = sum(gwp for *_, gwp in reuse_results + recycle_results)
    total_gwp_without_al = sum(gwp for mat, _, gwp in reuse_results + recycle_results if mat.lower() != 'aluminium')

    if show_plots:
        print(f"\nTOTAL MATERIAL SAVED: {total_kg_with_al:,.2f} kg (with Al),        {total_kg_without_al:,.2f} kg (without Al)")
        print(f"TOTAL GWP SAVED:      {total_gwp_with_al:,.2f} kgCO2e (with Al), {total_gwp_without_al:,.2f} kgCO2e (without Al)")

    # add material savings and GWP avoided through material reduction scenarios (e.g. -10% material use)
    total_kg_with_al += total_avoided_kg
    total_kg_without_al += sum(kg for mat, kg, _ in avoided_results if mat.lower() != 'aluminium')
    total_gwp_with_al += total_avoided_gwp
    total_gwp_without_al += sum(gwp for mat, _, gwp in avoided_results if mat.lower() != 'aluminium')

    if show_plots:
        print(f"\n=== GWP for Total Material Flows ({scenario_name}) ===\n")
        print(f"Total devices (reuse + recycled + ER + LF): {total_devices_all_flows:,.2f}")
        print(f"Exact GWP per device: {gwp_per_device_exact:,.2f} kgCO2e")
        print(f"GWP for total production: {total_gwp_all_flows_exact:,.2f} kgCO2e")
        print(f"Reuse GWP prevention:     {total_gwp_reuse:,.2f} kgCO2e ({perc_reuse_gwp:.2f}% of total GWP)")
        print(f"Recycling GWP prevention: {total_gwp_recycling:,.2f} kgCO2e ({perc_recycling_gwp:.2f}% of total GWP)\n")

# %% Return values from function to later use outside of function
```

```python

    include_aluminium = configurable_variable.get("include_aluminium_in_return", False)

    return {
        "scenario": configurable_variable["scenario_name"],
        "material_saving_kg": total_kg_with_al if include_aluminium else total_kg_without_al,
        "gwp_saving_kg": total_gwp_with_al if include_aluminium else total_gwp_without_al,
        "reuse_materials": [(mat, kg, gwp) for mat, kg, gwp in reuse_results],
        "recycle_materials": [(mat, kg, gwp) for mat, kg, gwp in recycle_results],
        "stock_series": modem_inflow["stock"].tolist(),
        "years": modem_inflow["year"].tolist(),
        "reuse_inflow": modem_inflow["reuse_inflow"].tolist(),
        "mun_waste_outflow": mun_waste_outflow.tolist(),
        "recycled": modem_inflow["recycled"].tolist(),
        "curve_surve_matrix_explorer": {"curve_surv_matrix": curve_surv_matrix},
        "reuse_times_1251": reuse_times_factor,
        "total_gwp_all_flows_exact": total_gwp_all_flows_exact,
        "total_gwp_reuse": total_gwp_reuse,
        "total_gwp_recycling": total_gwp_recycling,
        "perc_reuse_gwp": perc_reuse_gwp,
        "perc_recycling_gwp": perc_recycling_gwp,}

# %%##################
###########        ADJUSTABLE PARAMETERS BASELINE SCENARIO ###########
######################
# %%
# baseline scenario --> adjust these values for different modelling outcomes

if __name__ == "__main__":
    results = []
    default_config = {
        "scenario_name": "Baseline",
        "reuse_fraction": 0.8124,
        "use_normal_or_weibull": True, # True = Weibull distribution, False = normal distribution
        "weibull_shape": 1.3,
        "weibull_scale": 5.535,
        "show_plots": True, # True shows plots, Fals hides plots
        "use_max_reuse_cycles": False, # if true max_reuse_cycles used, otherwise infinite (based on surv. curve)
        "max_reuse_cycles": 3,
        "use_primary_cutoff": True, # if true year for primary cut-off is defined to value below, otherwise final stock year
        "primary_inflow_cutoff_year": 2026,
        "collected_recycling_rate": 0.7,
        "collected_energy_recovery_rate": 0.3,
        "collected_landfill_rate": 0.0,
        "mun_waste_recycling_rate": 0.6416,
        "mun_waste_energy_recovery_rate": 0.3120,
        "mun_waste_landfill_rate": 0.0464,
        "mun_waste_share": 0.1268,
```

```
        "recycling_efficiencies": {
            "aluminium": 0.816,
            "antimony": 0.0,
            "beryllium": 0.0,
            "bismuth": 0.0,
            "boron": 0.0,
            "cerium": 0.0,
            "cobalt": 0.0,
            "gallium": 0.0,
            "magnesium": 0.0,
            "palladium": 0.1398,
            "phosphorus": 0.,
            "rhodium": 0.1398,
            "ruthenium": 0.1398,
            "silicon": 0.0,
            "tungsten": 0.0},
        "data_path": "C:/Users/kuste515/Downloads/Python/data",
        "inflow_file": "ProductA1_flow_datafile.xlsx",}

    # run the baseline scenario and save the results
    baseline_result = dynamic_MFA(default_config)
    results.append(baseline_result)
    # Add the curve_surve_matrix to the variable explorer (i.e. extract it from the function)
    curve_surv_matrix = baseline_result["curve_surve_matrix_explorer"]["curve_surv_matrix"]

# %% EMBEDDED SCENARIOS

# %% antimony 28% recycling scenario
    antimony_scenario = copy.deepcopy(default_config)
    antimony_scenario["scenario_name"] = "Sb recycling +28%"
    antimony_scenario["show_plots"] = False
    antimony_scenario["recycling_efficiencies"]["antimony"] = 0.28
    #dynamic_MFA(antimony_scenario)
    results.append(dynamic_MFA(antimony_scenario))

# %% EU average recycling rates scenario
    EU_averages_scenario = copy.deepcopy(default_config)
    EU_averages_scenario["scenario_name"] = "EU average MR"
    EU_averages_scenario["show_plots"] = False
    EU_averages_scenario["recycling_efficiencies"]["antimony"] = 0.28
    EU_averages_scenario["recycling_efficiencies"]["tungsten"] = 0.42
    EU_averages_scenario["recycling_efficiencies"]["cobalt"] = 0.22
    EU_averages_scenario["recycling_efficiencies"]["cerium"] = 0.01
    EU_averages_scenario["recycling_efficiencies"]["boron"] = 0.01
    #EU_averages_scenario["recycling_efficiencies"]["aluminium"] = 0.32
    EU_averages_scenario["recycling_efficiencies"]["magnesium"] = 0.13
    results.append(dynamic_MFA(EU_averages_scenario))

# %% EU 2030 target recycling rates scenario
    EU_target_scenario = copy.deepcopy(default_config)
    EU_target_scenario["scenario_name"] = "EU target MR +25%"
    EU_target_scenario["show_plots"] = False
    #EU_target_scenario["recycling_efficiencies"]["aluminium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["antimony"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["beryllium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["bismuth"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["boron"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["cerium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["cobalt"] = 0.25
```

```
    EU_target_scenario["recycling_efficiencies"]["gallium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["magnesium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["palladium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["phosphorus"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["rhodium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["ruthenium"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["silicon"] = 0.25
    EU_target_scenario["recycling_efficiencies"]["tungsten"] = 0.25
    results.append(dynamic_MFA(EU_target_scenario))

# %% reuse +10% scenario
    high_reuse_scenario = copy.deepcopy(default_config)
    high_reuse_scenario["reuse_fraction"] = 0.9124
    high_reuse_scenario["scenario_name"] = "reuse +10%"
    high_reuse_scenario["show_plots"] = False
    results.append(dynamic_MFA(high_reuse_scenario))

# %% Weibull +10% scenario
    long_lifetime_scenario = copy.deepcopy(default_config)
    long_lifetime_scenario["weibull_scale"] = 6.15
    long_lifetime_scenario["scenario_name"] = "Lifetime +10%"
    long_lifetime_scenario["show_plots"] = False
    results.append(dynamic_MFA(long_lifetime_scenario))

# %% municipal waste -10% scenario
    low_mun_waste_scenario = copy.deepcopy(default_config)
    low_mun_waste_scenario["mun_waste_share"] = 0.0268
    low_mun_waste_scenario["scenario_name"] = "municipal waste -10%"
    low_mun_waste_scenario["show_plots"] = False
    results.append(dynamic_MFA(low_mun_waste_scenario))

# %% No antimony and rhodium scenario
    no_sb_rh_scenario = copy.deepcopy(default_config)
    no_sb_rh_scenario["scenario_name"] = "No Sb & Rh"
    no_sb_rh_scenario["show_plots"] = False
    no_sb_rh_scenario["material_use_multiplier"] = {"antimony": 0.0,"
        rhodium": 0.0}
    results.append(dynamic_MFA(no_sb_rh_scenario))

# %% all materials 10% reduction scenario
    all_material_reduction_scenario = copy.deepcopy(default_config)
    all_material_reduction_scenario["scenario_name"] = "All materials -10%"
    all_material_reduction_scenario["show_plots"] = False
    all_material_reduction_scenario["material_use_multiplier"] = "
        all_minus_10pct"
    results.append(dynamic_MFA(all_material_reduction_scenario))

# %% aluminium 97.2% recycling scenario

    al_scenario = copy.deepcopy(default_config)
    al_scenario["scenario_name"] = "Al recycling +15.6%"
    al_scenario["show_plots"] = False
    al_scenario["recycling_efficiencies"]["aluminium"] = 0.972
    al_scenario["include_aluminium_in_return"] = True
    results.append(dynamic_MFA(al_scenario))

    # Calculate the difference between the Al-scenario and baseline (
        because Al was previously excluded from calculations)
    baseline_al_config = copy.deepcopy(default_config)
    baseline_al_config["include_aluminium_in_return"] = True
    baseline_al_config["show_plots"] = False
```

```python
    baseline_with_al = dynamic_MFA(baseline_al_config)

    # search Al-scenario in results
    al_result = next(res for res in results if res["scenario"] == "Al recycling +15.6%")
    delta_kg = al_result["material_saving_kg"] - baseline_with_al["material_saving_kg"]
    delta_gwp = al_result["gwp_saving_kg"] - baseline_with_al["gwp_saving_kg"]

# %% scenario comparison graph

    df = pd.DataFrame(results) # extract results from dataframe
    baseline = df[df["scenario"] == "Baseline"].iloc[0] # set baseline values for results
    df["material_diff"] = df["material_saving_kg"] - baseline["material_saving_kg"] # identify deviation from baseline (materials)
    df["gwp_diff"] = df["gwp_saving_kg"] - baseline["gwp_saving_kg"] # identify deviation from baseline (GWP)
    df.loc[df["scenario"] == "Lifetime +10%", ["material_diff", "gwp_diff"]] *= -1 # Adjusted interpretation for Weibull +10% scenario

    # Correction for Al-scenario: deduct baseline scenario form Al +0.95% scenario to find delta
    df.loc[df["scenario"] == "Al recycling +15.6%", "material_diff"] = delta_kg
    df.loc[df["scenario"] == "Al recycling +15.6%", "gwp_diff"] = delta_gwp

    al_result = next(res for res in results if res["scenario"] == "Al recycling +15.6%")
    delta_kg = al_result["material_saving_kg"] - baseline_with_al["material_saving_kg"]
    delta_gwp = al_result["gwp_saving_kg"] - baseline_with_al["gwp_saving_kg"]
    df.loc[df["scenario"] == "Al recycling +15.6%", "material_diff"] = delta_kg
    df.loc[df["scenario"] == "Al recycling +15.6%", "gwp_diff"] = delta_gwp

    # divide data into Al scenario and other material scenarios
    df_al = df[df["scenario"] == "Al recycling +15.6%"]
    df_main = df[(df["scenario"] != "Baseline") & (df["scenario"] != "Al recycling +15.6%")].sort_values("material_diff")
    material_al, gwp_al = df_al["material_diff"].values[0], df_al["gwp_diff"].values[0]
    scenario_al = df_al["scenario"].values[0]
    rounded_mat, rounded_gwp = round(material_al, -3), round(gwp_al, -3)

    # extract values for material and GWP saving in relation to baseline scenario
    material_main = df_main["material_diff"].values
    gwp_main = df_main["gwp_diff"].values
    scenarios_main = df_main["scenario"].tolist()

    # Plot setup
    fig = plt.figure(figsize=(14, 6))
    gs = fig.add_gridspec(2, 3, height_ratios=[1, 7], width_ratios=[1, 0.39, 1], hspace=0.15, wspace=0.02)
    ax_al_mat, ax_lbl_al, ax_al_gwp = fig.add_subplot(gs[0, 0]), fig.add_subplot(gs[0, 1]), fig.add_subplot(gs[0, 2])
    ax1, ax_lbl, ax2 = fig.add_subplot(gs[1, 0]), fig.add_subplot(gs[1, 1]), fig.add_subplot(gs[1, 2])
```

```python

    # Y coordinates
    h = 0.2
    y_main = np.arange(len(scenarios_main)) * 0.4
    y_al = np.array([0])

    # Top graph for Al
    # Al - Material
    ax_al_mat.barh(y_al, [material_al], color='#C04F15', height=h)
    ax_al_mat.set(xlim=(material_al * 1.1, 0), ylim=(-0.23, 0.23), yticks=[])
    ax_al_mat.set_xticks([0, material_al])
    ax_al_mat.set_xticklabels([f"{0:,}", f"{int(material_al):}"], fontsize=10)
    ax_al_mat.set_title("Material savings vs baseline")
    ax_al_mat.grid(True, axis='x', linestyle='--')

    # Al - Label
    ax_lbl_al.axis('off')
    ax_lbl_al.set(xlim=(0, 1), ylim=(-0.2, 0.2))
    ax_lbl_al.text(0.5, 0, scenario_al, ha='center', va='center', fontsize=11)

    # Al - GWP
    ax_al_gwp.barh(y_al, [gwp_al], color='#156082', height=h)
    ax_al_gwp.set(xlim=(0, gwp_al * 1.1), ylim=(-0.23, 0.23), yticks=[])
    ax_al_gwp.set_xticks([0, rounded_gwp])
    ax_al_gwp.set_xticklabels([f"{0:,}", f"{int(rounded_gwp):}"], fontsize=10)
    ax_al_gwp.set_title("GWP prevented vs baseline")
    ax_al_gwp.grid(True, axis='x', linestyle='--')

    # Bottom graph for other scenarios
    # Other - Material
    ax1.barh(y_main, material_main, color='#C04F15', height=h)
    ax1.set(xlabel='Additional material savings (kg)', xlim=(100, 0))
    ax1.yaxis.set_visible(False)
    ax1.grid(True, axis='x', linestyle='--')

    # Other - Labels
    ax_lbl.axis('off')
    ax_lbl.set(xlim=(0, 1), ylim=(-0.2, y_main[-1] + 0.2))
    for i, txt in enumerate(scenarios_main):
        ax_lbl.text(0.5, y_main[i], txt, ha='center', va='center', fontsize=11)

    # Other - GWP
    ax2.barh(y_main, gwp_main, color='#156082', height=h)
    ax2.set(xlabel='Additional GWP prevented (kg CO2eq)')
    ax2.xaxis.set_major_locator(ticker.MultipleLocator(50000))
    ax2.yaxis.set_visible(False)
    ax2.grid(True, axis='x', linestyle='--')

    plt.tight_layout()
    plt.savefig(os.path.join(save_dir, 'combined_savings_comparison.pdf'), format='pdf', bbox_inches='tight', pad_inches=0.05)
    plt.show()

# %% export to excel

    # use pd.excelwriter to create an excel file in the current directory
```

```
    with pd.ExcelWriter("dynamic_MFA_quantitative_results.xlsx", engine="openpyxl", mode="w") as writer:
        summary_rows = []
        for r in results:
            reuse_kg = sum(kg for _, kg, _ in r["reuse_materials"])
            recycle_kg = sum(kg for _, kg, _ in r["recycle_materials"])
            material_total = reuse_kg + recycle_kg
            summary_rows.append({
                "scenario": r["scenario"],
                "material_saving_kg": round(material_total, 6),
                "gwp_saving_kg": round(r.get("gwp_saving_kg", 0), 6)
            })
        pd.DataFrame(summary_rows).to_excel(writer, sheet_name="Summary", index=False)

        # tab with total values per material for every scenario
        for result in results:
            sn = result["scenario"][:31]
            def fmt(v, is_pct=False): return round(v, 2 if is_pct else 6)
            # total values at the top
            top_metrics = [
                ("Material Saving", sum(kg for _, kg, _ in result["reuse_materials"]) + sum(kg for _, kg, _ in result["recycle_materials"]), "kg"),
                ("GWP Saving", result.get("gwp_saving_kg", 0), "kg CO2e"),
                ("Reuse * 12.51", result.get("reuse_times_1251", 0), "kg CO2e (based on KPN calculation)"),
                ("Total Production GWP", result.get("total_gwp_all_flows_exact", 0), "kg CO2e"),
                ("Total GWP Reuse", result.get("total_gwp_reuse", 0), "kg CO2e"),
                ("Total GWP Recycling", result.get("total_gwp_recycling", 0), "kg CO2e"),
                ("% GWP from Reuse", result.get("perc_reuse_gwp", 0), "%"),
                ("% GWP from Recycling", result.get("perc_recycling_gwp", 0), "%")
            ]
            # include everythin per scenario in one tab
            top_df = pd.DataFrame({
                "Metric": [m for m, _, _ in top_metrics],
                "Value": [fmt(v, "%" in u) for _, v, u in top_metrics],
                "Unit": [u for _, _, u in top_metrics]
            })
            # material specific values
            reuse_df = pd.DataFrame(result.get("reuse_materials", []), columns=["Material", "Total_kg_Reused", "GWP_Reused"])
            recycle_df = pd.DataFrame(result.get("recycle_materials", []), columns=["Material", "Total_kg_Recycled", "GWP_Recycled"])
            combined = pd.merge(reuse_df, recycle_df, on="Material", how="outer").fillna(0)

            for col in combined.columns:
                if combined[col].dtype in [float, int]:
                    combined[col] = combined[col].apply(lambda x: round(x, 6))

            # Add column for total GWP % savings per material
            total_gwp = result.get("total_gwp_all_flows_exact", 0)
            def pct_total_gwp(gwp):
                return round((gwp / total_gwp * 100), 2) if total_gwp else 0
```

```
                combined["%_GWP_Reused"] = combined["GWP_Reused"].apply(pct_total_gwp)
                combined["%_GWP_Recycled"] = combined["GWP_Recycled"].apply(pct_total_gwp)

                top_df.to_excel(writer, sheet_name=sn, index=False, startrow=0)
                combined.to_excel(writer, sheet_name=sn, index=False, startrow=len(top_df) + 3)

            # adjust column with to fit values in excel
            for sheet in writer.sheets:
                ws = writer.sheets[sheet]
                for col in ws.columns:
                    max_len = max((len(str(c.value)) for c in col if c.value), default=0)
                    ws.column_dimensions[col[0].column_letter].width = max_len + 2

# %% Monte Carlo simulatie op inflow, reuse_fraction, weibull shape en scale

years = baseline["years"] # get years from baseline to define x-axis
runs = 1 # set to 1 to prevent unintentional long modelling runs, set to 10000 for actual modelling result

# division of uncertainty per included variable
randomize_vars = pd.DataFrame({
    "inflow_factor": stats.uniform.rvs(loc=0.9, scale=0.2, size=runs), # 10%
    "reuse_fraction": stats.uniform.rvs(loc=0.7, scale=0.6, size=runs), # 30%
    "weibull_shape": stats.uniform.rvs(loc=1.17, scale=0.26, size=runs), # 10%
    "weibull_scale": stats.uniform.rvs(loc=4.982, scale=1.106, size=runs), # 10%
    "collected_recycling_rate": stats.uniform.rvs(loc=0.49, scale=0.42, size=runs), # 30%
    "mun_waste_recycling_rate": stats.uniform.rvs(loc=0.449, scale=0.502, size=runs), # 30%
})

# empty lists to save results
mc_stock = []
mc_reuse = []
mc_munwaste = []
mc_recycled = []

# Monte Carlo loop
# 1. run a dynamic_MFA(config_mc) scenario based on default_config
# 2. add paramters from default_config
# 3. run with inflow-factors as uncertainty parameters
# 4. repeat as much times as defined in 'runs' above
start = datetime.now() # measure time to run the MCS
for i, row in randomize_vars.iterrows():
    config_mc = default_config.copy()
    config_mc["scenario_name"] = f"MC_run_{i}"
    config_mc["show_plots"] = False
    config_mc["reuse_fraction"] = row["reuse_fraction"]
    config_mc["weibull_shape"] = row["weibull_shape"]
    config_mc["weibull_scale"] = row["weibull_scale"]
    config_mc["collected_recycling_rate"] = row["collected_recycling_rate"]
```

```python
    config_mc["mun_waste_recycling_rate"] = row["mun_waste_recycling_rate"]

    result = dynamic_MFA(config_mc)

    # adjust the inflow per simulated factor based on defined uncertainty values
    inflow_factor = row["inflow_factor"]
    stock_adj = np.array(result["stock_series"]) * inflow_factor # array for stock (is inherently cumulative)
    reuse_adj = np.cumsum(np.array(result["reuse_inflow"]) * inflow_factor) #cumsum for other variables
    mun_adj = np.cumsum(np.array(result["mun_waste_outflow"]) * inflow_factor)
    recycled_adj = np.cumsum(np.array(result["recycled"]) * inflow_factor)

    mc_stock.append(stock_adj)
    mc_reuse.append(reuse_adj)
    mc_munwaste.append(mun_adj)
    mc_recycled.append(recycled_adj)

    print(f"Run {i+1}/{runs}")

stop = datetime.now()
print(f"Monte Carlo duur: {stop - start}")

# structure results as numpy arrays for analysis
mc_stock = np.vstack(mc_stock)
mc_reuse = np.vstack(mc_reuse)
mc_munwaste = np.vstack(mc_munwaste)
mc_recycled = np.vstack(mc_recycled)

# percentile calculation to visualise uncertainty in plot
percentiles = [5, 25, 50, 75, 95]
stock_p = np.percentile(mc_stock, q=percentiles, axis=0)
reuse_p = np.percentile(mc_reuse, q=percentiles, axis=0)
munwaste_p = np.percentile(mc_munwaste, q=percentiles, axis=0)
recycled_p = np.percentile(mc_recycled, q=percentiles, axis=0)

# Plot
plt.figure(figsize=(12, 6))
for low, high, alpha in [(0, 4, 0.1), (1, 3, 0.2)]:
    plt.fill_between(years, stock_p[low], stock_p[high], color='tab:blue', alpha=alpha)
    plt.fill_between(years, reuse_p[low], reuse_p[high], color='tab:purple', alpha=alpha)
    plt.fill_between(years, munwaste_p[low], munwaste_p[high], color='tab:red', alpha=alpha)
    plt.fill_between(years, recycled_p[low], recycled_p[high], color='tab:orange', alpha=alpha)

plt.plot(years, stock_p[2], label="Stock", color='tab:blue')
plt.plot(years, reuse_p[2], label="Reuse (cumulative)", color='tab:purple')
plt.plot(years, munwaste_p[2], label="Municipal waste recycling (cumulative)", color='tab:red')
plt.plot(years, recycled_p[2], label="Collected waste recycling (cumulative)", color='tab:orange')

plt.xlabel("Year")
plt.ylabel("Number of Devices")
plt.legend()
plt.tight_layout()
```

```python
plt.savefig(os.path.join(save_dir, 'montecarlo_all_flows.pdf'), format='pdf')
plt.show()

# %% Scatterplot on quantity of materials reused and recycled

# retrieve the results for reuse and recycling from the model output
reuse_results   = baseline_result["reuse_materials"]
recycle_results = baseline_result["recycle_materials"]

materials   = [r[0] for r in reuse_results]
reuse_qty   = np.array([r[1] for r in reuse_results])
reuse_gwp   = np.array([r[2] for r in reuse_results])

# Only include non-zero recycling data
recycle_data = [(r[0], r[1], r[2]) for r in recycle_results if r[1] > 0 and r[2] > 0]
recycle_mats = [r[0] for r in recycle_data]
recycle_qty  = np.array([r[1] for r in recycle_data])
recycle_gwp  = np.array([r[2] for r in recycle_data])

fig, ax = plt.subplots(figsize=(10, 8))

# Scatter reuse and recycle
ax.scatter(reuse_qty, reuse_gwp, marker='o', s=100, label='Reuse', color='C0')
ax.scatter(recycle_qty, recycle_gwp, marker='s', s=100, label='Recycle', color='C1')

# specific offsets for materials
offsets = {
    'aluminium': {'xytext': (-0.2, -0.2), 'ha': 'right', 'va': 'top'},
    'cobalt':    {'xytext': (-0.2, -0.2), 'ha': 'right', 'va': 'top'},
    'gallium':   {'xytext': (-0.1, -0.1), 'ha': 'right', 'va': 'top'},
    'magnesium': {'xytext': (-0.2, -0.2), 'ha': 'left',  'va': 'top'},
    'beryllium': {'xytext': (-0.2, -0.2), 'ha': 'left',  'va': 'top'},
    'boron':     {'xytext': ( 0.2, -0.2), 'ha': 'left',  'va': 'top'},
    'phosphorus':{'xytext': (-0.2,  0.9), 'ha': 'right', 'va': 'top'}
}

# Annotations (reuse + recycle)
for dataset in [(materials, reuse_qty, reuse_gwp), (recycle_mats, recycle_qty, recycle_gwp)]:
    for mat, x, y in zip(*dataset):
        key = mat.lower()
        if key in offsets:
            dx, dy = offsets[key]['xytext']
            ha, va = offsets[key]['ha'], offsets[key]['va']
        else:
            dx, dy, ha, va = 0.1, 0.1, 'left', 'bottom'
        ax.annotate(
            mat, xy=(x, y), xytext=(x * (1 + dx), y * (1 + dy)),
            textcoords='data', fontsize=14,
            arrowprops=dict(arrowstyle='-', lw=1, color='gray'),
            horizontalalignment=ha, verticalalignment=va)

# Log scale
ax.set_xscale('log')
ax.set_yscale('log')
ax.set_xlabel('Materials saved (kg)', fontsize=14)
ax.set_ylabel('GWP Prevention (kg CO2e)', fontsize=14)
```

```python
ax.tick_params(axis='both', which='major', labelsize=14)
ax.grid(which='both', ls='--', alpha=0.4)
ax.legend(fontsize=14)

plt.tight_layout()
plt.savefig(os.path.join(save_dir, 'scatter_results.pdf'), format='pdf')
plt.show()
```

Table 30: Yearly stock data - product A (left) & Product A material and GWP data (right)

Year	Stock
y+1	396981
y+2	796470
y+3	969246
y+4	1080478
y+5	1134341
y+6	1145216
y+7	1110222
y+8	1059508
y+9	987912
y+10	917888
y+11	840568
y+12	767091
y+13	700100
y+14	632139

Materials	# Materials per Product	GWP Materials per kg
aluminium	[redacted]	21.9
antimony	[redacted]	23
beryllium	[redacted]	687
bismuth	[redacted]	0
boron	[redacted]	2.87
cerium	[redacted]	16.2
cobalt	[redacted]	44.9
gallium	[redacted]	171
magnesium	[redacted]	27.6
palladium	[redacted]	11200
phosphorus	[redacted]	4.67
rhodium	[redacted]	80400
ruthenium	[redacted]	0
silicon	[redacted]	10.8
tungsten	[redacted]	5.56

*Note: data used in excel format as **ProductA_stock** (left) and **ProductA_materials** (right) tabs for Python modelling code.*

Appendix J - WEEE and bar chart calculations

Table 31: Calculations on quantity of CRMs in Dutch WEEE compared to KPN reuse for Table 12.

Material	Small IT * 13	Total	Reused Total	% Small IT * 13 compared to reused total
aluminum	-	-	184787.57	n.a.
antimony	4685	499948	7.45	0.01%
beryllium	22	31	286	1.74%
bismuth	5	287	65	1.57%
boron	-	-	2.02	n.a.
cerium	17	1061	0.00	0.00001%
cobalt	8166	34240	106158	0.00101%
gallium	64	163	832	0.00238%
magnesium	16437	839896	213681	0.00197%
palladium	94	237	1222	0.0300%
phosphorus	-	-	0.85	n.a.
rhodium	2	4	26	8.5%
ruthenium	0	0	1.01	n.a.
silicon	-	-	596.85	n.a.
tungsten	1933	145843	25129	0.0079%

Based on Campbell-Johnston et al. (2024)

Table 32: Values used for bar chart in Figure 28.

Material	Quantity in Dutch WEEE	Quantity Reused by KPN	Material Savings (Short Term)
aluminum	0	184787.57	28321.56
antimony	60905	7.45	0.36
beryllium	286	4.96	0.24
bismuth	65	1.02	0.05
boron	0	2.02	0.10
cerium	221	0.00	0.00
cobalt	106158	1.07	0.05
gallium	832	0.02	0.00
magnesium	213681	4.21	0.20
palladium	1222	0.37	0.02
phosphorus	0	0.85	0.04
rhodium	26	2.20	0.10
ruthenium	0	1.01	0.05
silicon	0	596.85	28.82
tungsten	25129	1.99	0.10

Based on Campbell-Johnston et al. (2024)

Table 33: Values used for bar chart in Figure 29.

Material	Emissions in Dutch WEEE	Quantity Reused by KPN	Material Savings (Short Term)
aluminum	0	4099937.87	620242.23
antimony	1400815	171.25	8.27
beryllium	196482	3409.49	164.64
bismuth	0	0	0
boron	0	5.79	0.28
cerium	3580.2	0.00	0.00
cobalt	4766494.2	48.21	2.33
gallium	142272	3.39	0.16
magnesium	5897595.6	116.06	5.60
palladium	13686400	4323.19	184.98
phosphorus	0	3.96	0.19
rhodium	2090400	186094.52	7962.54
ruthenium	0	0	0
silicon	0	6445.93	311.26
tungsten	139717.24	11.06	0.53

Based on Campbell-Johnston et al. (2024)

Appendix K - Website Manual

The website introduced in Chapter 6 is essentially a formatted version of the code in **Appendix I**. A slightly adjusted version of this code runs in the back-end while the from end translates the parameters as adjustable fields in a website format. All functionalities and adjustable parameters are similar to the original modelling code, only the later parts are excluded. These where parts used to embed and assess the scenarios – since the website allows for scenario analysis through changing the input data – and the Monte Carlo simulation – since this was part of the academic process but argued as less relevant for commercial practices as long as data uncertainty is accounted for.

The input consists of two main section, the first relates to the product data on stocks and material compositions, the second defines the main downstream flows. The only exception is the recycling efficiency, which is defined besides the material composition since this can vary per material.

In Figure 49, the years under study can be filled by clicking 'add row' and entering the relevant year. For each year the stock – or install base – for the product under study can be entered as well. An important sidenote to this step, to make the model function correctly, is that the first stock should always build up from zero. Even if there already is a large stock from previous years excluded from the analysis, the first year should be the stock of that year minus the total existing stock. The following stocks can be calculated through $stock = stock_t + inflow_{t+1}$. This is necessary as the model otherwise incorporates all existing stock as potential for reuse therefore (greatly) overestimating this quantity.

The second step is to add the materials, their weight in the product in grams, the GWP in kg CO_2-eq and recycling efficiency per material. The GWP per kg can be found in databases such as Ecoinvent or similar, the recycling efficiency relates to the amount of materials are recovered if they end up in at the recycler.

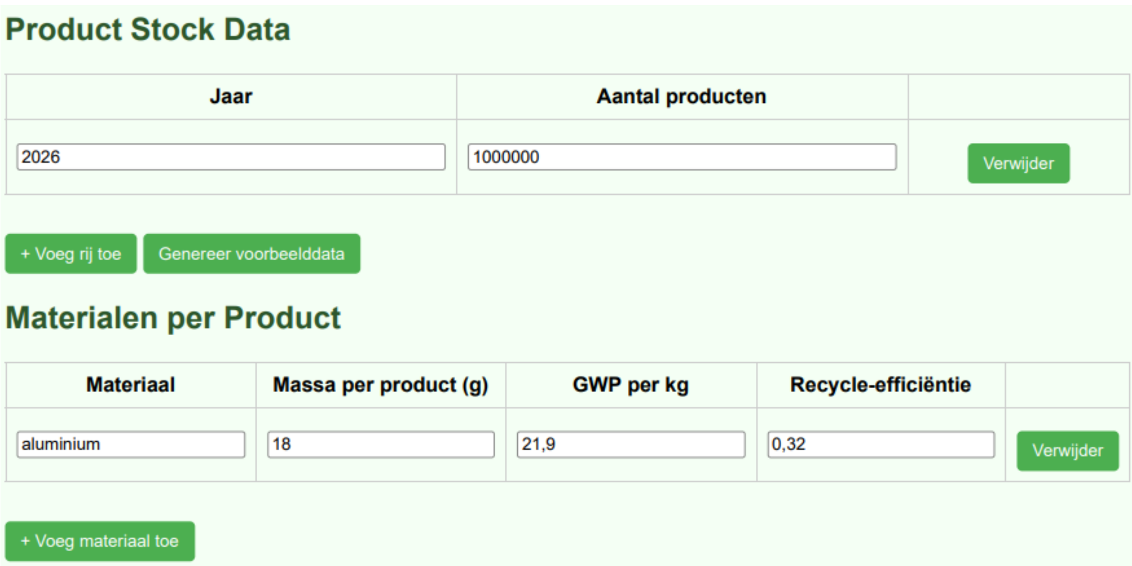


Figure 49: Screenshot 1: product stock data and material composition.

The second set of input values is seen in Figure 50, these input parameters relate to the same values in Table 3 from Chapter 4 and define the transfercoefficients for the downstream product or material flows. The input parameters for reuse defines how much of the yearly collected products – i.e. products sent back to KPN – is available for reuse in following years, the remainder goes to return product flows and is directed to recycling, energy recovery or landfill. The municipal waste share is defined as the amount of products which are not formally collected by KPN but are thrown away by customers themselves and also end up in recycling, energy recovery or landfill streams.

The recycling and municipal waste shares can never result in a total sum of more than 1. They can sum up to less than 1, in this situation the remaining share is collected products which can not be reused and are recycled by KPN's downstream partners. Two additional parameters in this box are the use of a maximum number of reuse cycles (i.e. a product can only be reused a predetermined amount of times) and a primary inflow cut-off year (i.e. a year in which the primary inflow stops and inflow must come from reuse).

The rates in which either returned products or those in municipal waste are sent to recycling, energy recover or landfill is defined in the two lower boxes. The top-right box defines the survival cure which can be set to either the Weibull variant (applicable to most electronics) or the normally distributed variant.

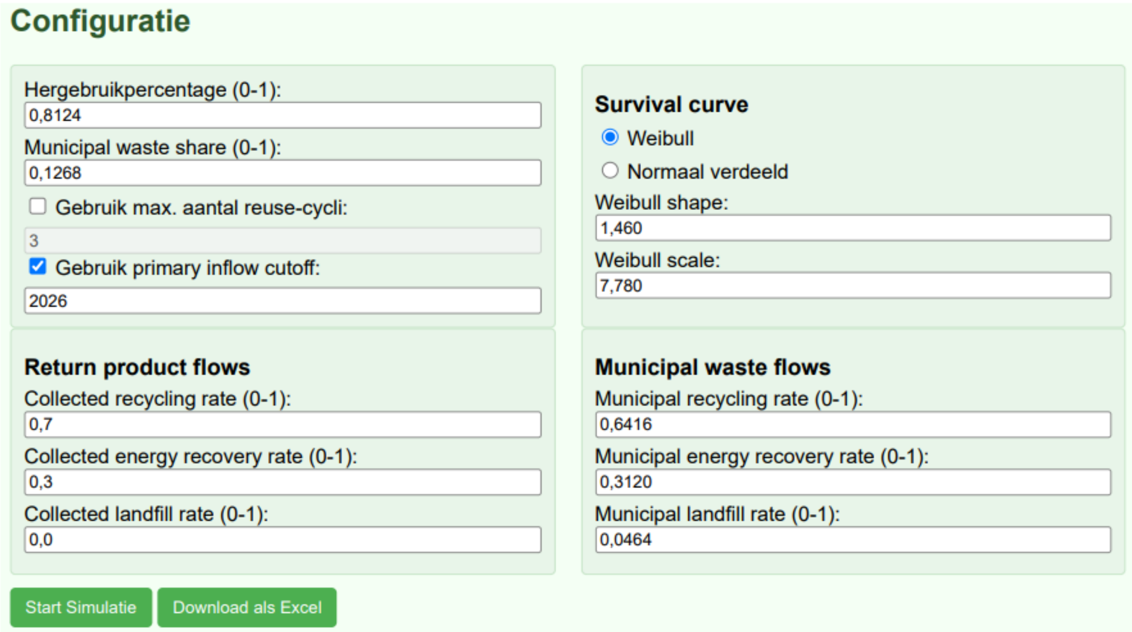


Figure 50: Screenshot 2: downstream product flows.

When all data is entered, the 'start simulation' button runs the model and provides the output below the entry fields. Additionally, the output can be downloaded in Excel format to save the data or for further calculations.

To visualize this process, a walk-through of the website is used as example, supported by the second case study requested by manufacturer B; who produce ONT boxes – devices which can translate the fibre optic data from the street cables to modems such as Product A. Note that the input data was more of an exploratory nature than for Product A and is therefore likely far less accurate and realistic. The main purpose of this study was to assess the future potential and test the model.

Below is a print from the website with all the data field filled and the simulation ran. The first number after running the simulation show the total amount of materials and GWP saved. Below the graph is shown for the product stock and cumulative reuse. Below this graph are the reuse and recycling results per material.

Simulatie Tool

Tool om scenario's voor hergebruik en recycling van apparaten te simuleren. Vul de gegevens in over voorraden, materiaalinhoud en configuratie-opties. Start daarna de simulatie om de impact te zien.

Product Stock Data

Jaar	Aantal producten	
2026	0	Verwijder
2027	250000	Verwijder
2028	500000	Verwijder
2029	750000	Verwijder
2030	1000000	Verwijder
2031	1200000	Verwijder
2032	1400000	Verwijder
2033	1600000	Verwijder
2034	1800000	Verwijder
2035	2000000	Verwijder
2036	2150000	Verwijder
2037	2300000	Verwijder
2038	2450000	Verwijder
2039	2600000	Verwijder
2040	2750000	Verwijder

+ Voeg rij toe Genereer voorbeelddata

Materialen per Product

Materiaal	Massa per product (g)	GWP per kg	Recycle-efficiëntie (0-1)	
aluminium	18	21,9	0,32	Verwijder
copper	11,66	5,96	0,8	Verwijder

Materiaal	Massa per product (g)	GWP per kg	Recycle-efficiëntie (0-1)	
silver	0,66	435	0,6	Verwijder
nickel	0,53	0,841	0,7	Verwijder
chromium	0,38	28,6	0,4	Verwijder
tantalum	0,2	172	0,2	Verwijder
palladium	0,05	11200	0,3	Verwijder
indium	0,05	66,9	0,1	Verwijder
beryllium	0,03	47500	0,1	Verwijder
gold	0,03	47500	0,9	Verwijder
gallium	0,03	220	0,05	Verwijder
germanium	0,1		0,05	Verwijder
rare earth metals	0,02		0,1	Verwijder

+ Voeg materiaal toe

Configuratie

Hergebruikratio (0-1):
0,8124
Gemeentelijk afval ratio (0-1):
0,1268
☐ Gebruik max. aantal reuse-cycli:
3
☐ Gebruik primaire inflow cutoff:
2026

Survival curve

◉ Weibull
○ Normaal verdeeld
Weibull shape:
1,46
Weibull scale:
7,78

Afvalstromen: geretourneerde producten

Geretourneerd: recycling ratio (0-1):
0,7
Geretourneerd: energie winning ratio (0-1):
0,3
Geretourneerd: afval stort ratio (0-1):
0,0

Afvalstromen: producten in gemeentelijk afval

Gemeentelijk afval: recycling ratio (0-1):
0,6416
Gemeentelijk afval: energie winning ratio (0-1):
0,3120
Gemeentelijk afval: afval stort ratio (0-1):
0,0464

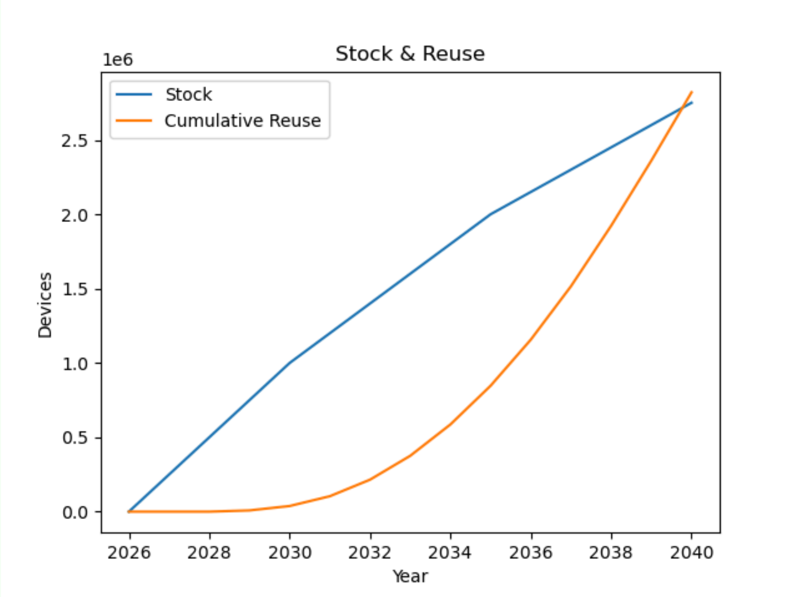
Start Simulatie | Download als Excel

Scenario: Reuse & recycling impact

Totale Materiaalbesparing: 92636.81 kg

Totale GWP-besparing: 12312553.53 kg CO_2e

Grafiek



Reuse Resultaten per Materiaal

Materiaal	Kg	GWP (kg CO_2e)
aluminium	50762.38	1111696.14
copper	32882.74	195981.14
silver	1861.29	809659.98
nickel	1494.67	1257.02
chromium	1071.65	30649.20
tantalum	564.03	97012.55
palladium	141.01	1579274.07
indium	141.01	9433.34
beryllium	84.60	4018688.49
gold	84.60	4018688.49
gallium	84.60	18612.87

Recycle Resultaten per Materiaal

Materiaal	Kg	GWP (kg CO_2e)
aluminium	1239.49	27144.89
copper	2007.29	11963.45
silver	85.22	37068.58
nickel	79.84	67.14
chromium	32.71	935.47
tantalum	8.61	1480.51
palladium	3.23	36151.87
indium	1.08	71.98
beryllium	0.65	30664.53
gold	5.81	275980.80
gallium	0.32	71.01