TRACKING SALES TO SCRAP

Incorporating Reverse Logistics Management into Dynamic Material Flow Analysis to increase transparency on downstream product flows for companies

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PREFACE

This thesis is the final work conducted for the Master of Science in Industrial Ecology at the TU Delft and Leiden University and was carried out in cooperation with Royal Philips.

First of all, I would like to express much gratitude to my company supervisor Markus Laubscher for making this project possible and for his guidance, vision and very interesting insights. The outcomes of our weekly brainstorms have been a crucial ingredient for the final result of this project. Furthermore, I would like to thank the entire Group Sustainability for the welcoming and pleasant atmosphere and eagerness to help and support me in my work.

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SUMMARY

Waste of Electronic and Electrical Equipment (WEEE) is a growing waste stream where overall circularity is low, which causes the leaching of hazardous material and loss of valuable resources. Governments aim to increase material recovery from WEEE and focus mainly on the material recovery when a product reaches the End-of-Life stage. The dynamic Material Flow Analysis (MFA) method has been successfully used to account the national (W)EEE stocks and flows, where the results are used to assess the circularity performance based on weight of recovered material. For companies, there are other more interesting circular loops to explore besides material recovery, such as repair, reuse, refurbishment and remanufacturing. In Supply Chain Management, the incorporation of these circular loops is managed through Reversed Logistics. This research project will aim to incorporate Reverse Logistics management concepts into the dynamic MFA method to render the method more useful to companies. Therefore, the main research assignment for this project is to *develop a dynamic MFA model for EEE companies to increase transparency of downstream product flows and provide insight on the impacts of Reverse Logistics strategies*. The assignment is carried out by firstly conducting a theoretical analysis on the incorporation of Reverse Logistic management concepts into the dynamic MFA method. Secondly, the findings from the theoretical analysis are assessed on data availability through an empirical analysis with a case study. The main scope of the project is to build a model on product-level for Royal Philips' small household appliances sold in the Netherlands.

The main outcome of the theoretical analysis is that the incorporation of Reverse Logistics management concepts can improve the reliability and insightfulness of dynamic MFA modelling for companies. Dynamic MFA approaches cluster product mainly on functionality, whereas stock and flow accounting methods in Reverse Logistics management, like the Installed Base Forecasting method proposed by Kim et al. (2016), cluster products on the monetary value of the product. The different perspectives from the two fields could complement each other for stock and flow accounting. The Reverse Logistics stock and flow accounting models serve the spare parts demand forecasting rather than the quantification of the product stocks and flows, which is likely the main reason that the stock and flow accounting in the two fields have not been connected before. In the empirical analysis, the different configurations of the stock and flow accounting methods with dynamic MFA and Reverse Logistics management are assessed on data availability within the context of the case study. Based on the data availability, Sales-Lifespan Distribution model is proven to be a suitable dynamic MFA approach, which will provide insights on the downstream products stocks and flows in the current production-consumption system.

To create Reverse Logistics scenarios, several Reverse Logistics concepts are considered in modelling the dynamic MFA model; 1) reverse flows are returned end-of-lease products (which is the only predictable return flow), 2) leasing the more durable and therefore relatively expensive (i.e. high-end) products, and 3) a marginal reuse rate is applied in the form of reduction in production demand for new products or spare parts due to returned products. The three Reverse Logistics scenarios that are defined for this project are;

Scenario 1- leasing products once

Scenario 2- leasing products, refurbishing the returned products and leasing the refurbished products

Scenario 3- leasing products, refurbishing the returned products and selling the refurbished products

To assess the performance of the three Reverse Logistics scenarios, the scenarios must satisfy the same performance requirement, which is to *satisfy the same in-use stock level of high-end products produced in the BAU simulation*. The main user entry variable for modelling the scenarios is the lease duration of the products. Since the stock size is the same for all three scenarios, the high-level environmental performance indicators are based on the size of the inflow and outflow by 1) assessing the decrease of input from new products, 2) the decrease of WEEE generation, and 3) the change of the collection and recycling rate. Lastly, financial information can be added to the associated stock and flow data, which enables the analysis on the fourth performance indicator; profitability.

First, it was found that the case study outputs for recent years under the Business-as-Usual condition with the Sales-Lifespan Distribution model are consistent with real-world collection and recycling weight reports and stock data. Secondly, regarding the Reverse Logistics scenarios, increasing the lease duration boosts the positive effects for all performance indicators. Furthermore, the difference in output from a conservative and optimistic sales projection input is insignificant for the environmental indicators and therefore the outcomes for the environmental indicators are not sensitive to large differences in sales. However, the profitability outcomes do seems to be sensitive to the input.

The general conclusions for the performance of the three Reverse Logistics scenarios compared to the Business-as-Usual baseline in the context of the case study are as follows;

Scenario 1- With a relatively short lease duration, this Reverse Logistics scenario will require more input and decreases the WEEE generation insignificantly, however all WEEE is scrapped responsibly. Increasing the lease duration can negate the negative effect on the input.

Scenario 2- Both input and WEEE generation are decreased considerably and all WEEE is scrapped responsibly, although the scenario might be the least profitable of all. The lease fee for a refurbished product is expected to be lower than that of a new product and therefore the costs for logistics and maintenance are high compared to the revenue from fees. Furthermore, (some) products might not guarantee acceptable product survival rates suitable for 2 lease cycles.

Scenario 3- The impact on the input of high-end products is the same as in scenario 1. However, in this scenario the input from new low-end products decreases due to the replacement effect, since the refurbished product prices compete with the low-end market prices. WEEE generation is delayed considerably, although the WEEE flows will not be entirely end up at the recycling scheme. Furthermore, this scenario is likely the most profitable compared to the other scenarios.

While all scenarios contain trade-offs, the third scenario is recommended as the most strategic Reverse Logistics scenario based on the lowest financial risk while decreasing the WEEE generation significantly. Based on a general influence of longer lease durations seen in all three scenarios, it can also be recommended that efforts increasing product lifespans by design will pay off when shifting towards a more circular production-consumption system.

From the evaluation with the target audience it was found that the stock and flow insights provided for the current downstream product flow has been evaluated as potentially useful. Regarding the RL scenario modelling, Philips would be more interested in leasing the products for a similar duration to the warranty period, which is 2-4 years. This is mainly because the products are more likely to be replaced than repaired after the warranty period. Additionally, the profitability analysis has to be compared with similar in-house economic models to determine the reliability of the results. If it is the case that the results for the Reverse Logistics scenarios are reliable, the model could play a role in strategic decision making with regards to Reversed Logistics.

The limitations of the model regarding data are (in)availability of data, outdated sources and the relatively high sensitivity of the UNU product lifespans. Other major limitations are the lack of testing the model on more case studies for other countries and companies and the lack of consumer behavior influences considered in the model. Recommendations are made on improving the accuracy by initiating data collection for a more complete and modern data. Furthermore, recommendations are made on improving the reliability of the model by applying the model to multiple countries and companies and, lastly, to explore the effects of leased and refurbished products on consumer demand and behavior.

TABLE OF CONTENTS

GLOSSARY

ACRONYMS

C&R	Collection and Recycling
CBA	Cost Benefit Analysis
CE	Circular Economy
CLSC	Closed Loop Supply Chain
CSV	Comma Separated Value
EEE	Electronic and Electrical Equipment
EMF	Ellen MacArthur Foundation
EPR	Extended Producer Responsibility
EoL	End-of-Life
FAEM	Fully Automatic Espresso Machine
IB	Installed Base
IBE	Economic Installed Base
IBL	Lifetime Installed Base
IBW	Warranty Installed Base
L	Lease scenario
LCA	Life Cycle Analysis
LCC	Life Cycle Costing
LRL	Lease-Refurbish-Lease scenario
LRS	Lease-Refurbish-Sell scenario
LD	Lease Duration
MFA	Material Flow Analysis
POM	Put On Market
PPP	Purchasing Power Parity
RBP	Retail Buying Price
RL	Reverse Logistics
S&OF	Stock and Outflow
SCM	Supply Chain Management
TC	Transfer Coefficient
VAT	Value Added Tax
WEEE	Waste of Electronic and Electrical Equipment
WG	WEEE Generation

WORKING DEFINITIONS

2016-level sales projection	Sales projection where the sales unit quantity for 2016 is duplicated
High-end	Relatively durable and expensive products
Installed Base	Term in supply chain management for In-use stock
Philips	Royal Philips N.V.
Philips lifespan	The minimum expected average timespan for the use phase according to Philips
POM quantity	Unit sales quantity
Replacement effect	Intended cannibalization of own products and parts
Scrapping	Recovery where parts are harvested and the residual is recycled
Trendline sales projection	Sales projecion where the trendline for earlier sales figures is followed

1. INTRODUCTION

The first chapter introduces the problem based on the provided background information. The problem definition is followed by the research objectives, consisting of the research goal and scope, and lastly, the research process.

1.1 Circular Economy and (W)EEE

As a more sustainable alternative to the traditional take-make-dispose 'linear' economy, the Circular Economy (CE) implies that materials in our economy should be kept at their highest value for as long as possible in pursuit of a more sustainable economy (Bakker et al., 2015). While waste production and raw material input is expected to be inevitable, it is strived to be minimized (EMF, 2013). The CE approaches material flows as loops in which one process' output can serve as the input for another process. The Ellen MacArthur Foundation (EMF) developed a system diagram illustrating what the loops for the biological and technical nutrients flows are in a CE (see figure 1). When considering the technical material flows only, the diagram in figure 1 communicates operations that can be applied to a product, its components and its materials. The value of a product can be exploited to its full potential by circular product design, increasing utility, extending product and component lifetimes, and material recovery (EMF, 2013). Increasing the utility of the product can be facilitated by sharing platforms and new access models (EMF, 2013). Increasing the lifetime of a product and its components can be organized through reversed flows like maintenance, reuse, refurbishment, remanufacturing, and finally, the value of the material can be recovered through recycling (EMF, 2013). The size of the loops and the number of intermediate steps to get a product to the user, as illustrated in figure 1, indicate the difference in intrinsic value destruction and energy input; the closer the activity is to direct reuse, the higher the residual value extraction (EMF, 2013).

A CE implies that the supply chain of the future will not end after the point of sale. End-of-Life (EoL) products, can now be seen as an environmental liability and an economic opportunity (Geyer & Jackson, 2004). The environmental liability can be analyzed with Life Cycle Assessments (LCA) and Life Cycle Costing (LCC) and other environmental risk assessment methods, whereas economic opportunities can be explored with Reversed Logistics (RL) concepts and Closed Loop Supply Chain (CLSC) concepts (Geyer & Jackson, 2004). The environmental liability can play a significant role in the transition to a sustainable supply chain because there is a growing demand from stakeholders, policy makers and customers for partial responsibility of the End-of-Life (EoL) products to alleviate the environmental burden from society (Geyer & Jackson, 2004). This can be enforced through environmental legislation based on Extended Producer Responsibility (EPR) and 'polluter

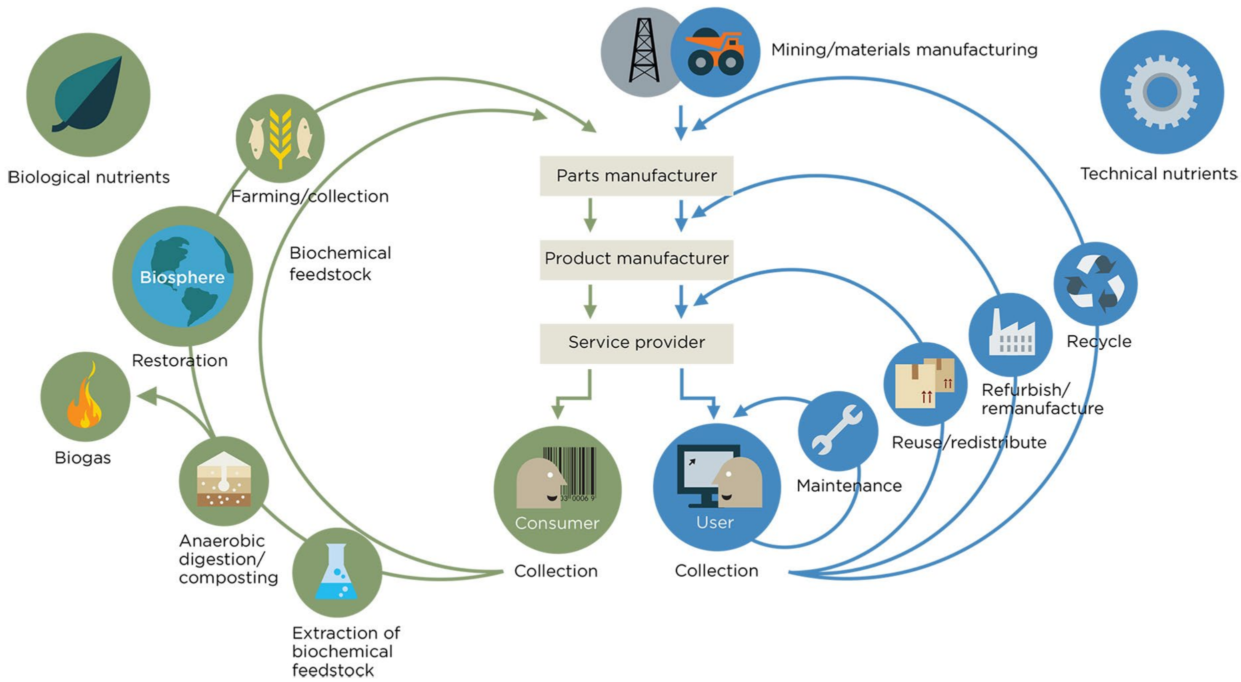


Figure 1: the EMF Circular Economy system diagram (EMF, 2013)

pays'-principles (Geyer & Jackson, 2004). Economic opportunities through increased RL and organizing a CLSC have been proven to increase revenues, which leads to the assumption that EoL-product management can lead to an economic-environmental win-win (EMF, 2013).

From all the anthropogenic materials in the economy, a transition towards a CE for Electronic and Electrical Equipment (EEE) is particularly valuable. WEEE (Waste of Electronic and Electrical Equipment) is a very complex, mobile and heterogenous waste stream (Baldé et al., 2015b). Furthermore, the stream of WEEE is rapidly growing due to technological innovations, which makes the products cheaper and more accessible to a growing consumer market and, furthermore, causes products to become obsolete faster (Baldé et al., 2015b). Currently, the overall circularity for EEE is rather low for most countries. In 2012, the WEEE collection through official recycling channels for China was around 20% of all domestic generated WEEE weight and for the EU the size was around 35% of all generated WEEE weight (EMF, 2014; Huisman et al., 2015). Extensive studies have been done to explain this gap, such as a study done by Huisman et al. (2012) for WEEE flows in the Netherlands. In the study, the authors have been able to document the WEEE flows for up to 80% in a system where only 30% of all generated WEEE ended up in the official Collection and Recycling (C&R) schemes. The other identified WEEE destinations are unofficial recycling, residual waste streams and possibly export. The focus in these national (W)EEE studies is on exposing illegal export, addressing the risks for public health and environment of bad disposal practices (the "toxic mine") and exposing the lost valuable secondary resources (the "urban mine") (Huisman et al., 2015; Baldé et al., 2015b; Wang et al., 2012). The studies describe only the material recovery, or lack thereof. For example, in the Netherlands in 2012 alone, 27 million euros worth of gold embedded in WEEE ended up in the residual recycling stream and is thus lost to incineration (CBS, 2015).

In order to stimulate an increase for the Collection and Recycling (C&R) rate to recover more valuable and hazardous materials, the EU is tightening its national WEEE collection target for all member states. The new WEEE directive, Directive 2012/19/EU, sets a weight-based collection target of 45% of all EEE sold, effective from 2016, and raises the target for 2019 to 65% collected of the average of all EEE sold in the previous three years - or- a collection rate of 85% of all WEEE generated. To ensure proper collection and recycling practices, the target is only valid for processing through official recycling schemes, not through complementary recycling schemes (which are generally much less transparent in their practices with respect to the environment) (Council Directive 2012/19/EU, 2012). Given the fact that the EU had only collected on average 35% of all generated WEEE weight in 2012, the target of 85% for 2019 will undoubtedly pose challenges for some of the member states. This challenge faced by the national government could result in the tightening of EPR policies, which leads to increased liability for companies with regards to EoL product management. This development can either pose as a risk for a company or serve as a competitive advantage.

When it comes to WEEE, national and international governments are largely focusing on increasing the material recovery. However, according to the CE principles, this is the least favorable loop from an environmental perspective (least energy efficient) and the least favorable loop from a company perspective (lowest value extraction). Also, because material recovery is generally organized in an open loop supply chain configuration, it is impossible to create a CLSC where the recovered material returns to the source company. Furthermore, because WEEE recycling management practices generally do not trace the source of the products, it is highly unlikely for a company to know how many of their EoL products are retrieved through C&R. To conclude, there is overall a lack of incentive for a company to increase the material recovery from their products due to the collective nature of WEEE recycling management and the lowest value extraction compared to other CE loops. It will be more valuable for a company to also explore the effects of circular loops of CLSC practices other than open-loop material recovery, such as repair, reuse. refurbishment and remanufacturing.

Material Flow Analysis (MFA) is a method used in Industrial Ecology to quantify stocks and flows of materials or substances for a certain system (Brunner and Rechberger, 2004). In a dynamic MFA, the change in stocks and flows are defined over time. A dynamic MFA is frequently applied in national and EU wide WEEE studies (Magalini et al., 2015) to assess the current movement of the (W)EEE flows. However, it is also possible with a dynamic MFA to estimate the influence of new implementations. In the context of a dynamic MFA for a company, it would be interesting to examine the influence of RL operations within a CLSC on the circularity of the production-consumption system. Quantifying product stocks and flows, along with their associated environmental and financial dimensions, will provide support for building business models with reversed flows.

1.2 Problem definition

It is suggested that a CE for (W)EEE can be beneficial for both company and public, yet present-day studies on (W)EEE stocks and flows have been only applied to a country or region. These national and regional(W)EEE studies are done with a different objective that a company might have and do not explore any other RL activity other than recycling through material recovery. However, a company's focus will more likely be on reversed loops such as reuse, refurbishment and remanufacturing, which are also more economic and environmentally preferable reversed flows according to the CE principles and, furthermore, more applicable in a CLSC.

To the researcher's knowledge, there is no such dynamic MFA model developed for companies to quantify and analyze their current and possible future (W)EEE stocks and flows with the main intention of exploring different reversed logistic activities. Such a model can lead to insights for new business practices that are both economically and environmentally attractive, thereby benefitting both the company and the public.

1.3 Research objectives

1.3.1 Research goal

From the problem definition, one can derive that a dynamic MFA to quantify and analyze (W)EEE stocks and flows can be useful for companies. A dynamic MFA could cover the stocks and flows of downstream products. This could provide the company insight on the current situation, i.e. the "Business As Usual" (BAU) situation. However, to bring more useful insights to companies, a dynamic MFA model should be developed to also explore various reversed flows for the future. This prospective dynamic MFA model should also allow for extension with economic and environmental dimensions, so it can be more suitable support for strategic decision making. The research will be done by exploring the possibilities of incorporating RL concepts into the dynamic MFA method and develop a prospective model that will suit the needs of a company as much as possible to develop into a useful support tool in business modelling and decision making. To summarize, the research assignment is for this thesis is:

to *develop a prospective dynamic MFA model for EEE companies to increase transparency of downstream product flows and provide insight on the impacts of RL strategies.*

The thesis project will successfully satisfy the research assignment when the following research questions can be answered;

Research question 1 - *How can RL management concepts and/or methods be incorporated into dynamic MFA methods; both theoretically and empirically?*

Research question 2 - *How can the dynamic MFA model with incorporated relevant reversed flows assess the environmental and economic impacts of RL strategies?*

Research question 3 - *What strategic recommendations can be made to the company based on the built model?*

Research question 4 - *How can this model be further developed for increased reliability, accuracy and added features?*

1.3.2 Research scope

Given the restricted time for the research project, it is necessary to set main scope limitations. Firstly, the modelling will only focus on mapping the stocks and flows of entire products and not on tracking subassemblies, components or materials. Reversed flows on the component level, such as parts harvesting, will not be quantified, but its possibilities will be considered.

The second main scope limitations will be the number of case studies. To gain the best results for bridging theory to practice in this research project, it would be advised to do several case studies to ensure increased usefulness for any company within the field . This study will focus on a case study with one company only, but intends to communicate each step enough for new studies to be carried out for different companies.

Lastly, there is no aim for a perfect model from the start, but rather there is the aim to explore the possibilities to run a model with the current data availability. The modelling can present the fundamental building principles that can be further built upon. Additionally, the model might already produce several interesting insights that can incentivize the further development of the model.

1.3.3 Research process

The research is set out to be executed both on theoretical and empirical ground (in chapter 2 and 3 respectively) and should provide insights for BAU modelling and prospective modelling with RL loops. The report structure is visualized in figure 2.

To gain insight on modelling the current situation, literature is reviewed on dynamic MFA approaches applied in (W) EEE stocks and flows studies (section 2.1). Section 2.2 consists of a literature review on RL management theories for stocks and flows analysis. In section 2.3, the insights from section 2.2 and 2.3 will be synthesized to lay out the theoretical possibilities of incorporating RL into MFA of (W)EEE.

In chapter 3, the theoretical research is followed up by empirical research through a case study. Section 3.1 introduces the company for the case study and it elaborates on the goal and scope for this specific case study. This step of the case study describes the intended use, system boundaries and scenario definitions. Following, section 3.2 will cover the building the model. First, in section 3.2.1, the data requirements of the theoretical methods and models will be compared with the data availability of private and public data. Since a MFA is purely data driven, the model is designed around the current data availability. The modelling steps and approaches for all scenarios will be covered in section 3.2.2. To make the model more tangible, wireframing concepts are presented in section 3.2.3. These concept should show the model's options and manual entries would it be developed into an in-house application. Section 3.2 and 3.3 together will provide answers for research questions 3 and 4. The case study will be completed with an evaluation by the target audience. All prior research will provide insights for answering research question 1 and 2.

Chapter 4 covers the discussion about the quantitative results of the model and the model as a result itself, its limitations and the implications. The discussion will cover answers for research question 3 and 4. In chapter 5, conclusions are drawn about the research project and recommendations on further research on the topic and development of the model will be provided.

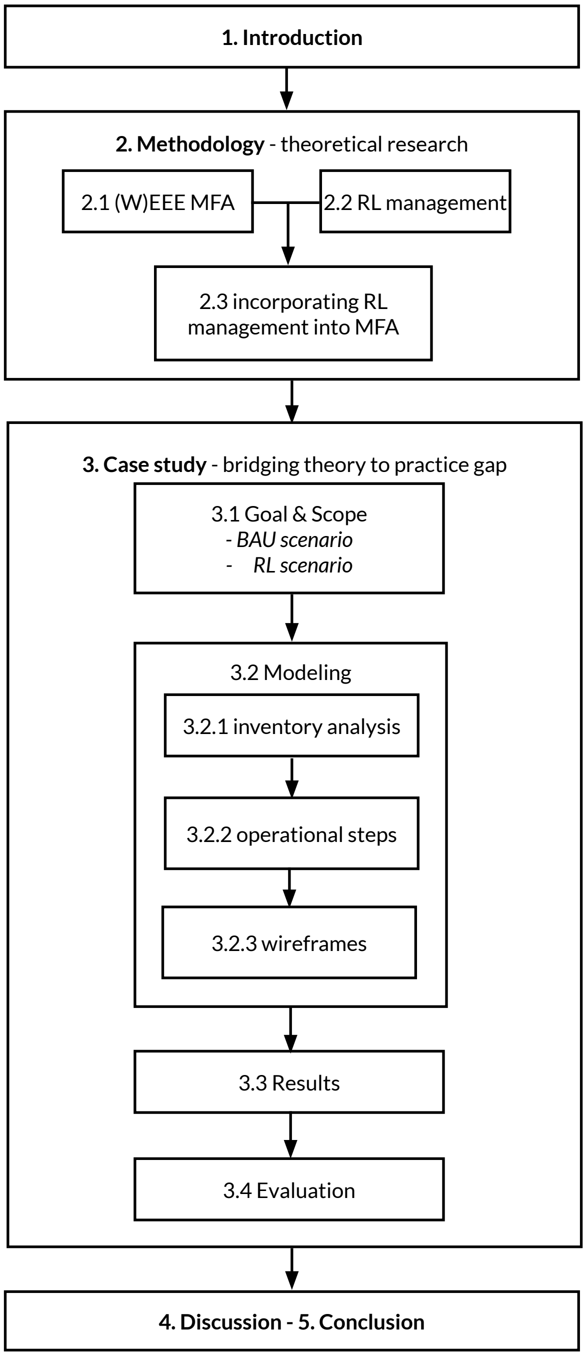


Figure 2: visualized report structure

2. METHODOLOGY

This chapter will cover the study of methods for modelling stocks and flows in Industrial Ecology, i.e. MFA, and in Supply Chain Management, i.e. RL management. The first part of the chapter will be on the MFA method. First, the fundamentals of MFA will be laid out. Then, the different MFA approaches and several prospective modelling techniques for (W)EEE will be explored. The second part of the chapter will include the fundamentals of RL and examines stock and flow modelling techniques used in RL management. The chapter finishes with a synthesis of the stock and flow modelling techniques for (W)EEE from RL and MFAs to outline the possibilities for modelling RL flows into a MFA.

2.1 Material Flow Analysis and (W)EEE

2.1.1 Fundamentals of MFA

A method for analyzing and quantifying material stocks and flows is a Material Flow Analysis (MFA). A MFA is an analytical tool used to analyze the input, throughput and output of substances and goods in a system. A MFA is suitable to use for decision-making in policy, public and private strategy, and can be applied on a global level, regional-level, economy-wide level, a company-level and on a household-level (OECD, 2008). An MFA can be used to track specific substances, materials, aggregated mass (bulk) and products. Since the material flows are accounted in mass, it is possible to identify the origins, stocks and leakages (Laner and Rechberger, 2016).

A MFA can be modeled statically or dynamically. A static MFA provides a "snapshot" of the material flows in a system to gain an overall understanding of the current situation. A dynamic MFA defines the movement of flows within the system over a certain time span. The advantage of a dynamic MFA over a static MFA is the possibility to study different scenarios. Dynamic MFAs are mostly carried out study the stock buildup and material dissipation over time,

Dynamic MFAs can be approached in a top-down or bottom-up fashion. With a top-down approach, the stock is quantified by calculating the difference between the input and the output of a material. In the case of a MFA for a country, the input would be the imports and domestic extraction, and the output would be the export and recovered materials from recycling. (Graedel et al., 2010). The bottom-up approach aims to represent the quantity of the stock by aggregating all the weight of the bulk material that is considered in-use or hibernating. The two different approaches can also be used to validate one another and indicate the shortcoming of one versus the other. In practice, it is often seen that a combination of the top-down and bottom-up approach is used to complement each other by filling data gaps and by exposing uncertainties.

The discarding and recycling of a material are considered the outflow of the material (Laner and Rechberger, 2016). To estimate the outflow of the materials with a bottom-up approach, the composition of the stock must be modelled first. Modelling the stock composition can be done by input-driven models or stock-driven models. Input-driven models commonly use historical data (e.g. the number of shipments for previous years), whereas stock-driven models use product diffusion data (e.g. 0.8 cars per capita for a certain country) (Vásquez et al., 2016). The outflow from the stock can be modelled by applying a delay to the materials in the stock. This delay dictates the stock and outflow dynamics and is referred to as a delay model.

In order to compute the material outflow from products that are put on the market, product lifespan functions are used as the delay model (Elshkaki et al., 2005; Laner and Rechberger, 2016). A comprehensive overview of all different product lifespan definitions is illustrated in Marakami et al. (2010) in figure 3. Since product lifespans are difficult to observe, they have to be estimated. To estimate the lifespan distribution, reliability engineers prefer a statistical distribution (parametrical approach), such as often is found in literature. These distributions are often based on product failure rates and result in a survival distribution function (Murakami et al., 2010). Non-parametric approaches are more convenient when the reason for discarding a product can also be something else besides failure, e.g. discarding an outdated product or discarding products to follow trends (Murakami et al., 2010). Non-parametric approaches in this context are data intensive and require close observance and reporting. A statistical distribution of the lifespan needs fewer input information and is modeled with a function such as the normal distribution, log-normal distribution or Weibull distribution (Oguchi, 2010).

By subtracting the observed outflows from the estimated outflow through modelling, the invisible and unobservable outflow can be estimated (Murakami et al., 2010). The

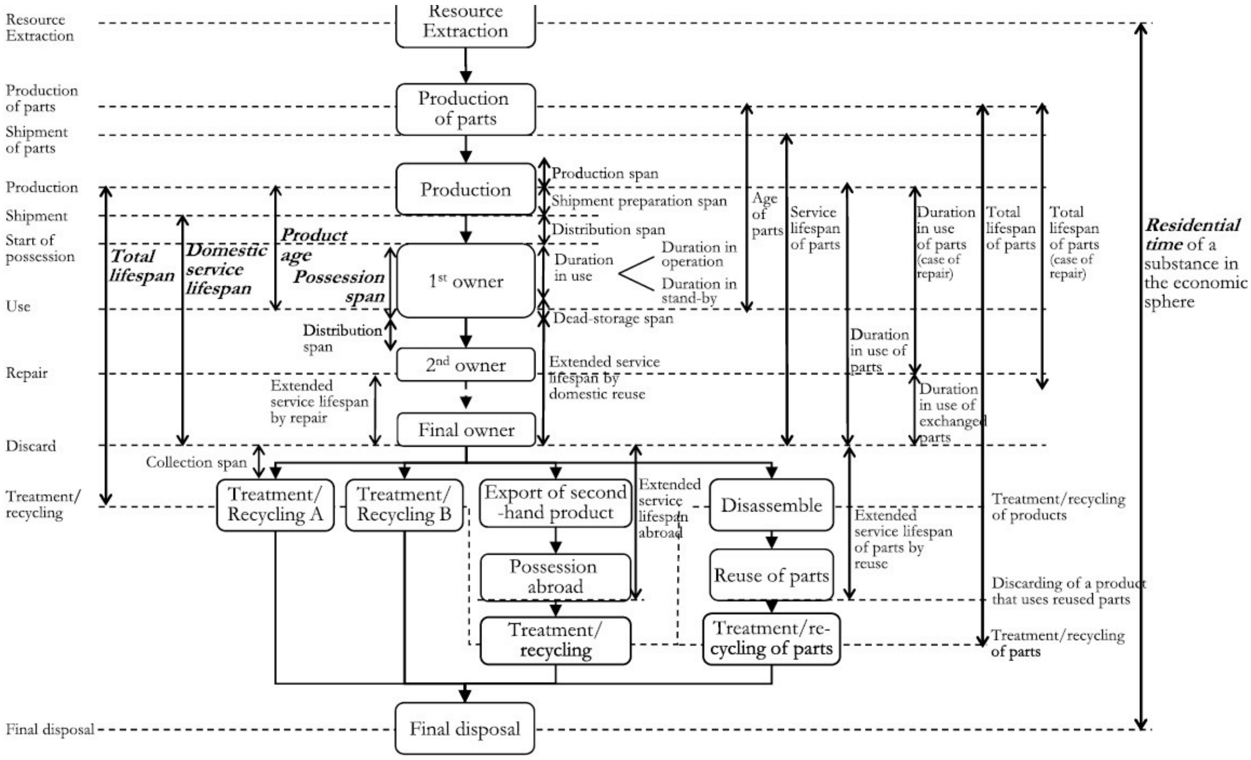


Figure 3: Processes included in various lifespan terminologies for consumer durables (Murakami et al., 2010)

invisible or unidentified flow can then be uncovered by further research into e.g. stock dynamics, consumer discarding behavior and/or undocumented flows

Regarding the general usefulness of the MFA method, a relevant shortcoming has been recognized. The actors who have control over the material flows cannot be derived from current state-of-the-art MFAs, although this is crucial information for material flow management (Hinterberger et al., 1996). For a company, it is also of vital importance to know which material flows it could start managing and which actor is exerting control in the current situation. Without the extra dimension of the responsible actors, the MFA model cannot be used as a useful policy or strategy tool (Hinterberger et al., 2003).

2.1.2 Studies on (W)EEE stocks and flows

2.1.2.1 Stock and flow modelling approaches

WEEE Generation (WG) and WEEE collection and recycling are a growing concern globally. As described in the introduction, this waste stream is predicted to grow quickly in the coming years, growing along with the concerns about the environmental hazards and lost valuable resources. With the updated WEEE directive (Directive 2012/19/EU), the national C&R targets is set to to either 65% of the average of Put On Market (POM) weight of the previous last year - or - to 85% of all WEEE Generated. For the latter, it is necessary to make domestic WG estimates to support the assessment of the targets. However, it is generally difficult to estimate the WG quantity due to lack of useful data and lack of transparency in consumer behavior. As laid out by Wang et al. (2013), there is a variety of WG estimation methods, which can be categorized into four groups; disposal related analyses, time-series analyses, factor models and input-output analyses.

The first method, the *disposal related analysis* method, uses empirical data from C&R channels and other disposal channels. Secondly, the *time series analysis* uses historical WG data to forecast the expected WG for future years. The *factor model* takes WG samples from a significant number of cities and searches for potential correlation with socio-economic indicators. For example, the study by Beigl et al. (2003) showed that of all the socio-economic indicators, the infant mortality rate seemed be the most correlated with WG. This correlation coefficient could the theoretically be applied to other cities for calculating the WG based on the infant mortality rate.

The fourth method, the *Input-Output Analysis* (IOA), models the WG flow by creating mathematical relationships between EEE sales, stock and/or lifespan (Magalini et al., 2015). Dynamic MFA and IOA can be used interchangeably regarding mass balances. Since the dynamic MFA method is more adopted in WG studies, 7 different approaches have emerged over time that can be further classified in five groups. These approaches use the link between two or three of the following variables to calculate the WG (Wang et al., 2013);

- weight of product sales (**POM**)
- weight of stock (**S**)
- domestic lifespan of products (**L**)

The main outlines of the approaches are the following;
Group A: Time step models (POM + S)
In the time step model, the WG is calculated through subtracting the product sales for the current year by the change of the stock size compared to the previous year in relation to. Equation 1 shows the mathematical relationship (with years in *n*). This approach can be highly accurate when using high quality data for product sales and stocks (Wang et al., 2013).

Eq. 1) $$WG(n) = POM(n) - [S(n) - S(n-1)]$$

Group B: Market Supply models (POM + L)
The first market supply model is the *Sales-Average Lifespan (simple delay) model.* Equation 2 shows the relationship of product sales and the average lifetime ($L^{(av.)}$) over *n* years. In the simple delay model, the average lifespan of the product is considered the moment the product becomes WEEE. This method can only provide useful results for saturated markets with a stable population.

Eq. 2) $$WG(n) = POM(n - L^{(av.)})$$

The second market supply model is the *Sales-Distributed Lifespan model*. This approach uses sales data in combination with their respective obsolescence rate for the evaluation year. In equation 3, t_0 is the initial year that the product has been placed on the market and $L^{(p)}(t,n)$ is the probabilistic distribution profile for the discarding of the product for evaluation year *n*.

Eq. 3) $$WG(n) = \sum_{t=t_0}^{n} POM(t) \cdot L^{(p)}(t,n)$$

The last market supply model is the *Carnegie Mellon model*(also referred to as the *End-of-Life model).* The Carnegie Mellon model uses lifespan averages in its calculations, but applies the lifespan average to different corresponding lifecycle stages, thereby also taking lifespans into account for reuse and storage. Transfer coefficients are used to estimate how many products flow from one lifecycle stage to the other. This model requires extensive data collection, but will deliver a more comprehensive result for the stocks by regarding different life cycle stages. Figure 4 showcases an example of such a model used in a study by Steubing et al (2010).

Group C: Stock& Lifespan distribution model (S + L)
A *stock and lifespan distribution model* combines the historical stock data with lifespan distributions of the products. With this model, it is possible to derive the historical sales data, which then can be used to calculate the WEEE with a time step model or sales-distributed lifespan model (see eq. 4).

Eq. 4) $$\begin{aligned} WG(n) &= POM(n) - S[(n) - S(n-1)] \\ &= \sum POM(t) \cdot L^{(p)}(t,n) \end{aligned}$$

Group D: Leaching model (S + L)
The *leaching model* can be useful to calculate WG in cases with very little data availability, but is only applicable to saturated markets and for products with relatively low lifespans. WG is calculated by dividing the stock with the average lifespan of the products (see equation 5).

Eq. 5) $$WG(n) = S(n)/L^{(av.)}$$

Group E: Multivariate (POM + S + L)
This method consolidates the previously described mathematical relationships when data is available for all three variables. The method proves that using multiple data sources for all three pillars will improve data quality and enhance the reliability of the WG estimates.

Having laid out the 5 groups with different data requirements, now the focus will be on the groups that use data that should be generally available. In the EU, producers should already report the POM weight to comply with the WEEE directive article 16. The POM weight data is also used to measure the performance of the member states for the new WEEE targets (Magalini et al., 2015). Furthermore, stock data on EEE appliances in businesses and households are also generally unavailable or not easily convertible to an absolute stock amount (Magalini et al., 2015). Generally speaking, for the EU at least, the Market Supply Model is the group with the most suitable approaches to estimate WG. The approaches in the group and its applicability will be examined further.

<u>The Sales-Average Lifespan approach</u>
One of the Market Supply Models is the Sales-Average Lifespan models. While the data requirements for this model can be satisfied relatively easy, the model is only supposed to be applicable in a market with an EEE stock saturation and stable population. This goes against general global trends, where population growth is expected and the number of EEE products per households is expected to rise. By way of illustration, the ownership of EEE in Dutch households has shown an increase of 26% from 2000 to 2010 (Huisman et al., 2012). With current trends, it is highly unlikely to find a saturated EEE market with a stable population.

<u>The Carnegie Mellon approach</u>
Another market supply model, the Carnegie Mellon model, models not only the disposal, but also the different stock

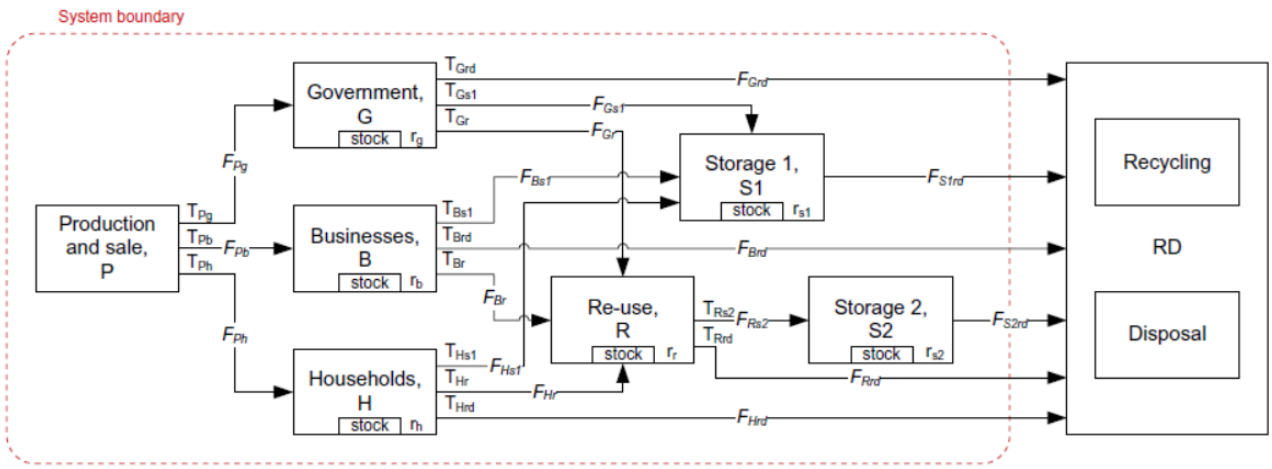


Figure 4: The processes and transfer coefficients in a study using the Carnegie Mellon model (Steubing et al., 2010)

phases using the average lifespan for each phase. It is initially developed to model the EoL product flows for discarding of PCs in the USA by Matthews et al. (1997). This study models the four available destinations for products that are deemed obsolete to the owner (in the case for the USA; reuse, store, recycle and landfilling). This method elaborates on the different stock options (storage and reuse), whereas other lifespan methods only speak of in-stock products, which include all non-discarded products, whether they are in-use or not. With this model, it is possible to forecast how many of the products are in use, reuse, storage (hibernation), recycling, landfilling or incineration in the year of evaluation after the initial year.

The application of the Carnegie Mellon model has so far only been done for a specific set of products, i.e. computer equipment or household appliances such as TVs, air conditioners and washing machines (Matthews et al., 1997; Dwivedy and Mittal, 2009; Peralta and Fontanos, 2005; Steubing et al., 2010). In theory, the Carnegie Mellon model could provide very detailed insight to the stocks and flows of products in different life cycle stages after the point of sale. Quantifying the hibernating stock can be very valuable to companies and governments, since it can be considered an untapped readily available resource for C&R or product returns. Furthermore, this type of model allows for the introduction of other circular flows like refurbishment.

Since the transfer coefficients for the flows in the system can vary between customers, the B2G, B2B and B2C sales have been modelled differently in the study by Steubing et al. (2010), seen in figure 4. The study by Huisman et al. (2012) describes how in the Netherlands WEEE originating from businesses generally end up 100% in recycling, while this is not the case for the consumer segment. Modelling the product flows separately based on their customer market can therefore lead to more accurate estimation for the C&R flows.

Limitations to the applicability of the Carnegie Mellon method relate to data requirements of the transfer coefficients and the average lifespans for the different life cycle stages. These figures require intensive observations and therefore have been assumed and have not been properly backed by consumer studies and surveys. Furthermore, the use of average lifetimes is highly simplified, resulting in less reliable results.

<u>The Sales-Lifespan Distribution approach</u>
The Sales-Lifespan Distribution model is the last and most frequently applied market supply model that needs to be covered. This model has been used in studies to support the updated WEEE directive targets. The studies disclose most of the used variables and inputs in the model and the data collection is clearly communicated. This model has been deemed most appropriate for calculating the WG for each EU member state over all other WG estimation methods because of its relative high-quality data availability, simplicity and the relative high compatibility of the model with all countries (Magalini et al., 2016).

As mentioned before, the Sales-Lifespan Distribution model requires two sets of input: 1) historical POM data and 2) the lifespan distribution function for the product (type). The lifespan distribution projects how much of the POM batch will be discarded in the years following the original sales. Since the product does not necessarily have to be broken to be discarded in today's society, one must not confuse the lifespan distribution function with the survival function discussed in section 2.1.1. A product lifespan distribution is based on the discarding rate, whereas the survival distribution is based on the failure rate.

Probabilistic lifespan distributions shapes can differ between product types, individual owners and groups of populations (Wang et al., 2013). The lifespan distribution function can be derived from consumer surveys and through observing and sampling WEEE at C&R facilities to determine the age profile (Magalini et al., 2016; Wang et al., 2013). The results from these studies appeared to have the best fit with a Weibull distribution function out of all other probabilistic distribution functions (Wang et al., 2013). A Weibull distribution is defined by two parameters; the scale parameter (β) and the shape parameter (α). As one might derive from the names of the variables, the shape parameter dictates the shape of the distribution and the scale parameter dictates the stretching of the distribution shape. By way of illustration, the difference in shape and scale parameters of the distribution functions can be seen in the graph in figure 5. Equation 6 shows the Weibull distribution function applied in lifespan modelling ($L^{(p)}(t,n)$=discarding probability, *t* =initial year, *n* = year of evaluation)

Eq. 6) $$L^{(p)}(t,n) = \frac{\alpha}{\beta^{\alpha}}(n-t)^{\alpha-1}\, e^{-[(n-t)/\beta]^{\alpha}}$$

Some lifespan distributions can change shape over time due to social and technical developments. (Magalini et al., 2016). In the case of time-varying shape and scale parameters, the Weibull distribution function is formulated as equation 7. However, data on time-varying parameters is difficult to obtain (Magalini et al., 2016).

Eq. 7) $$L^{(p)}(t,n) = \frac{\alpha(t)}{\beta(t)^{\alpha(t)}}(n-t)^{\alpha(t)-1}\, e^{-[(n-t)/\beta(t)]^{\alpha(t)}}$$

The scale parameter is related to the average lifespan of the product and can be calculated with use of the shape parameter and the Gamma function, see equation 8.

Eq. 8) $$\beta = \frac{L^{(av)}}{\Gamma\left(1 + \frac{1}{\alpha}\right)}$$

The United Nations University (UNU) carried out consumer surveys in several EU member states in order to obtain the shape and scale parameter for as many WEEE products as possible. The shape and scale functions have been assigned on a UNU-key level. Products that fall under the same UNU-key share roughly the same product functionality, legislative relevancy and recycling aspects- by similar weight, material composition, average lifespan (Baldé et al., 2015a). This UNU-key classification, consisting of 54 categories, has been useful in building national WG models, which serves as a harmonizing categorization of many worldwide and European classification systems, such as the collection categories according to the EU WEEE directive. The link between the different classification systems are made available, as are the (current and historic) average weight, shape and scale parameters for each UNU key for some EU member states (Wang et al., 2012; Baldé et al., 2015a). In the study by Magalini et al. (2016) on WG estimates for all EU member states, the uncertainty in the lifespan was tested through a sensitivity analysis based on two extreme scenarios; 30% shorter and 30% longer average lifespans for all 54 UNU-key categories. By computing these different configurations for all member states of the EU28, the lowest margin of error for the WG estimates was 5% and the highest 31%. The lack of accurate national data has been assigned as the main cause of the margin of error

Once the WG is estimated, it is then compared with reported data from national recycling schemes to identify the size of the flows that did not enter the official take back systems. WEEE destinations can be split by transfer coefficient into four groups i.e. official recycling scheme, waste bin, local complementary recycling (by traders and brokers) and illegal trading and export to developing countries (Baldé et al., 2015b).

The Sales-Lifespan Distribution model is a widely used WG estimation model for countries and can provide high accuracy estimations when using highly accurate POM data, product weight data and lifespan data. However, the limitations of this model are due to the lifespan distribution function for some all-encompassing product groups. Furthermore, little insight on the stock is created with this model, since it makes no distinctions for different lifecycle

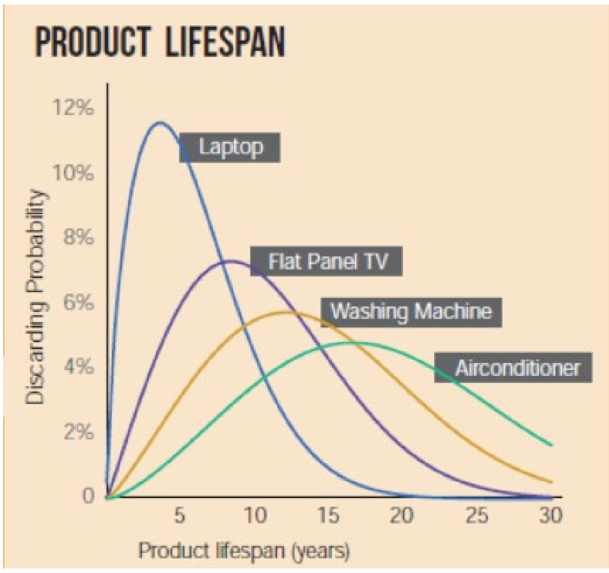


Figure 5: Example of Weibull product lifespan distributions , Baldé et al. (2015b)

stages within the domestic service lifespan (for reference, see figure 3).

2.1.2.2 Prospective stock and flow modelling

With using a market supply model to assess future scenarios, it is necessary to forecast the POM EEE for the future years. In the study by Magalini et al. (2016), the EEE POM were forecasted based on the apparent correlation of Purchasing Power Parity (PPP) and the historical EEE POM data. This apparent correlation has been explored in the study by Huisman et al. (2008). For each UNU-key, the growth of the EEE POM has been linked to the growth rate of the PPP in scenarios for economic downturn, economic growth and for the PPP growth trendline based on previous years.

Although the EEE POM-PPP correlation method is accepted for future WG modelling, this calculation ignores the link to more realistic situations for the EEE stock in households. The method does not consider any appliance saturation within the market. Within the field of forecasting residential electricity for households, the focus is on building EEE stock models in units per household, which can be considered a stock-driven stock modelling approach (although with different modelling intentions). The appliance ownership rate, also referred to as the diffusion and saturation-level function, has three macroeconomic parameters; 1) the domestic household expenditure data (i.e. PPP), 2) the number of households for the country and 3) the saturation rate of a certain product in a household. The basis of this function is that when households have more expendable income, the number of appliances in households tend to rise, until the point of saturation (Daioglou, 2010). The saturation rate is something to be observed from consumer research and can be assumed to some extent. For example, the saturation level for dishwashers in a Dutch household can be assumed to be close to 1, while the number of televisions in Dutch households can be more than one.

The diffusion and saturation rate is expected to reflect the curve of a Gompertz function, see equation 9 (Diaoglou, 2010). Phi_1 represents the saturation level, Phi_3 represents the PPP/capita growth rate and Y represents the PPP/capita year. Phi_2 can be extracted by fitting the curve to real data with a regression analysis.

Eq. 9) $$Diff = \varphi_1 \cdot EXP(-\varphi_2 \cdot EXP(-(\varphi_3/1000) \cdot Y))$$

Other functions using the basis of the Gompertz function have also integrated saturation level dynamics and diffusion rates dynamics that could be caused by product price development or income based delay (Diaoglou, 2010).

To conclude, when using a market supply model, the stock development should be examined for realism to assess the validity for modelling future scenarios.

2.1.3 Summary and Conclusion

Material Flow Analysis is a method used in the field Industrial Ecology to analyze stocks and flows within a defined system. Executing a MFA concerns main modelling choices as *static* vs *dynamically* modelling, taking a *top-down* or *bottom-up* approach and (in the case of a dynamic MFA) taking a *stock-driven* or *input-driven* approach. Most studies on (W)EEE stocks and flows conduct dynamic MFAs on are usually done on a national level. 7 different dynamic MFA approaches can be clusered in 5 groups according to the necessary input for running the model. From these groups, the Market Supply model group is most practicle, given the fact that stock data is generally unavailable. This group contains the Sales-Average Lifespan approach, the Carnegie Mellon modelling approach and the Sales-Lifespan Distribution approach. The Sales-Average Lifespan approach requires a saturated and stable market, which goes against current global market trends and is therefore not suitable. The other two approaches are deemed suitable for addressing the research assignment, both have their limitations and potentials, although it has to be notes that the Sales-Lifespan Distribution has been the most frequently applied dynamic MFA model and therefore there are many resources available for this approach. These studies have also included prospective modelling, for which often the POM is extrapolated according to the apparent correlation with the PPP trends. However, the EEE stock modelling approach in a different field, i.e. residential electricity forecasting, calculate the stock through a diffusion and saturation-level function instead. This function can be used to provide a more realistic picture for future demand for EEE by taking into account, besides the PPP, also the growth of households in the country, saturation levels for products.

2.2 Reversed logistics

2.2.1 Reversed logistics fundamentals

With an increase of pressure on companies from policy makers, investors and other stakeholders on taking more responsibility for the EoL-products due to the growth of awareness on environmental sustainability, strategies for EoL-product management had to be developed. Industrial Ecology and LCAs focus mostly on the environmental performance of these strategies, whereas RL and CLSC are solely focused on the economic performance of strategy (Geyer and Jackson, 2004). Traditional supply chains have always been regarded as the forward supply chain only, where generally the "chain" ends at the point of consumption (for reference, see figure 6). RL involves interventions to collect used products from the consumer either for value recovery or to ensure proper disposal. The most universally accepted definition for RL is "*the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of origin to the point of consumption for the purpose of recapturing value or proper disposal.*" (Rogers and Tibben-Lembke, 1998).

A supply loop can be defined "closed" if the recovered resource comes from the original company's product, whereas a loop is "open" when the secondary resources come from products from different companies (Geyer and Jackson, 2004). Together, the forward supply chain and the reversed supply chain form the CLSC. CLSC management has been defined by Guide and van Wassenhove et al.

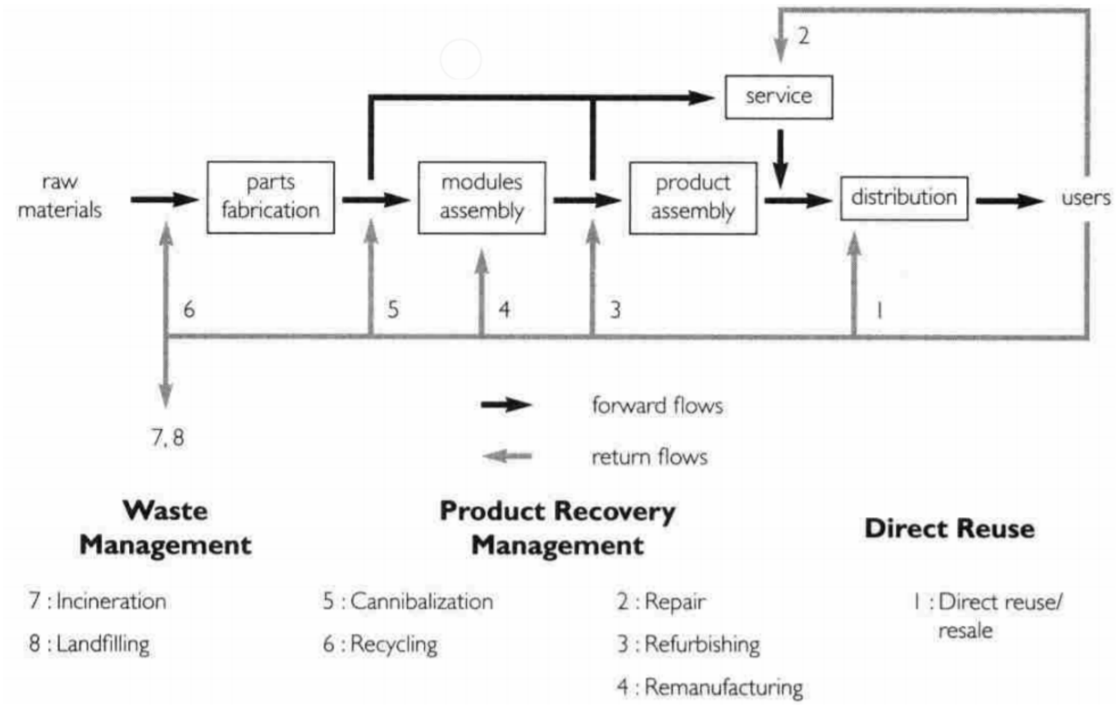


Fig 6: The integrated supply chain (Thierry et al., 1995)

	DISASSEMBLY- LEVEL	QUALITY REQUIREMENTS	RESULTING PRODUCTS
reuse	arbitrary	check for functioning product	no intervention
repair	to product level	restore product to working order	some parts fixed or replaced by spares
refurbishing	to part/sub-assembly level	inspect all critical modules and upgrade to specified quality level	some modules repaired/replaced; potential upgrade
remanufacturing	to part level	inspect all modules/parts and upgrade to good-as-new quality	used and new modules/parts combined into a new product; potential upgrade
parts harvesting	selective part retrieval	depends on process in which parts are reused	some parts reused; remaining product recycled/disposed
recycling	to material level	high for production of original parts, less for other parts	materials reused to produce new parts

Table 1: Product recovery options (adapted from Thierry et al., 1995)

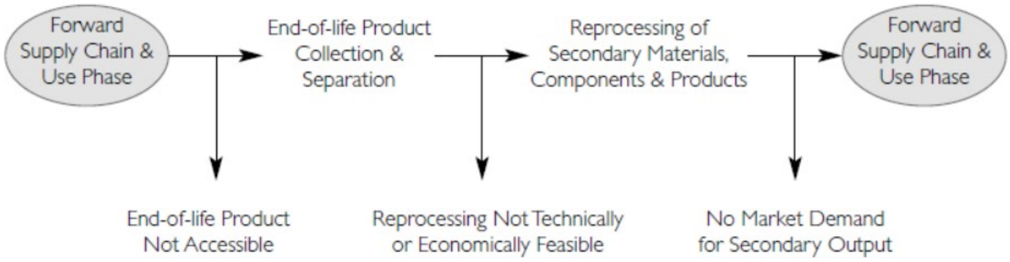


Figure 7: The three main supply constraints in CLSC managements (Geyer and Jackson, 2004)

(2009) as the "*design, control and operations (of a system) to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of return over time*". This definition of CLSC implies a shift from an environmental and societal objective of the RL interventions to an economic objective, where integrating a reversed supply chain can also be economically attractive (Govindan et al., 2015). EoL-product management interventions are in line with the CE recovery loops with reuse, repair, refurbishing, remanufacturing and recycling (see fig 6). The disassembly level, quality requirements and resulting products from these different EoL-product management interventions are laid out in table 1.

Product return flows are considered a supply in a CLSC and is therefore a driver in CLSC management. There are several different kinds of product return flows for which Thierry et al. (1995) identified the following four types:

- product returns as required take-back by law or contract (i.e. responsibility of disposal)
- product returns from ending leases and rental contracts
- product returns from technical failures within the time of service contract or warranty
- buy-backs of used products

Geyer and Jackson (2004) identified three main supply constraints for CLSC management, illustrated in figure 7. The first constraint is the inaccessibility of EoL-products. The second constraint covers the technical or economic limitations to EoL-product reprocessing. The third constraint is the lack of market demand for reprocessed products. Thierry et al. (1995) proposed interventions for companies to overcome these three constraints. Controlling and accurately predicting the return flows can overcome the constraint of EoL-product inaccessibility. Redesign of the products through modular design, design for recycling or design for disassembly can greatly benefit the feasibility of reprocessing the EoL-products. Lastly, to overcome the last constraint, it will be necessary to generate market demand for reprocessed products and, furthermore, quality control for such products will be crucial. Other more general essentials to successful CLSC management are good collaboration with RL partners, adequate information technology support systems and the setting of an internal recovery target (Thierry et al.,1995).

According to Janse et al. (2009), the consumer electronics industry is a perfect candidate for RL practices. Firstly, it is because of the large WEEE volumes worldwide. Secondly, there is pressure backed by legislation to take-back products in the EU (i.e. the EU WEEE directive) and several other countries. Thirdly, the positive environmental impact of RL in the consumer electronics sector can be significant because, as described before in the introduction, the WEEE flows can cause great harm to the environment when not disposed properly. Through several case studies, Janse et al. (2009) discovered that the principles of RL were already embraced to some degree in the consumer electronics industry in the four following ways; 1) there is already more strategic focus on reversed logistics, 2) there is closer cooperation between forward and reverse supply chain partners, 3) there is more use of swapping of products and components in the repair process, 4) sustainability is viewed as a competitive advantage.

2.2.2 RL stocks and flows modelling

2.2.2.1 Stock modelling

Also for systems and companies that have not implemented CLSC concepts there is a vested interest in knowing the EEE stock size and characteristics and/or the WEEE flows size and characteristics. One of the main contributors for this is the 'service part end-of-life inventory' problem for goods being manufactured in the final phase of its product life cycle (here referring to product sales introduction, growth, maturity and decline) (Pourakbar et al., 2014). Manufacturers are often legally required to repair products or provide parts for failed products within the warranty time or service contract. Some manufacturers also choose to supply spare parts to customers who want to repair their products themselves after the expiration of the warranty or service contract. Another challenge within spare part inventory management is the continuous shortening of the products and parts lifespan due to technological innovation, which results in a larger obsolescence risk for the spare parts (Pourakbar et al., 2014). Spare parts shortage costs can get very high if they cannot be supplied timely to the customer when needed (Dekker et al., 2013). So, with the final stage of production of a certain product, the final

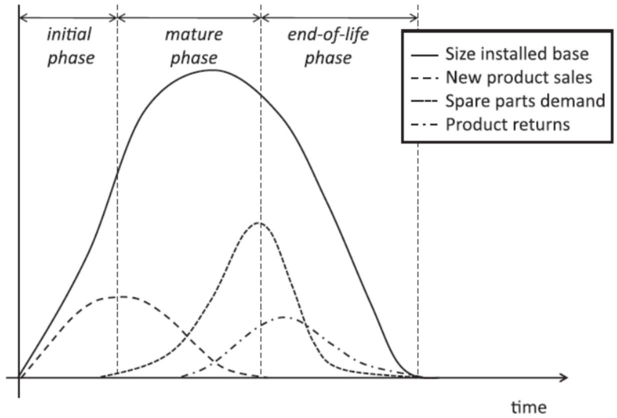


Fig 8: A sketch of the relationships between sales, installed base, spare parts demand and EoL returns (Dekker et al., 2013)

order quantity for the spare parts needs to be based on a reliable forecast on future product failures; in other words, forecasts on when and how many products are expected to need repair or part replacement in the upcoming years.

Spare parts inventory control is generally important to guarantee the availability of spare parts for in-use products that would require service. Spare part demand models are usually based on the Installed Base (IB) information. IB is a term in SCM that refers to information (e.g. location, size and age) on products that are in-use by customers. When drawing a parallel to the MFA method, the IB essentially is the same as in-use stock. Jin and Liao (2008) modelled the spare part demand for a stochastically growing IB, as there was no research before on forecasting the growth of the IB otherwise. A few years later, the study by Dekker et al. (2013) introduced IB forecasting. The IB growth is based on the product life cycle; modelling the growth and decay of the market demand for a specific product. In figure 8, you can see the input (new product sales), stock size (size installed base) and the interrelated spare parts demand and product returns as sketched by Dekker et al. (2013). The demand of spare parts will follow the demand for new product with a delay and, furthermore, the demand for spare parts will be linked to product failure and wear and tear. To be able to model or estimate the future IB size, the following information is needed according to Dekker et al. (2013);
- From the sales phase: the expected product life and failure rates of the products/parts
- From the use phase: location of the system, usage of the system and maintenance information
- From the EoL phase: information about the abandonment of a system when they are no longer needed by the customer. Not only does this provide information on the IB, but a returned obsolete product can also be a source of useful recoverable spare parts.

Information on the IB is generally more available for B2B products sold with a service contract, which is rarely the case for B2C products in today's time. Generally, manufacturers of B2C goods have a good knowledge of sales, but do not know how many of those products are still in use and whether they already entered the EoL stage; all of which is essential input for IB forecasting and, consequently, spare part demand forecasting (Kim et al., 2016). Given the lack of information on the IB for B2C products, Kim et al. (2016) developed a new method for spare part demand forecasting method based on consumer behavior. The study proposes four different IB concepts related to the perceived value of the product and repair costs;
- Lifetime IB (IBL) - covers products that are expected to stay in-use during their expected lifetime, even when the warranty for covering repair costs has expire. This is usually the case for relatively expensive, high-end products.
- Warranty IB (IBW) - covers products that will be repaired during the years covered by the legal warranty, but will not be repaired in case of failure after the warranty expires. This is the case for most low to mid-end consumer products
- Economic IB (IBE) - covers products that will be repaired during the years covered by the legal warranty, and might be repaired only when economically attractive. This is the case for mid to high-end consumer products
- Mixed IB (IBM) - is similar to the IBE, however, consumers do not all show the same evaluation to the costs of repair. The consumer base should therefore be split up by product adoption (i.e. innovators, early adapters, early majority, late majority and laggards).

Regarding the IBL and IBW, all products sold in the initial year would be still in use until reaching the expected lifetime or warranty respectively. After reaching that turning point, the IB size graph will follow the curve of the product's survival function. For the IBE and IBM, the turning point will be determined by the product price, repair costs and depreciation rate (perceived by consumer). Figure 9 shows the relationship between these factors and indicates until when the product would still get repaired in case of failure. The IB modelling is done with a econometric model incorporating reliability statistics for the four IB types. The result of such a model for consumer electronics in a case study on fridges by Kim et al. (2016) is seen in figure 10.

The notion that the sole motivation for product repair is the relation of the repair costs to the original product costs is supported by consumer product replacement models (McCollough, 2010). These consumer product replacement models, used both by consumers and by company, to assess whether it is economically attractive to replace a product rather than repair it. Other reasons for not repairing or abandoming a product are fashion obsolescence or obsolescence by technological innovation and are rather

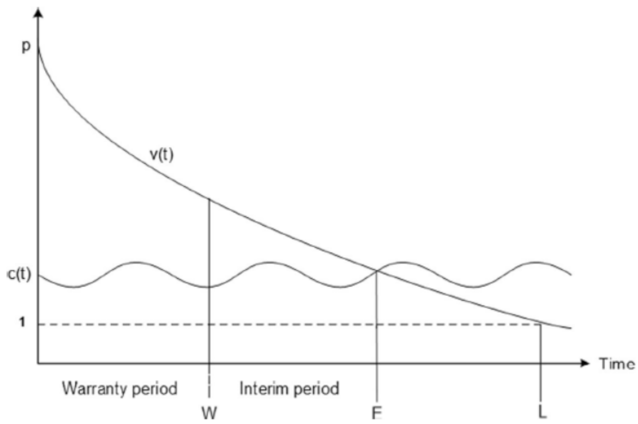


Fig 9: A sketch of the relationships between product value and repair costs over time (Kim et al., 2016)

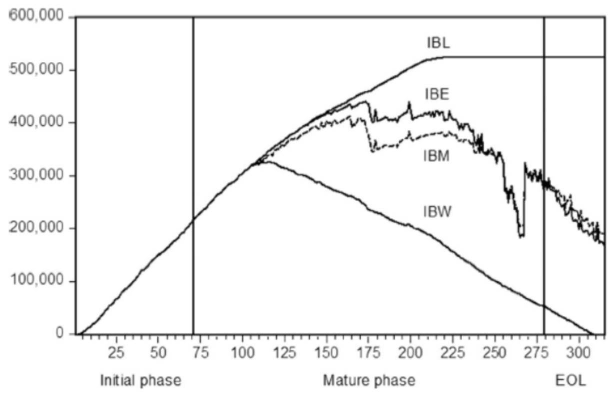


Fig 10: Outcome of case study on the Installed Base for refrigerators (Kim et al., 2016)

difficult to model (McCollough, 2010).

2.2.2.2 Reversed flow modelling

IB modelling is about estimating the in-use stock size, thereby focusing on the repair through spare part demand forecasting for the final order quantity for spare parts once the product will be phased out. Reuse of parts from returning products is a more environmentally sound alternative to the production of spare parts and can complement the spare parts inventory. Together with costs, remaining lifetime and quality, understanding the supply-demand dynamics of reusable parts is critical for successful implementation in RL (Umeda et al., 2006).

The study by Umeda et al. (2006) analyzed the reusability of EoL-products parts by applying a 'marginal reuse rate'. As represented in figure 11, the marginal reuse rate is the overlap of the production distribution curve and the disposal distribution curve for a certain product. Only when both production and disposal occurs, reuse is possible. The marginal reuse rate can be increased by designing new products to be compatible with the components from older products, thereby shifting the production distribution curve to the right, resulting in a bigger overlap with the disposal distribution. This overlap represents the fewer production input needed from new produced parts. In order to model the marginal reuse rate, the distribution functions for the production and disposal should be known.

Overall, forecasting product returns is a subject with early on-going development. Forecasting returns is also used to estimate how many products can be re-introduced to the market as refurbished or second hand. The main issues in forecasting the returns for this objective are the uncertainty in return timing and unpredictable consumer behavior (Potdar, 2009). For this reason, many of the earlier research done on modelling the CLSC are basing the return flows on stochastic modelling (Fleischman, 2000). However, more recent research has aimed for more accurate estimation modelling. Studies on quantifying reversed flows are mostly done on forecasting returning products due to (claimed) product failure or dissatisfaction within the warranty period (Potdar, 2009; Plewa and Jodejko-Pietruczuk, 2012; Calmon, 2015). This research is undeniably important for the producers within the industry, but this modelling approach leaves out the value recovery of all other products that survived the warranty period without being returned. To forecast product returns after the warranty expired, only controlled, forecastable product returns can only be organized through leasing the product (Pourakbar et al., 2014).

2.2.3 Short summary and conclusion

The forward loops and reverse loops managed by a company together form the CLSC. While organizing a CLSC can face major contstrains, the EEE industry serves as a candidate with a lot of potential for it. Product stock and (reverse) flow modelling is done to ultimately forecast spare part demand. The IB forecasting method is used to forecast future need for repair for in-use stock size and the marginal reuse rate is applied to calculate how harvested parts from returned products can decrease production for new spare parts. Regarding reversed flows through product returns, only returns from lease can be accurately forecasted. There are many studies on quantifying reversed flows from other types of product returns, however, these studies focus only on the return within the warranty period, which is not the aim in this research.

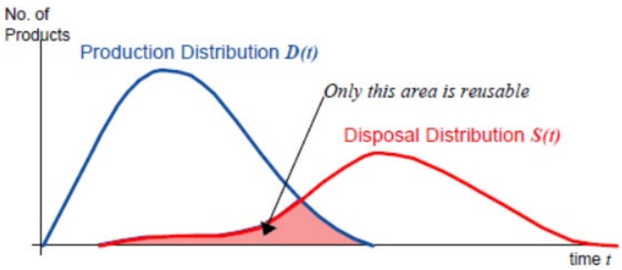


Fig 11 : Marginal reuse rate of components from returning products (Umeda et al., 2006)

2.3 Synthesis

2.3.1 Main methodology findings

In the previous sections in this chapter, the stock and flow estimation methods used in MFA and CLSC management have been explained and reviewed. In the synthesis, it is strived to provide an overview of the methods found in both disciplines and how they could be used to complement each other or harmonize with one another.

Firstly, the existing MFA approaches for stock and flow modelling of (W)EEE have been explored. From all methods, it was concluded that there are two approaches that are generally applicable to a company, i.e. the Sales-Lifespan Distribution model and the Carnegie Mellon method. Both methods have potentials and limitations. Earlier studies with the Sales-Lifespan Distribution model provide exhaustive data and is already an accepted method for nation-wide (W)EEE stock and flows accounting. However, the method does not provide any information on the dynamics within the stock. On the contrary, the Carnegie Mellon model does provide more insight into the dynamics within the stock and acknowledges differences between B2B and B2C product-user behavior, but requires much more data (for which intensive observation is required).

In addition, it was found that stock modelling for (W) EEE does not only occur in the field of Industrial Ecology. For instance, for national residential electricity demand forecasting, an EEE stock model is provided using a diffusion and saturation model (ownership rate) for households in a specific country. This is especially useful for assessing the realism for prospective MFA models, as the stock levels should not surpass the saturation rate.

Also, stock and flow methods also been developed in the field of SCM. Studies on RL have created methodologies for companies to be able to forecast the size of the IB (i.e. the in-use stock), which is used for spare part demand forecasting for repair. For building RL scenarios, some studies are devoted to quantifying the usefulness of return flows as a secondary source of spare parts for CLSC management (e.g. the marginal reuse rate). Most of the other studies on reversed flows are on returns within the warranty period, be it from product failures or disssatisfied customers. These models are highly complex and are limited to predicting the product return flows within the warranty time. Therefore, these product return models will not be considered in the synthesis. Furthermore, from the four type of product returns that are identified by Thierry et al. (1995), only products from ending leases and rental contracts can be predicted with certainty.

Table 2 provides an overview of all reviewed and theoretically suitable methods and their data requirements. An interesting thing to note is that the grouping of products to calculate the stock size with the Sales Lifespan Distribution method is done based on mainly functionality whereas in the Installed Base method, the products are grouped based on retail price.

2.3.2 Synthesis results

To see how the methods from the two different disciplines will complement each other, their usefulness was explored

DISCIPLINE	METHOD	DESCRIPTION	DATA REQUIREMENTS
Industrial Ecology	Carnegie-Mellon model (EoL model)	estimation of the size of use, reuse, storage stocks and waste flows to EoL destinations to module level	- Product sales - 1st use average product life - Reuse average product life - Average storage time - TC for reuse - TC for storage - TC for EoL destinations
	Sales-lifespan distribution model	calculating the waste generation from sales with a Weibull distribution	- Product sales - Weibull shape and scale - TC for EoL destinations
Closed Loop Supply Chain Management	Installed base forecasting	estimates the stock size from sales on repair/replace decisions of consumers based on the perceived value of the product	- Product sales - Retail price - Expected product lifespan - Survival function parameters - Avg. repair costs
	Marginal Reuse rate	Calculating how many EoL products can be useful for spare parts harvesting	- Sales distribution function - Discarding distribution function

Table 2: Overview of the different stock and flow estimation models and the corresponding the data requirements

LIFECYCLE STAGE	CONFIGURATIONS 1	 2	 3
in-use	IBF_{use}	CM_{use}	SLS_{stock} - $CM_{hibernate}$
hibernating	$CM_{hibernate}$	SLS_{stock} - IBF_{use}	$IBF_{out\text{-}of\text{-}use}$ - $SLS_{discard}$
stock	SLS_{stock}	CM_{use} + $CM_{hibernate}$	IBF_{use} + $CM_{hibernate}$
outflow	$SLS_{discard}$	$CM_{discard}$	$IBF_{out\text{-}of\text{-}use}$ - $CM_{hibernate}$
useful return flows	MRR through lease returns		

IBF_{use}	size of in-use product stock from Installed Base Forecasting
$IBF_{out\text{-}of\text{-}use}$	size of product outflow from in-use stage from Installed Base Forecasting
CM_{use}	size of in-use product stock from Carnegie Mellon model calculations
$CM_{hibernate}$	size of hibernating product stock from Carnegie Mellon model calculations
$CM_{discard}$	size of EoL product outflow from Carnegie Mellon model calculations
SLS_{stock}	size of product stock from Sales-Lifespan distribution model calculations
$SLS_{discard}$	size of EoL product outflow from Sales-Lifespan distribution model calculations
MRR	size of useful product return flow through Marginal Reuse Rate calculations

Table 3: Overview of the different configurations for calculating the stock/flow size of the lifecycle stages for a given year

per product lifecycle stage, seen simplified in table 3. It suggests the configurations that can be made to calculate certain stock and flow sizes. The information can either be used to validate one another or to replace one configuration with the other in the case of data inavailability.

Theoretically, MFA appproaches and stock and flow modelling methods in CLSC management can be complementary to one another in stock and flow size estimations. However, when it comes to predicting the reversed flows, no suitable method has been discovered from CLSC management that can predict the closed loop return flows after the warranty period has expired when the product have originally been sold to the customer. Therefore, more accurate modelling of closed loop product return flows can only be done through lease or rental product services. Leasing products to customers will overcome the first of three main constraints in CLSC management as identified by Geyer and Jackson (2004).

With accurate product return estimations, the marginal reuse rate can be used to calculate how many spare parts can be saved from production by using harvested part from returning EoL products. It could alo be used to predict the savings from new product production if the returning products were sold as refurbished or second hand, although it would still need to be acknowledged that spare parts will be needed in these processes as well.

2.3.3 Conclusion

To conclude, the stock and flow modelling techniques from the SCM field can theoretically complement the stock and flow modelling with a dynamic MFA. Incorporating the RL modelling methods into the dynamic MFA method could lead to more elaborate insights on the stock dynamics and will likely also increase the reliability and accuracy for stock and flow size estimations. It is likely that the connection between the two modelling approaches from the different fields has never been explored due to the different objectives of the dynamic MFA method and IB forecasting method. Dynamic MFAs for (W)EEE are used to estimate flow sizes in order to connect with real-world weight data for evaluating the performance of e.g. the recycling rate, whereas the RL stock and flow estimation methods are focused on predicting the spare part production demand.

3. CASE STUDY

After the theoretical methodological research done in the previous chapter, the applicability of the findings will be tested with an empirical analysis through a case study. The ultimate aim of the case study is to deliver a dynamic MFA model with incorporated RL loops. After a brief background description about company on which the case study will be based, the goal and scope are laid out. Additionally to examining the applicability of the theoretical findings, it is also strived to consider other wishes from the company to increase the usefulness of the deliverable. The goal and scope is followed by defining the scenarios that will be simulated in the model. An important part of the modelling process is the inventory analysis, where the data requirements from the theoretically suitable models will be tested on the data availability. The model will be built based on results from the inventory analysis and will be communicated through flowcharts. The suggested interaction with the final model will be presented through wireframes. Both the model and its outputs will be checked on its sensitivity and consistency with real life data where possible. The chapter ends with an evaluation of the model by the case study target audience.

3.1 Goal and Scope

3.1.1 Royal Philips

This case study will be done for Royal Philips N.V., that will henceforth be referred to as Philips. Philips is a Dutch technology company operating in consumer electronics (division Personal Health) and healthcare equipment (division Health Systems). Philips is one of the largest electronic concerns worldwide and is the 8th biggest public company of the Netherlands (Forbes, 2017). From 2012, Philips has incorporated CE principles in its strategic vision and mission. The main circular activities Philips is currently practicing are refurbishment of large medical equipment and using recycled materials in consumer products.

In the Health Systems division, the large hospital equipment is sold to B2B/B2G customers under service contracts, which makes it possible to monitor whether the products are still in use and when the products are replaced for another system. With the motto "*No customer left behind, no machine left behind*", the stocks and flows of the healthcare products that operate under a service contract are well documented where possible and processed in an IB database. The use of such a database facilitates customer retention methods and facilitates the possibility for Philips to buy back their products at the end of the initial use stage for refurbishment within the Diamond Select program. With regards to disposal practices outside Philips' control, it is expected that most of the healthcare equipment will be scrapped for its highly valuable components and materials.

On the consumer electronics division Personal Health, besides using recycled plastics, Philips is encouraging consumers to consciously discard products through official recycling schemes (Fleming and Zils, 2014). However, Philips' Small Household Appliances (SHA) are sold to the consumer under the legally obliged warranty that usually does not cover the expected average lifetime for the products. B2C customer relationships are weak compared to the B2B/B2G customer relationship, which makes it nearly impossible to track products after the point of sale.

CEO Frans van Houten stated in a panel discussion with fellow CE100 partners: "*Our wish is to track material consumption all the way*" (The Guardian, 2014). This case study aims to set the first steps to do so.

3.1.2 Goal

The research assignment for this project is, as stated before in the introduction, to *develop a dynamic MFA model for EEE companies to increase transparency of downstream product flows and provide prospective insight on the impacts of RL strategies*. In the empirical part of the research (i.e. the case study), it is not only the goal to make the model feasible regarding data availability, but also to make it as useful as possible for the company.

From the company's background description, one can derive that a focus on SHA is much more impactful than focusing the model on medical devices. Firstly, since Philips' Health Systems has IB monitoring systems in place (which is easier to manage in a B2B/B2G customer relationship) and, secondly, the healthcare products are more likely to be scrapped for its valuable materials. With the downstream SHA product flow, there is little idea of what the in-use stock is and what happens with the products once they reach the EoL stage. The only feedback the company gets from the EoL product stream is a weight-based C&R resultsreported by their national WEEE recycling partner. The company indicated that it seeks the connection between the POM quantity and the weight-based C&R data to be able to track the C&R performance over time. Therefore, the deliverable for this case study needs also to create that insight. Since the feedback from the C&R partners is based on the bulk of all SHAs (WEEE category 2), the case study will also cover all Philips SHA products to be able to make a proper connection.

Furthermore, with the invested interest of becoming more circular, it is interesting for the company to see how RL activities will affect the circularity performance of the company compared to the current system However, in a business context, the profitability of the implementations of such activities is essential. For that reason, the model will be paired with financial data to make both an environmental assessments and economic assessments. Another reason to add the financial information to the model is because that will allow the MFA model to be comparable and possibly adjusted with the econometric models currently used in SCM for RL management.

Another requirement from the model by the company is to provide insight on as many aggregated and disaggregated levels as possible; thereby being able to filter products based on any kind of product characteristic. business unit, etc., down to the level of analyzing the results for one product specifically. This will make the model more useful for a larger audience throughout different layers in the company.

In summary, from the business perspective, the model can be useful and impactful when the link can be made between the SHA POM sales and the SHA C&R results, when financial data can be incorporated into the model to compare profitability of different strategies and when the model results can be analyzed on different levels of aggregation. This can guarantee successful use of the model for strategic decision making for the implementation of RL activities.

3.1.3 Scope

In the introduction, the following three general research scopes were presented; 1) the research would be done on product level, not on part or material level, 2) the empirical research would be based on only one case study, and 3) the model will not aim for a perfect representation of reality, but will rather show what is possible with the currently available resources. In this section, the scope will be more specific towards the case study. The scope will be set on the following aspects to make the research feasible within the restricted time.

3.1.3.1 System boundaries

Philips sells SHA globally, but this case study research will focus only on the product downstream flows for SHA in the Netherlands. The most advanced (W)EEE stocks and flows studies have been applied to the Netherlands, which is something that has been made possible through well documented and detailed public data. (J. Huisman, personal communication, March 2017)

3.1.3.2 Circumventing CLSC constraints

In the Methodology chapter, three main constraints in CLSC management have been identified by Geyer and Jackson (2004). The three constraints will be circumvented by the following scope conditions:

1) Inaccessibility of EoL product

From the four types of product returns identified by Thierry et al (1995), i.e. buy-backs, failed products under warranty, products with producer responsibility of disposal and lease/rental returns, the products return from ending lease contracts are the only return flows for which can be accurately predicted (Pourakbar et al., 2014). This case study will therefore only model reversed flows from leased products.

2) Technical and economical infeasibility of reprocessing the returned products

This constraint will be strived to overcome by focusing only on modelling the reversed flows for high-end products for the following reason. Most companies use replacement models for making capital budgeting decisions, including whether a product/part should be repaired or replaced within the legal warranty period (McCollough et al., 2010). The replacement model often uses the discount rate, repair price and replacement rate as its variables (McCollough et al., 2010). The case study company also works with such a replacement model. In practice, the decision on whether a product will be replaced or repaired in case of failure often can differ per product. So, if the model would aim to be as accurate as possible, it would be necessary to find the repair-replace strategy for each product separately. Instead, this model will focus on high-end (relatively expensive) products, because it will be more likely that replacing the high-end product would be much less economical than repair. Repair costs are often more or less fixed costs (labor cost), so the more expensive the product, the smaller the repair to replacement cost ratio. Furthermore, by assuming that high-end models will be repaired rather than replaced in case of failure within the legal warranty period, it is also assumed that the high-end product are made repairable to avoid replacement. By this notion, it is assumed that a focus on RL for high-end products will be economically and technically feasible.

Another way of increasing successful technical and economical processing of returned products is by applying similar procedures that are used in the successful Diamond Select program. In this program, products are only refurbished once, as it will be both economically and technically unattractive to refurbish an earlier refurbished product for an additional cycle. So, by replication of the same concept onto SHA products, SHA products will only be refurbished once in its entire lifetime.

3) Lack of market demand for secondary output

By reviewing RL networks models, Fleischman (2000) found that models either use 'push' or 'pull' reuse market drivers. A 'push' reuse market driver implies that all recovered products will be put back on the market, whereas the 'pull' reuse market driver will only deliver recovered products for which there is a market demand. In this case study, the 'push' strategy will be applied, thereby implying that all recovered products will be purchased or leased. There is market research on the topic of consumer acceptance of recovered products, both company internal studies and public studies, although no study is useful within the scope for making quantified estimations what the market demand for a recovered product will be.

3.1.3.3 Prospective modelling approach

Regarding prospective MFA modelling of EEE stocks and flows, the Methodology chapter covered two different methods; 1) taking an input-driven approach by using the historical POM data to make projections for the future under certain economic scenarios, and 2) taking a stock-driven approach by calculating the future stock with the diffusion and saturation-level function. The second approach will require a significant amount of data collection and modelling and will not be suitable without product market share data. Although the diffusion and saturation-level function could be more accurate compared to the first prospective modelling approach, it is decided to use the first approach due to time restrictions. However, the main concept of the diffusion and saturation-level function can still be applied to assess the realism of the produced stock from the projected future input.

Overall, it is rather impossible to be able to predict what the future sales of a certain product will be. The company's market share can increase or decrease completely, technological innovation might render certain products obsolete within a short time and economic booms or crises can influence sales significantly. In this case study, it is assumed that the outside influences (e.g. competitor landscape, disruptive innovations and macroeconomic fluctuations) are balanced and have insignificant influences on the sales projections.

3.1.3.4 Comparative performance requirement

The model aims to compute the stocks and flows for the current situation and then compare the performances of RL strategies with the current situation as a baseline, which can be referred to as the Business as Usual (BAU). To make the current situation and RL scenarios comparable, all scenarios must be filling the same performance requirement. This performance requirement will be:

to satisfy the same in-use stock level of high-end products under BAU conditions

With this performance requirement, it is assumed that households in the Netherlands will require the same number of in-use products in their households with whichever business model. However, it must be acknowledged that the overall product diffusion and saturation rate might increase (thus overall stock increase) by offering of high-end products through lease (by making it more financially accessible to the market) and through selling/leasing recovered products (with generally lower prices/costs also accessible to a larger market). However, the latter factors will not be considered.

3.1.3.5 Environmental performance indicators

It is not within the scope to compute environmental emissions and their associated environmental impacts through combining the MFA with a LCA. The combination of MFA with a LCA would be much more suitable when applying the model to one specific product given the modelling and data requirements to achieve accuracy and reliability. However, this study is focused on the bulk of many products. Instead of focusing on environmental impact midpoints or endpoints, which cannot be assessed through a MFA alone, the environmental assessment is approached high-level without any backing of associated environmental emissions. Since the performance requirement for all scenarios is based on producing the same in-use stock, the focus will lie on the change of the size of the inflow and outflow. The following three high-level environmental performance indicators for the RL scenarios can be derived from the inflow and outflow and will be assessed by the percental change compared to the BAU scenario within a given time frame;

- Decrease of input from new products

The concept of the marginal reuse rate is applied. The basis of this indicator is that, with recovering returned products, the need for new products to satisfy the same stock levels might decrease. By reintroducing the recovered product to the market, the production of new products and the associated environmental impacts, might be avoided.

- Decrease of WEEE generation

Another CE principle is the longer circulation of products and therefore an overall delay and/or decrease in waste generation. This will be measured by comparing the EoL product outflow for the scenarios within the given time span. It is necessary that upon further analysis the distinction must be made for delaying WG or decreasing WG.

- <u>C&R rate</u>

This third environmental indicator is used to assess how much the loop of the production and consumption is closed by assessing the change in C&R rate. The C&R rate is expected to change with different RL management strategies when different actors are exerting control over the (waste) stream.

3.1.3.6 Economic performance indicator

To this day, quantifying the profitability of RL strategyies has been done through econometric modelling. To check the developed model with existing econometric models, it is necessary to introduce financial information to the model. However, the researcher of this project has little knowledge with economics associated with the production and supply chain management, so a rather simplified version will be applied. The model will allow for incorporating more accurate financial information, so the model can be compared and tweaked according to the existing econometric models. Furthermore, the economic performance indicator will not considering external costs.

3.1.3.7 Consistency check

Since the goal of the project is partly to deliver insight to the current situation of the downstream product flows, it is necessary to be able to check the computed stock and/or flow with real world data. For companies that have partnered with official recycling schemes, the estimated mass recycled on behalf of the company is reported yearly. In the case of data availability, the consistency check could also be done for the stock size.

Unfortunately, the only way to check the consistency of the future scenarios are through comparison of the financial results of the MFA model with existing RL econometric models. However, this is out of scope for this research project.

3.1.3.8 Tools

In this case study, modelling will be done with programming language Python (v2.7). The Pandas library is used exhaustively, which allows for easy and powerful data manipulation and data analysis. Similar programming languages that can be used for this case study can be R or MATLAB. The output of the model will be exported in a CSV or MS Office Excel file and are then visualized in Tableau, a data visualization software. However, the last two intermediate steps can also all be done within Python using a data visualization library such as Bokeh.

3.1.3.9 Confidentiality

In the case of use of sensitive company data, the results will be presented on an aggregated level and/or will be reported in weight instead of quantity where necessary.

In short, the scope delimitations of the case study for modelling a dynamic MFA with incorporating RL are;

Regarding system boundaries;
- Modelling SHA products in the Netherlands on product-level

Circumventing CLSC constraints by;
- Modelling for RL strategies for high-end products
- Modelling reversed flows from lease only
- Considering the reuse market driver to be a 'push' reuse market driver
- Refurbishing products only once

For the prospective modelling approach;
- Projecting future sales based on historical POM sales quantity data

For the comparative performance requirement;
- All scenarios should satisfy the same in-use stock level as would be computed for BAU conditions

For the environmental performance indicators,

The impacts of the RL strategies will be assessed on;
- The (negative) growth of new product input,
- The (negative) growth of WG
- The change in the overall C&R rate

For the economic performance indicator;
- Profitability will be assessed on estimated cost and revenue elements associated with the stocks and flows

For the consistency check;
- Comparing the C&R performance computed by the model with the report by the C&R recycling partners
- Comparing the market share computed by the model with the market share estimated by the company

Regarding tools;
- Modelling and data analysis is done in Python v2.7 andTableau is used for data visualization.

Regarding confidentiality;
-Results will be brought to an aggregated level or reported in weight metrics to cover sensitive information.

3.1.4 *Scenario definitions*

With the delimitations stated in the scope, it is possible to define the scenarios that will be simulated in the model. Since the performance requirement is determined by the model outcomes under BAU conditions, it is necessary to simulate the BAU first. Before having done the inventory analysis (which will be covered in the next section), it is already clear from basic business practices and legal requirements that we have the following information available:

- product sales in units, reffered to as POM quantity, for a set of consecutive years until 2016
- corresponding weights to the sold products
- reported recycled weight from the official recycling scheme partners

3.1.4.1 *Simulating the BAU*

Retrospective POM extrapolation

First, the aim is to extrapolate the yearly aggregated POM quantity to the point where the POM quantity for a given year is 0 by following a retrospective trendline. For the year where POM quantity is zero, the stock size is also zero. Since the model is done in a bottom-up fashion, the model reliability can then be checked with the following top-down equation provided in Equation 10:

Eq. 10) $$S_t = \sum_{T_o}^{T} (Inflow_t - Outflow_t) + S_o$$

In Equation 10, *t* is time, T_0 is the initial time step, S_0 is the stock at the initial time step, *T* is the current time step and S_t is the stock at the current time step (Graedel et al., 2010). There is no way of knowing the stock size for the year of the last recorded POM quantity, therefore it is necessary to set the stock size at zero in order to check the results with the top-down method. Having the POM quantity historically extrapolated to zero makes possible to check the bottom-up approach with the top-down approach. Obviously, products can have been sold before the given point where S_0=0, but this case study only considers the product portfolio for which historical sales quantities are available. The same approach (i.e. finding the stock age start) has also been applied in the Dutch WEEE flow study by Huisman et al. (2012).

A sensitivity check is required to determine the effects of this historical extrapolation. This is done by comparing the stock and flow results with the retrospective trendline extrapolation for the stock with 2 extreme historical scenario extrapolations. The first extreme historical sales scenario would be to have zero sales before the last recorded POM quantity. The second extreme historical sales scenario would be to have the POM quantity for the last recorded year duplicated to preceding years. Besides the sensitivity analysis on the outcomes of the different historical inputs, the outcomes of the two extreme scenarios will also undergo the consistency check to show if the retrospective extrapolation has an effect on the real-world consistency of the model.

Prospective POM extrapolation

If the modelling results are deemed consistent with real-world data, the modelling approach can be further extended for future stock and outflow estimations. This case study will build a future scenario for stocks and flows from 2016 to 2030. The extension is 14 years and the final year is arbitrarily set to the first year of a new decennium. Modelling the stock and flow further beyond 2030 comes with an increasingly greater uncertainty by each successive year. Figure 12 demonstrates how many products that were sold in 2016 are still in stock by 2030. This is done by applying the Weibull distribution discarding function (Eq. 6) to the SHA UNU-key with the largest scale (thereby implying the largest average lifespan) to calculate the stock size (i.e. not-discarded products) over the years until 2030. The UNU-key shape and scale parameters can be found in Appendix A and are retrieved from Baldé et al. (2015a). From the stock development of a UNU-key 202 product in figure 12, it is estimated to be 31% of the stock for the initial year will remain in Dutch households. Although it is clear from this graph that the stock for the products sold in 2016 will not reach zero, it still is reduced in size significantly. For the other SHA UNU-key products, the remaining stock for products sold in 2016 will be lower than 31%.

Unfortunately, there is no simple way of projecting future sales accurately. Instead, the future sales projections will be using the most recent reported data for a complete

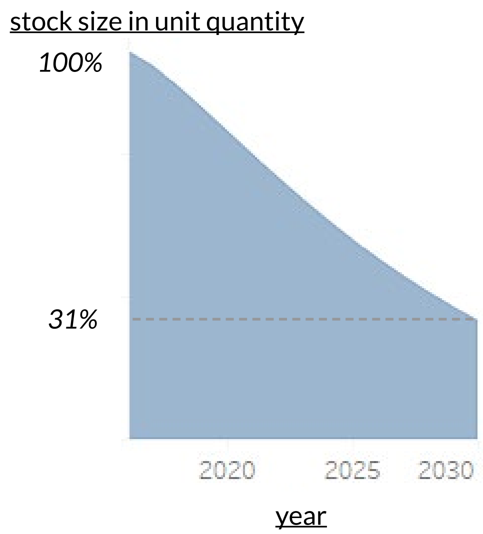


Figure 12: The stock development of UNU-key 202 product sold in 2016 according to UNU scale and scale parameters

year, which is the sales data for 2016, and duplicate the POM quantity for the successive years until 2030. This projection of zero growth is a conservative projection, and therefore a sensitivity analysis will be done by comparing the results with that of a highy optimistic sales projection.

3.1.4.2 RL scenarios

To reiterate, the RL scenarios will only be applied to high-end products from 2016 until 2030, with product returns from lease as the only source of predictable closed loop return flows. Reflecting to the raison d'être of this project, RL strategies will be implemented to increase the circularity of the downstream product flows. According to the EMF, the enabling activities to increase the overall circularity of a production-consumption system are (see figure 1 for reference);

- maintenance/repair
- reuse/redistribution
- refurbishment/remanufacturing
- recycling (material recovery)

The following step is to go over all four circular activities in order to come to RL scenarios;

Increase maintenance/repair - With adequate maintenance and repair, products are guaranteed to survive at least their minimal expected lifetime. In the case of selling EEE, there is an EU minimum of *2 years* of warranty to guarantee repair in case of product failure. However, in the Netherlands consumer laws protect the Dutch consumers more generously. In the Netherlands, either the manufacturer or the retailer must cover the costs of repair for failed products within the *minimal expected lifetime* (ConsuWijzer, 2017). Increasing repair claims can be done through spreading awareness on the consumer rights. Other than that, companies that sell products can do little to make consumers apply for repair of failed products. In the case of a lease contract, the consumer pays a fee for using a functional product while Philips keeps ultimate the ownership of the product, so repair of the product within the lease duration is implied (when economically viable). Besides providing service constracts at purchase, the main way to guarantee repair of a failed SHA product during its expected lifetime, is through leasing the product rather than selling.

Increase reuse/redistribution - Reuse amongst consumers is something that is happening increasingly. The phenomenon is hard to model and prove, but one indication is that revenue of thrift shops has doubled in the last 10 years (CSB, 2016). Also, with the widespread use of websites such as Marktplaats and Facebook, it has become rather easy for Dutch consumers to sell the products that the owner considers obsolete. It is likely redundant for the company of the product to play a role in facilitation of reuse. One way to control the reuse/redistribution of the products is through leases. Once a product become obsolete to one consumer, Philips can redistribute the product to another consumer until the acceptable lifetime has reached.

Reintroducing EoL products by refurbishment or remanufacturing - Refurbishing and remanufacturing are ways for a company to extract further value out of an existing product. Remanufacturing is the extensive process of restoring a product to an 'as good as new' condition through disassembly, cleaning, repairing and replacing parts and reassembly (Hauser and Lund, 2003). Since remanufacturing includes complete disassembly and reassembly, it does not fit within the scope of building the model on a product level. Modelling remanufacturing would be more feasible when considering a model built on part or subassembly level.

Refurbishment requires less work than remanufacturing, but requires more work than simply repairing a product or redistributing the a used product. The difference between a used product and a refurbished product is that the product has been tested and has been brought back to an optimal state to ensure proper functioning for the years to come. Since the obligatory minimum period of 2 years in the EU and the minimum expected lifetime in the Netherlands applies to not only new products, but also to recovered products, it is sensible for the company or retailer to test and restore the product before, rather than selling it directly as second hand.

In order to refurbish a product, the EoL-product must find its way back to the company. In the Philips Health Systems division (B2G and B2B), products return from buy-backs. It is made possible to buy-back the products due to the IB monitoring system and the relatively long service contracts. It is rather complex to model the return from buy-backs, since it involves many economic considerations by the customer to sell it back to the company. In the Health Systems division, a product will only be refurbished once and the refurbished product's lifespan is on average around 50% - 70% of the original product. Buy-backs are easier with B2B customers, since companies generally have closer relationships with B2B customers than B2C customers (Kim et al., 2016). As stated before, controlled, forecastable EoL-product returns can only be organized through leasing the products.

Increase recycling through C&R - The material recovery loop is part of an open loop supply chain through recycling by the national compliance schemes. In the BAU system, Philips can only steer or stimulate consumers to properly discard their products. One interesting way to do so from a business point of view would be to reward returned Philips products at retailers with a discount voucher for a new Philips product. This would likely increase consumer retention, while the retailer potentially has more customers. Unfortunately, it is still impossible to accurately forecast how much affects the C&R rates. Only when the companies are directly responsible for discarding the products, such as is the case for product returns from leases, a 100% C&R rate can be guaranteed.

The scope delimitations and the exploration of the different circular activities within the scope has brought the following three RL scenarios:
1) Leasing high(er)-end products - returning EoL-products will be scrapped
2) Leasing high(er)-end products - returning EoL products will be refurbished and leased once more - returning EoL refurbished products will be scrapped
3) Leasing high(er)-end products - returning EoL products will be refurbished and sold as refurbished products

The case for having two different scenarios that include refurbishment, one where the refurbished product is sold and one where the refurbished product is leased, is due to the perceived definition of *high-end*. It is stated in the scope to only lease high-end products, and it is unclear whether refurbished high-end product will still be considered high-end or not is up to the company. In the case of SHA, the definition of high-end in the traditional sense is often defined by the price and the durability. Given the Dutch consumer laws regarding EEE, warranty is based on the minimal expected lifetime. UNETO-VNI, a technological retailer organization, divides products on retail prices in order to suggest the minimal expected lifetime for *new* products (UNETO-VNI, 2014). However, it is unclear how this will apply to *refurbished* products, since it is assumed that the original product is made with high quality material, is built to last and probably also built for repair - and all these features would still apply to the refurbished high-end product except for it is probably sold for a significantly lower price. It is up to the company to define whether the refurbished high-end product can be perceived as high-end or low-end.

The last step of the goal and scope section will be the description of the three RL scenarios. on what the implications are and what the expected effect is.

RL scenario 1 - leasing high-end

In this scenario, high-end products will be leased for their decided maximum lease period. The product can change owner over time, but will only be used within the maximum lease period. With the lease construction, it is assumed that the stock size remains 100% of the input until the final day of the lease period. With the ending of the lease, products will return to the company and will all be sent to the official C&R scheme or will be properly scrapped in-house. The implications of leasing products instead of selling are, firstly, that there is no build-up of unused stock. Once the still functional product is deemed obsolete to the first owner, it can be transferred to the next owner. Secondly, the company will keep ownership all products will still be owned by the company, so all products can be properly recycled. Thirdly, since the lease construction makes it possible to do maintenance when needed, the product could have a longer lifespan. The products can then possibly be leased for a longer time than the minimum expected lifespan or average lifespan

The possible high-level environmental benefits could be:
a) less need for production of new products due the inability to create hibernating stock
b) less input and waste production when products are redistributed in case of obsolescence to the first owner(s)
c) 100% C&R rate for high-end products, so a higher (overall) C&R rate
d) less need for spare part production, since the returned products can be scrapped for useful parts.

RL scenario 2 - leasing high-end - leasing refurbished

In this scenario, where the refurbished product is considered high-end, the returned products from ending leases will be refurbished and lease again. The lease duration for the refurbished products will likely not as long as the original product lease duration. Returned products will be mostly scrapped and parts that are not too old or worn already can be harvested, since it is expeced that the spare part marginal reuse rate will likely yield lower compared to RL scenario 1. The implications of this scenario are the same as RL scenarion 1 with the addition that products will have two separate use lifestages by having two consecutive lease periods.

The possible high-level environmental benefits could be:
a) b) c) from RL scenario 1
e) by circulating the product for two separate use stages, less input from new high-end product is necessary and also WG is decreased and delayed.

RL scenario 3 - leasing high-end - selling refurbished

In this scenario, where the refurbished product is considered low-end, the returned products from ending leases are refurbished and sold. The refurbished products prices will compete with new low-end products prices for similar products. Therefore, also the replacement of new low-end products by refurbished products, also known as cannibalization, will be considered to see how selling refurbished products can affect the low-end market. This scenario implies that products will receive two separate use cycles and therefore will reduce input and WG, but this is only the case when the refurbished products will replace new low-end products. However, the company has no control over the sold product stream, and therefore has no influence on the C&R rate.

The possible high-level environmental benefits could be:
a) b) from RL scenario 1 and 2
f) the decrease of input from new low-end products by substitution with refurbished products.

3.1.4.2 Economic performance indicator

As described in the scope, the economic model is applied in the case study to make the model outcomes comparable to that of econometric RL models. However, the main aim for now is to set up the structure to add in the economic information and not to model the economic dimension into great detail to make an accurate cost benefit analysis. The economic information that is suggested to be added to the MFA model for the different scenarios is shown in table 4.

3.1.4.3 Summary

For building the BAU simulation model - To allow for a top-down check of the bottom-up MFA model, the historical data will be extrapolated to the year where POM quantity is zero, which means that the stock size at that point is zero as well. A sensitivity analysis will be applied on the model outputs with two extreme historical sales scenarios. Once the results for the BAU simulation are deemed consistent with real-world data, the POM quantity will be further extrapolated towards 2030. Considering the time restriction of the project, since there is no simple way to accurately predict future POM quantity. Therefore, it is chosen to duplicate the last known sales for all successive years until 2030. This is likely a rather conservative sales projection, and therefore the influence of sales projection will undergo a sensitivity analysis with a positive projection.
Defining scenarios - Through the analysis of the different circular activities, it becomess clear that lease is an suitable way to increase maintenance, repair and redistribution and, most importantly, will enable product returns with certainty, which will additionally allow for recovery of the returns through refurbishment, remanufacturing and material recycling. Within the scope of the case study, only high-end prodcts will be leased, and refurbishment will only take place once. Remanufacturing is left out of scope because the model will be built on product-level. Due to the uncertainty of the position of companies on refurbished high-end products (whether they are considered high-end or low-end), two scenarios involving refurbished products are made.
RL scenarios -
Scenario **1)** Leasing high(er)-end products - returning EoL-products will be scrapped;
Scenario **2)** Leasing high(er)-end products - returning EoL products will be refurbished and leased once more - returning EoL refurbished products will be scrapped;
Scenario **3)** Leasing high(er)-end products - returning EoL products will be refurbished and sold as refurbished products
To enable the profitabilty analysis, financial information can be added to the stocks and flows according to table 4.

	BAU	Lease	Lease-Refurb.-Lease	Lease-Refurb.-Sell
Revenue				
Retailer buying price for new product	X			
Retailer buying price for refurbished product				X
Monthly fee for new product (minus VAT)		X	X	X
Monthly fee for refurbished product (minus VAT)			X	
Costs				
Manufacturing cost	X	X	X	X
Refurbishment cost			X	X
Monthly maintenance costs covering		X	X	X
Monthly logistical costs covering		X	X	X
Monthly spare parts costs covering			X	X

Table 4: Overview of the scenarios and suggested associated costs and revenues

3.2 Modelling

		METHOD	DESCRIPTION	DATA REQUIREMENTS	SOURCE(S)	LEVEL	UNIT	YEAR	GEO-GRAPHY	APPEN-DIX
theoretical methods	Industrial Ecology	Carnegie-Mellon model (EoL model)	estimation of the size of use, reuse, storage stocks and waste flows to EoL destinations	- POM sales quantity	- **company data**	- product	- pcs	- 2005-2016	- NL	- confid.
				- consumer info (B2B/B2C)	- N/A*	-	-	-	-	-
				- 1st use average product life	- N/A	-	-	-	-	-
				- reuse average product life	- N/A	-	-	-	-	-
				- average storage time	- N/A	-	-	-	-	-
				- TC for reuse	- Hendriksen (2009)	- SHA type (3)	- % pcs	- 2006	- NL	- B
				- TC for storage	- Hendriksen (2009)**	- SHA type (3)	- % pcs	- 2006	- NL	- C
				- TC for EoL destinations	- Hendriksen (2009)	- SHA type (3)	- % pcs	- 2006	- NL	- D
		Sales-lifespan distribution model	calculating the waste generation from sales with a Weibull distribution	- POM sales quantity	- **company data**	- product	- pcs	- 2005-2016	- NL	- confid.
				- product weights	- **company data**	- product	- kg	- 2005-2016	-	- confid.
				- discard distr. func. parameters	- Baldé et al. (2015a)	- UNU-key	-	- 2015	- NL	- A
				- TC for EoL destinations	- Hendriksen (2009)	- SHA type (3)	- % pcs	- 2006	- NL	- D
					- Huisman et al. (2014)	- WEEE cat.	- % kg	- 2010	- NL	- E
	CLSC management	Installed base forecasting	estimates the stock size from sales on repair/replace decisions of consumers based on the perceived value of the product	- POM sales quantity	- **company data**	- product	- pcs	- 2005-2016	- NL	- confid.
				- retail price	- **company data**	- product	- €	- 2005-2016	- NL	- confid.
				- expected min. product lifespan	- **company data**	- product	- yr	- 2016	- EU	- confid.
				- survival function parameters	- N/A*	-	-	-	-	-
				- average repair costs	- N/A*	-	-	-	-	-
		Marginal Reuse rate	calculating how many fewer new products are needed	- sales distribution function	- N/A	-	-	-	-	-
				- discard distr. func. parameters	- Baldé et al. (2015a)	- UNU-key	-	- 2015	- NL	- A
case study	RL modelling	lease stock and return flow modelling	stock and outflow modelling of leased products with using a set maximum leasing duration	- company's expected min. product lifespan	- **company data**	- product	- yr	- 2015	- EU	- confid.
				- average product stock lifespan based on scale parameter	- Baldé et al. (2015a)	- UNU-key	- yr	- 2015	- NL	- A
				-- average product stock lifespan	- Hendriksen (2009)	SHA type (3)	- yr	- 2006	- NL	- F
		separate high-end low-end products	serve the case study scope by focus on high-end only	- price based categorization	- UNETO-VNI (2014)	-SHA type (2)	- €	- 2014	- NL	- J
	consistency check	C&R outflow consistency check	checking the outflow size with real world data on C&R	- real C&R data recycled on behalf of the company	- Company recycling partner WeCycle	- WEEE cat.	- kg	- 2015	- NL	- G
		Stock diffusion consistency check	checking stock size with real world data on product ownership in HH	- total product stock	- Hendriksen (2009)	- product group	- pcs	- 2006	- NL	- H
				- number of HH in the NL	- CBS Statline	-	- HH	- 2000-2040	- NL	- I
				- company's product market share	- **company data**	- product group	- %	- varies	- NL	- confid.
		RL modelling consistency check with CBA	checking the scenario modelling with econometric models outcomes	- costs and revenues associated with product/service	- **company data*** **	- product	- €	- 2015	- NL	- confid.
				- econometric model outcomes	- **company data******	- product	- €	- 2015	- NL	- confid.

Table 5: Comprehensive overview of the methods and techniques and their respective data requirements and data availability (both public and company data)
Abbreviations: N/A = not available; confid. = confidential; TC = Transfer Coefficient; cat. = category; min. = minimal; distr. = distribution; func. = function; HH= household; CBA= Cost Benefit Analysis; pcs= pieces; % pcs = share of total pieces; yr= year;
** - data are possibly available within the organization of the company, but requires extensive data collection and thus left out of scope*
*** - as a share of total stock*
**** - considered data for one product only considering time restrictions*
***** - this data is available, but the CBA consistency check is out of scope in this research*

3.2.1 Inventory analysis

3.2.1.1 Data availability

All methods and techniques discussed in the methodology and the goal and scope description are examined on data availability in this section. Table 5 shows the breakdown for all methods and techniques earlier discussed; whether data is available, and, if yes, what the source, unit, year and geography of the data is.

In the theoretical analysis, it is established that the model will be input-driven dynamic MFA with the POM quantity as input. The procedure of preparing POM quantity data will be described as follows. Philips is a large organization with a diverse product portfolio and therefore products will be categorized under certain (sub) groups. Within the Personal Health cluster, there are a set of Business Groups (BG); Coffee, Domestic Appliances, Health&Wellness, Personal Care and Sleep & Respiratory Care. Only the first four BGs will be considered in the case study, since the products in Sleep & Respiratory Care not fall under WEEE category 2 (which is the category that covers SHA). The BGs can be further broken down in Business Units (BU), MAG (Main Article Group) and is presented on a product-level as Article Group (AG). The break-down of the BGs to MAGs is presented in the first three columns in the table in appendix K. For the scope of the project, the focus is on EEE on a product-level, so non-EEE, accessories, parts need to be filtered out. Furthermore, the available POM quantity data is for the years 2005-2016. However, this timespan does not represent all years that the products might have been on the market.

To proceed, all methods and techniques shown in the overview in table 5 will be examined on applicability. Regarding the theoretical methods, the gaps between theory and practice will become clear. Furthermore, the data requirements for the case study specific approaches will be matched with available data where possible. The result of this inventory analysis is to provide the final modelling options for the deliverable.

3.2.1.1.1 Theoretical methods

Carnegie-Mellon model

The Carnegie-Mellon model is based on product unit quantity and requires a lot of data relative to the other methods. One of the considerations in the Carnegie-Mellon model is that it regards the product flows for the B2B and B2C market differently. According to Huisman et al. (2012), it can be assumed that around 100% of EoL products in the B2B market will go into official scheme recycling or complementary scheme recycling. In the B2C market, the flows are less predictable and have 'lost' flows, such as EoL products ending up in the residual waste stream. Unfortunately, when collecting data in this case study, there was no central database accessible with market information on the sold products. This information could be added in future research, but within the time scope of this project, it will be assumed that all products will be sold to the B2C market.

Furthermore, the Carnegie-Mellon model will provide more insight to more product life stages than other methods, such as storage and reuse. The model requires the average 1st use lifespan, average reuse lifespan and average storage lifespan. Thus far, suitable data have not been found to cover the requirement on lifespan data for the Carnegie Mellon model. However, the study by Hendriksen et al. (2009) provides information on the required transfer coefficients. The sources to derive the transfer coefficients used for reuse and EoL destinations can be found in appendix B and D respectively. Determining the size for storage is not derived from modelling the product flow, but by applying the stored products' share to the total stock (see appendix C). The study by Hendriksen et al. (2009) applies the parameters on SHA in three groups; Kitchen, Personal Care and Other (e.g. vacuum cleaners and air conditioners. How the three groups apply to Philips' products can be seen in the table in appendix K.

The gathered data for the Carnegie-Mellon model displays many data gaps that need to be filled in order to make the model run. However, the search for the average lifespan and transfer coefficients have lead to interesting findings, such as the share of stored products. Nevertheless, one must keep in mind that the data is from 2006 and will likely be outdated. Unfortunately, there is no more modern survey available that is as rich in data as the study by Hendriksen (2009).

Sales lifespan distribution model

All data requirements for this method can be met. As stated before in the Methodology chapter, the United Nations University (UNU) provides Weibull distribution function parameters to create probability discarding distribution functions. The UNU-keys are structured by WEEE category, and for WEEE category 2 there are 5 UNU-keys; 202-Food, 203-Hot Water, 204-Vacuum Cleaners, 205-Personal Care and 201-Other. How the categories correspond with the Philips portfolio can be seen in appendix K. The UNU-keys and the corresponding scale and shape parameter suitable for the Netherlands, Belgium and France is shown in Appendix A. According to Magalini et al. (2016), there is a relatively high margin of error of +/- 33% to +/-37% for WG weight in the Netherlands for a sensitivity analysis with 30% shorter and 30% longer average lifespans for all 54 UNU-key categories.

There are two different sources found that can be used to calculate the size of the C&R weight. As mentioned in the description of the Carnegie-Mellon model, the study by Hendriksen (2009) provides unit quantity based transfer coefficients for different EoL destinations based on 3 different SHA groups. Once the size of the outflows to the different destinations are calculated, the products can be converted into weight to make a weight-based C&R rate assessment. The study by Huisman et al. (2012) provides insight to the WEEE category 2 group and its weight-based performance on recycling. The C&R rate found for 2010 could be applied to 2016. Both sources can be used, but this case study will work focus on the data provided by Hendriksen (2009) because this study elaborates on consumer behavior on discarding different product types within the SHA category (e.g. electric toothbrushes are more likely to end up in residual waste than a larger, heavier vacuum cleaner). With the use of the data from the study by Huisman et al. (2012) the product composition would be the same for each waste stream for lack of more disaggregated information.

Installed Base forecasting

The IB forecasting method relies solely on in-house data. The products are grouped on monetary value and therefore can be categorized using the retail price of the products. In this case study, the company's sales database provides POM quantity data coupled with the total revenue made from the sold products. The revenue made by sales from the products is based on the retailers' buying price. The price for the products were assumed to be the *((total revenue/unit quantity) + 50% (retail margin) + 21% VAT)*. Also, the minimum expected average timespan for the use phase (referred to as *Philips lifespan* from now on) is available within the company, which is also used in the Lives Improved calculations (Royal Philips, 2016). Due to the Dutch consumer laws for EEE warranty, it is expected that similar figures are also available in other companies in the same sector.

The survival distribution function parameters (based on the failure rate) and the average repair costs are likely to be retrieved from the reliability engineering department(s). However, there was no centralized database containing this information found within the researcher's reach. Instead, it would require manual collection of that data, which the time restriction did not allow. So overall, the data requirement for the IB forecasting method can be met, but the data should be organized centrally for retrieving the data within the scope of this case study.

<u>Marginal Reuse rate</u>

While the Marginal Reuse rate incorporates the concept of calculating the reduction of input from new products or parts, its application is unrealistic. Firstly, the sales distribution function (i.e. the representation of 'introduction', 'growth', maturity' and 'decline' of sales) is not easily applied to the real world. Sales of a product is often cut abruptly or milked for a longer time than predicted by the product lifecycle curve. Furthermore, the discarding distribution function and its parameters are provided by Baldé et al. (2015a), but these would only apply to an open loop chain where the products do not return to the company. Return from leases will not be calculated through a probability distribution function, but rather from a predictive algorithm. Although the Marginal Reuse rate as presented by Umeda et al. (2006) cannot be applied is described in the study, the concept of calculating the number of reused products and decline in new products by comparing the return flow with the original BAU input flows can still be applied in the case study.

3.2.1.1.2 Case study specific

Now, the modelling decisions and techniques derived from the goal and scope of this case study and the data availability will be explored.

<u>Lease stock and return flows modelling</u>

When calculating the stock and return flows for leased products, it is assumed that the 100% of the products will stay in use within the set lease duration. Once the lease duration has expired, the products will return immediately. The only data needed to model this, is the lease duration of the product. The source could be the expected average lifetime set by the company. However, the averages set by the company are conservative and can be assumed as *minimum* expected average lifetimes, simply because the company cannot prove to auditors the actual average time their product are used in households. What the company data on average lifetime does reflect more accurately is the difference in lifetimes for more expensive, higher quality products versus cheaper products. Public data on average product lifespans based on product functionality groups can be derived from the study by Baldé et al. (2015a), by calculating the average lifespan from the scale parameter (see appendix A), and from the study by Hendriksen (2009) - see appendix F. These average lifespans are longer than the ones set by the company, but are also set on a more aggregated level and accounts for other companies' products and therefor are not accurate. Instead, the modelling will focus on the Philips lifespan and add an appropriate number of years to represent a more realistic average lifespan.

<u>Separation of high-end and low-end products</u>

As discussed before in the RL scenario definitions, the RL modelling will only focus on RL strategies for high-end products. The UNETO-VNI released a sheet with the suggested years of warranty based on the retail price of the consumer electronics to give consumers a method to assess whether they are in the rights of receiving full repair coverage under the Dutch consumer law. Two product categories apply to Philips; the Full Automatic Espresso Machine (FAEM) group, further divided into 3 price categories, and the SHA group, further divided into 2 price categories (see appendix J). This case study will focus on the high-priced category for the SHA group and the 2 high-er priced (assumed mid-end and high-end) categories for the FAEM group.

<u>Consistency check - C&R outflow size</u>

One of the main goals of the research project is to create insight on what currently happens after the point of sale of SHA in the Netherlands by finding out how to relate the historical sales data to the real-world C&R data. At the end of each year, WeCycle reports how much WEEE weight is collected and recycled on behalf of Philips (see the certificate in appendix G). Since WEEE will not be separated by brand prior to processing, a top-down method is used for calculating the share of Philips C&R weight. WeCycle combines the entire yearly C&R weight by WeCycle and WEEE NL (the other official recycling scheme in the Netherlands) as the starting point of the calculation. In 2015, WeCycle and WEEE NL both collected and recycled 6,839 T of WEEE. Additionally, WeCycle's partner companies, which are major EEE producers that are active in the Netherlands, report their EEE POM weight for 2015 (whole products - no accessories or parts). From all EEE POM weight by all producers Philips' share is calculated and this share is applied to the C&R weight. This calculation is based on the current sales and not based on the 'source years' of the WEEE that end up in the C&R stream in 2015. Therefore, the C&R weight processed on behalf of Philips is not an accurate representation of reality. However, the WeCycle report does provide an upper limit (i.e. the 6,839 T of total C&R weight) and provides an amount which the C&R weight calculations from the BAU simulation model should approach. In order to pass this consistency check, the C&R weight results computed by the model should be lower than the physical upper limit of 6,839 T.

Consistency check - stock size
Besides checking the consistency of the model with real world data on C&R, it would also be possible to check the stock size with real world data. The consumer survey study by Hendriksen (2009) provides the total amount of SHA products currently in stock on a relatively disaggregated level (see appendix H). With this data, it is possible to get the household diffusion figures for the products when dividing the stock quantities with the number of households (resulting in the product diffusion). The stock quantity by Hendriksen (2009) accounts for 2006, so the figures have to be divided by the number of households in the Netherlands in 2016 (provided by CBS Statline, see appendix I for the overview of historical and projected number of households). When assuming that the product diffusion in 2006 is roughly the same as the product diffusion in 2016, it is possible to derive the market share of the products when comparing the product diffusion with the stock quantities computed by the model. Firstly, the stock size for the products cannot be higher than the product diffusion numbers. Secondly, the market share data can then be checked with those that are knowledgeable about product market shares. In the case that in-house market share knowledge is available, the model can be deemed consistent when the computed market shares are similar to the real market shares. However, in the case of this case study, the model is deemed consistent when the average number of Philips products per household does not surpass the product diffusion numbers provided by Hendriksen (2009).

LIFECYCLE STAGE	CONFIGURATION
in-use	SLS_{stock} - (SLS_{stock} * % hibernation)
hibernating	(SLS_{stock} * % hibernation)
stock	SLS_{stock}
outflow	$SLS_{discard}$
useful return flows	predictive algorithm for lease returns

Table 6: Overview of the applicable methods calculations
SLS = Sales Lifespan distribution function

Unfortunately, there is no more recent study with detailed stock information available as is presented in Hendriksen (2009). It is likely that the product diffusion numbers have changed in the last 10 years, so for some product types the market share might be off and will need some extra research to explain the discrepancy.

Consistency check - Cost Benefit Analysis
In the scope, it is stated that a consistency check through CBA will not be executed in this research. However, the model will provide the opportunity to do so. Financial information on lease business model has only been provided for one product; the GranBaristo, a FAEM that falls under the high-end category under the UNETO-VNI guidelines (see appendix Q.1). So, when applying financial information to the MFA to make a CBA possible with econometric RL models, it will be only done for one product and will serve as an example. The data provided for the lease business models are not based on the same RL scenario and do need tweaking, but the data provide figures on which this case study's RL scenario costs and revenues can be based (see appendix Q.2 for the assumptions for costs and revenues).

3.2.1.2 Conclusion
The inventory analysis is used to bridge theory with practice by delving into the data requirement needed for the theoretical methods. This conclusion of the inventory analysis will go over the current possibilities of calculating stocks and flows and what could be the future possibilities for the non-applicable options.

Reflecting on table 3, it is possible to make the method configuration from the empirical analysis. Table 6 shows which methods will be used for the model based on the data availability. The Sales Lifespan Distribution method will be applied as the method for calculating stock and outflow size. Although the IB forecasting method will not be applied in this model, one of the main principles of the IB forecasting method will be integrated in another way. That is by providing the opportunity to make distinctions between the more durable products and less durable products by creating the option of using scale parameters with Philips lifespans. A more realistic average lifespan for a Philips product could be calculated easily by e.g. adding 2 years or 30% of the Philips lifetime. Although this is not proven yet, the option will be included in the model to make the model more versatile nonetheless.

The IB forecasting method runs on data that could be made available in-house. The organization could choose to start collecting and centrally report the data so this method could be applied in the future, but for now this method is left out of scope. As for the Carnegie-Mellon model, it cannot be applied since it lacks the average lifetime for the different lifecycle stages. This method will require years of extensive consumer observation, so this method is not considered applicable soon. However, the principles of the Carnegie-Mellon method, i.e. providing insight to the size of the stock and flows for different in-stock lifecycle stages, will be included by using the share of unused and defect products that are in-stock to calculate the size of hibernating stock from the total stock.

Regarding the Marginal Reuse rate, using sales and discarding probability distribution functions will not be considered, but the main concept will be applied in the model to calculate how many fewer new products are needed as input in a RL scenario compared to the BAU simulation.

Considering the lease return modelling, it is most logical to base the lease duration on the expected minimum lifespan. Since the expected minimum lifespan are generally a lot lower (3-7 years) than the other found average lifespan resources (roughly 8-12 years), it should be possible to increase the Philips lifespan data.

For the stock size and C&R outflow consistency checks for the BAU simulation model it is not necessary to approach the real-world data to a single digit. However, the real-world data do provide physical upper limits and can ultimately give an indication whether the outcome is realistic or not. Regarding the CBA consistency check, financial information will be added to one product, but it is assumed that the financial information could be applied proportionally to other products as well.

How all this data will be processed in the model, will become clear in the next section; the operational steps.

3.2.2 Operational steps

This section will cover the build-up of the model, which is broken down in sequential operational steps. This section will describe the model by going through the different so-called stages of the model, shown in figure 12. It is recommended to read this section as a two-page spread rather than individual pages, because for each stage the flowchart and the description will be displayed separately on facing pages. Each stages is broken down in so-called blocks, which are clusters of operational steps that together produce an intermediate output. Lastly, all blocks are further broken down in sequential operational steps using flowcharts shapes as the means of illustration. The functions of the different shapes of the flowcharts can be looked up in appendix L.

Seen in figure 12, the consistency check is incorporated as a “go-no go” step rather than an evaluation step after building the entire model. When the BAU simulation model outcomes have been evaluated the for consistency with the real world for existing data, the projections for 2030 can be considered useful. If the outcome from the consistency checks are not considered consistent with real-world data, the used parameters and/or input need to be revised.

The results from the assessments, consistency checks and sensitivity analyses will be presented and discussed in section 3.3 Result interpretations.

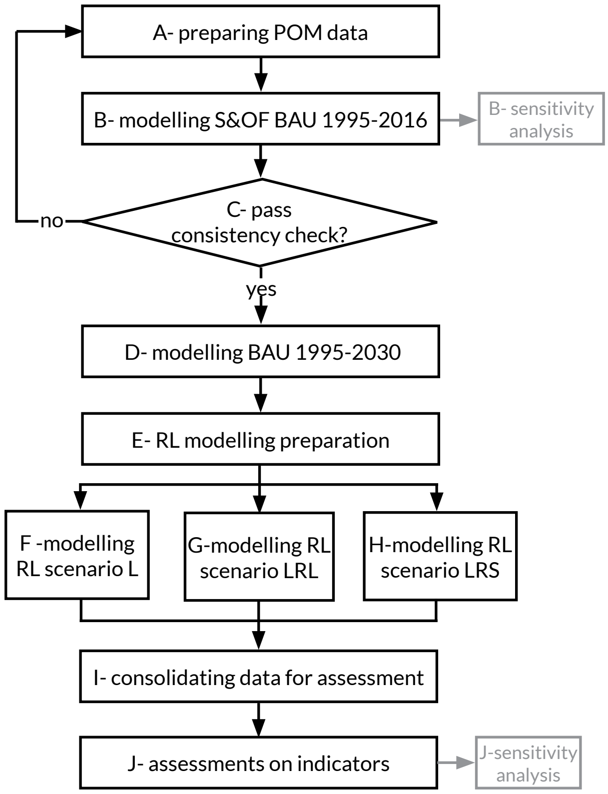


Figure 12: Stages of the model

3.2.2.1 *Stage A - Preparing POM data*

This stage of the model will prepare different data sets that will be used as input in the stock and outflow modelling stage. The flowchart can be seen on the page on the right. In favor of a clearer description of the flowchart, the processes, inputs and outputs are divided into 5 blocks.

Block A.1 - Filtering POM data

The Personal Health POM quantity is extracted from the database on product-level (AG) with the corresponding years, the corresponding revenue for the product, the country and the associated in-house categories (i.e. MAG, BU and BG) from the company database. This will be followed up by filtering out the non-SHA category Sleep & Respiratory Care, accessories, parts and non-categorized products and finally also by filtering out non-EEE.

Block A.2 - Adding dimensions

The basics of building the model is to add dimensions (columns) to the product on the AG-level. Based on these dimensions, which are characteristics, categorizations and parameters related to the categories, measurements can be made and also allows for filtering products on these dimensions. In this case study, the list contains 186 different AG-level products. Based on the outcome in the inventory analysis, the following dimensions are added to each product; product weights, Philips lifespan, B2B/B2C info (if available), corresponding UNU categories and their scale and shape, corresponding SHA categories used in Hendriksen (2009) and their EoL channel transfer coefficients and, lastly, the high-end/low-end categorization according to the UNETO-VNI chart.

Block A.3 - preparing 3 historical sales scenarios

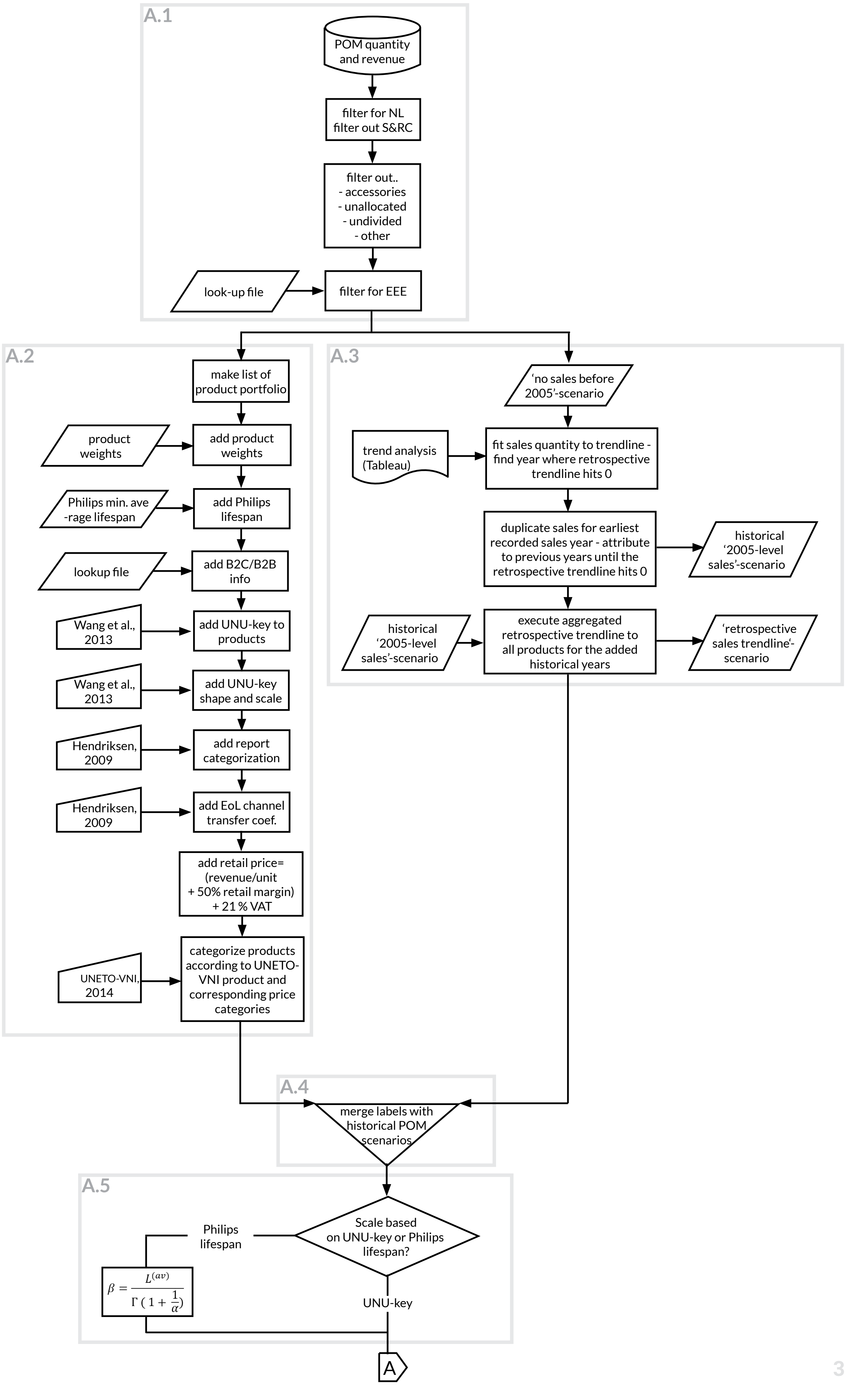
The POM quantity data have only been provided for 2005-2016. As discussed in the scope, the POM quantity data will be retrospectively extrapolated to the year where POM quantity=0 and, furthermore, the two extreme historical sales extrapolations (i.e. ‘no sales before 2005’ and ‘2005-level sales‘ scenarios) will be used for the sensitivity analysis. The output from block A.1 can be directly used as the ‘no sales before 2005’-scenario POM data. This data is then also used to find the trendline function for the retrospective extrapolation with a trend analysis. Tableau was used for the regression analysis. According to the trend analysis, POM quantity=0 around 1995. Because the assumed stock start is now known, it is possible to prepare the second historical sales scenario. This extreme scenario duplicates the sales of 2005 for all years back until 1995. Then lastly, to build the retrospective sales according to the trendline, the trendline function is applied for the aggregated POM quantity. Since the time series data is based on whole years, the year for which POM quantity=0 was added manually for 1995. In appendix M, you will find the graphs for the different sales extrapolations and how it breaks down on the BU-level

Block A.4 - Merging sales figures with product labels

The product labels will be added to the POM quantity outputs by merging the outputs from block A.3 with the output from block A.2.

Block A.5 - Option to use different source for scale

As discussed in the inventory analysis, the model will include an option to use (a configuration of) the Philips average lifetime data to base the discarding probability distribution function on. The use of a scale derived from the Philips lifetime recognizes that more high-end products will likely have a longer average product lifetime. The shape of the distribution function is more related to the type of product and therefore can be kept according to the UNU-keys. The use of this option will not be examined for the time being for reasons explained in the inventory analysis (section 3.2.1.2).


A.1
POM quantity and revenue
filter for NL filter out S&RC
filter out..
- accessories
- unallocated
- undivided
- other
look-up file
filter for EEE
A.2
make list of product portfolio
product weights
add product weights
Philips min. ave -rage lifespan
add Philips lifespan
lookup file
add B2C/B2B info
Wang et al., 2013
add UNU-key to products
Wang et al., 2013
add UNU-key shape and scale
Hendriksen, 2009
add report categorization
Hendriksen, 2009
add EoL channel transfer coef.
add retail price= (revenue/unit + 50% retail margin) + 21 % VAT
UNETO-VNI, 2014
categorize products according to UNETO-VNI product and corresponding price categories
A.3
'no sales before 2005'-scenario
trend analysis (Tableau)
fit sales quantity to trendline - find year where retrospective trendline hits 0
duplicate sales for earliest recorded sales year - attribute to previous years until the retrospective trendline hits 0
historical '2005-level sales'-scenario
historical '2005-level sales'-scenario
execute aggregated retrospective trendline to all products for the added historical years
'retrospective sales trendline'-scenario
A.4
merge labels with historical POM scenarios
A.5
Scale based on UNU-key or Philips lifespan?
Philips lifespan
$\beta = \frac{L^{(av)}}{\Gamma\left(1+\frac{1}{\alpha}\right)}$
UNU-key
A

3.2.2.2 Stage B - Modelling S&OF BAU 1995-2016

This stage involves the calculation of the stock and flow sizes in quantity and weight for the three different retrospective POM quantity extrapolation. The last step of the stage is doing a sensitive analysis on all outcomes.

Block B.1 - Computing stock and outflow (S&OF)

This block contains an iterative feature based on counter *n*. Since the POM quantity data starts a 1995, there is a need to make at least (2016-1995=) 21 computations to calculate the stock and outflow in 2016 from products sold in 1995. Every computation *n* stands for the stock and outflow for year POM+*n* from product sold in year POM. For example, when *n*=3, the S&OF size is calculated for 1998 for products sold in 1995, the S&OF size is calculated for 2013 for products sold in 2010, and so on. The calculations for the stock and outflow is based on the Weibull distribution function and calculated with the shape and scale parameters connected to the product. The stock size is calculated with a Cumulative Distribution Function (CDF) by inverting the CDF for the outflow distribution function (equation 10).

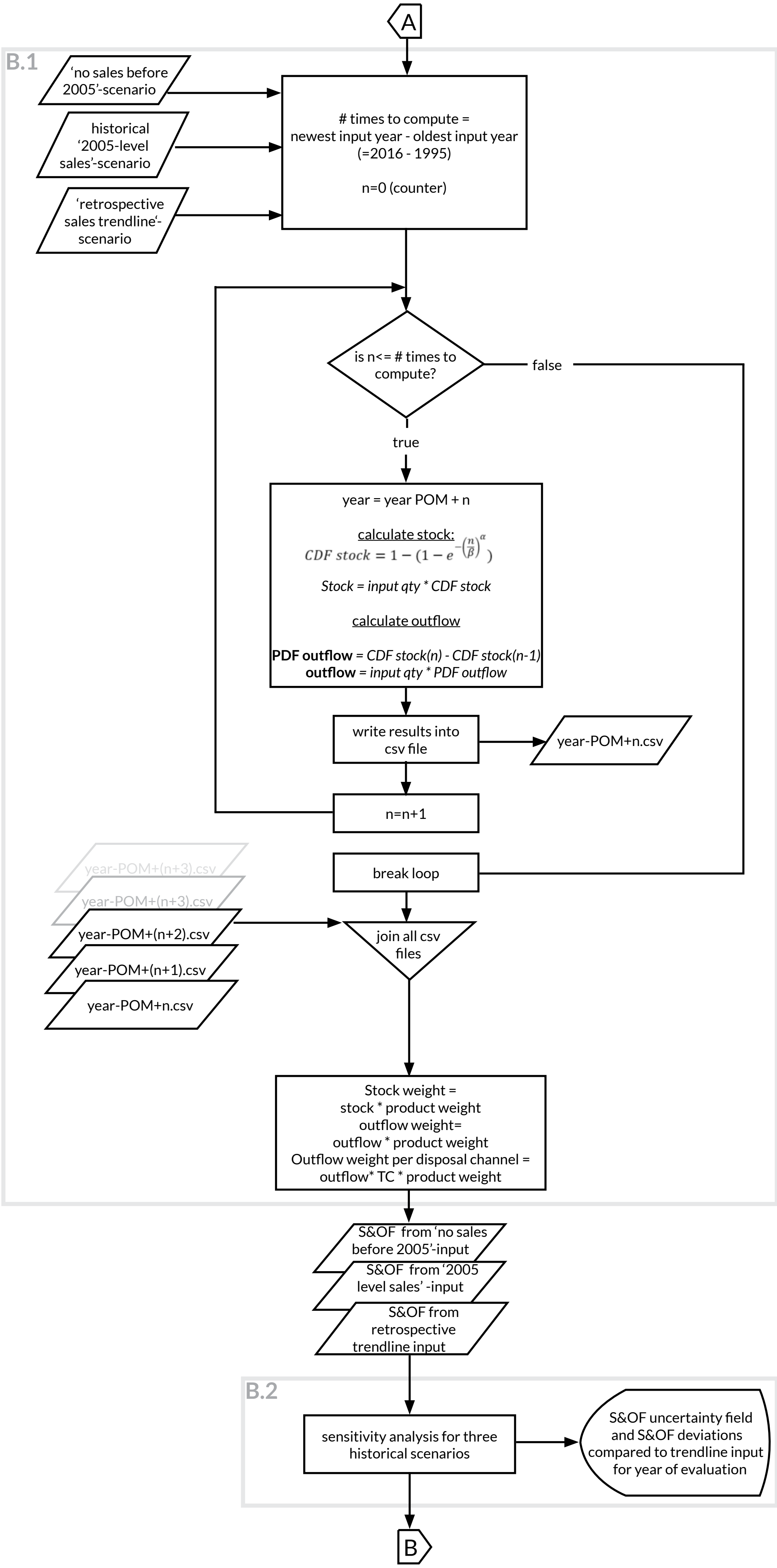
Eq. 10) $$CDF\ stock = 1 - (1 - e^{-\left(\frac{n}{\beta}\right)^{\alpha}})$$

The outflow from the Probability Distribution Function (PDF) can be calculated with using the PDF as described in equation 6 or it can also be calculated with the difference in stock size compared to the previous year. The latter method is applied in the model.

For computation n=0 to n=21, the results will be exported to a Comma-Separated-Values (CSV) file. All 22 CSV files will then be merged into one file. This output contains the S&OF size in unit quantity. However, for the sensitivity analysis and consistency check, it is necessary to include the conversion of the S&OF in weight. So, the stock and outdflow is converted into weight with the corresponding product weights.

Block B.2 - Sensitivity analysis historical POM

A sensitivity analysis can be done here based on the stock and flow results for the retrospective extrapolations by having fed all three retrospective POM extrapolations into block B.1. The two extreme historical projections will reveal the uncertainty field for the S&OF quantity and weight. Furthermore, the deviation for the S&OF quantity and weight compared to the trendline extrapolation will be calculated.


A
B.1
'no sales before 2005'-scenario
historical '2005-level sales'-scenario
'retrospective sales trendline'-scenario
# times to compute = newest input year - oldest input year (=2016 - 1995)
n=0 (counter)
is n<= # times to compute?
false
true
year = year POM + n
calculate stock:
$CDF\ stock = 1 - (1 - e^{-\left(\frac{n}{\beta}\right)^{\alpha}})$
Stock = input qty * CDF stock
calculate outflow
PDF outflow = CDF stock(n) - CDF stock(n-1)
outflow = input qty * PDF outflow
write results into csv file
year-POM+n.csv
n=n+1
break loop
year-POM+(n+3).csv
year-POM+(n+3).csv
year-POM+(n+2).csv
year-POM+(n+1).csv
year-POM+n.csv
join all csv files
Stock weight = stock * product weight
outflow weight= outflow * product weight
Outflow weight per disposal channel = outflow* TC * product weight
S&OF from 'no sales before 2005'-input
S&OF from '2005 level sales' -input
S&OF from retrospective trendline input
B.2
sensitivity analysis for three historical scenarios
S&OF uncertainty field and S&OF deviations compared to trendline input for year of evaluation
B

3.2.2.3 *Stage C - Consistency checks*

In this stage, the output from stage B will be checked on the consistency with real-world data. Block C.1 covers the consistency check on the C&R weight outflow and block C.2 covers the stock size consistency check. The outcome of the consistency checks must be evaluated on the criteria in order to decide to continue building for future scenarios.

Block C.1 - C&R outflow consistency check

There are two sources available on which the C&R outflow size can be based. The first source is the national weight-based SHA WEEE C&R rate calculated for 2010 by Huisman et al. (2012) (see appendix E). The outflow weight calculated in the previous stage will be multiplied with the C&R rate. Since we assume all products to be sold to the B2C market, we have a weight-based C&R rate of 1.6 [kg/hh]/(6.20 [kg/HH]-0.23 [kg/HH])= 26.8%.

The second and more insightful source are the Transfer Coefficients (TC) for the EoL channels for the three different SHA product types according to Hendriksen (2009) (see appendix D). From all 5 EoL-channels (i.e. 'WEEE pick-up service', 'WEEE collection point', 'return to retailer', 'household waste' and 'other'), it is agreeable that most of the products through the 'WEEE pick-up service' and 'WEEE collection point' will end up at the official recycling scheme, since these two EoL-channels are mostly directed by municipalities. For the 'return to retailer'-channel it is unclear whether most/all partners are partnered with WeCycle or WEEE NL. However, this stream is relatively small, so it will be considered a C&R channel regardless. Next, the outflow size for the 3 EoL channels must be converted to weight by using the product weights.

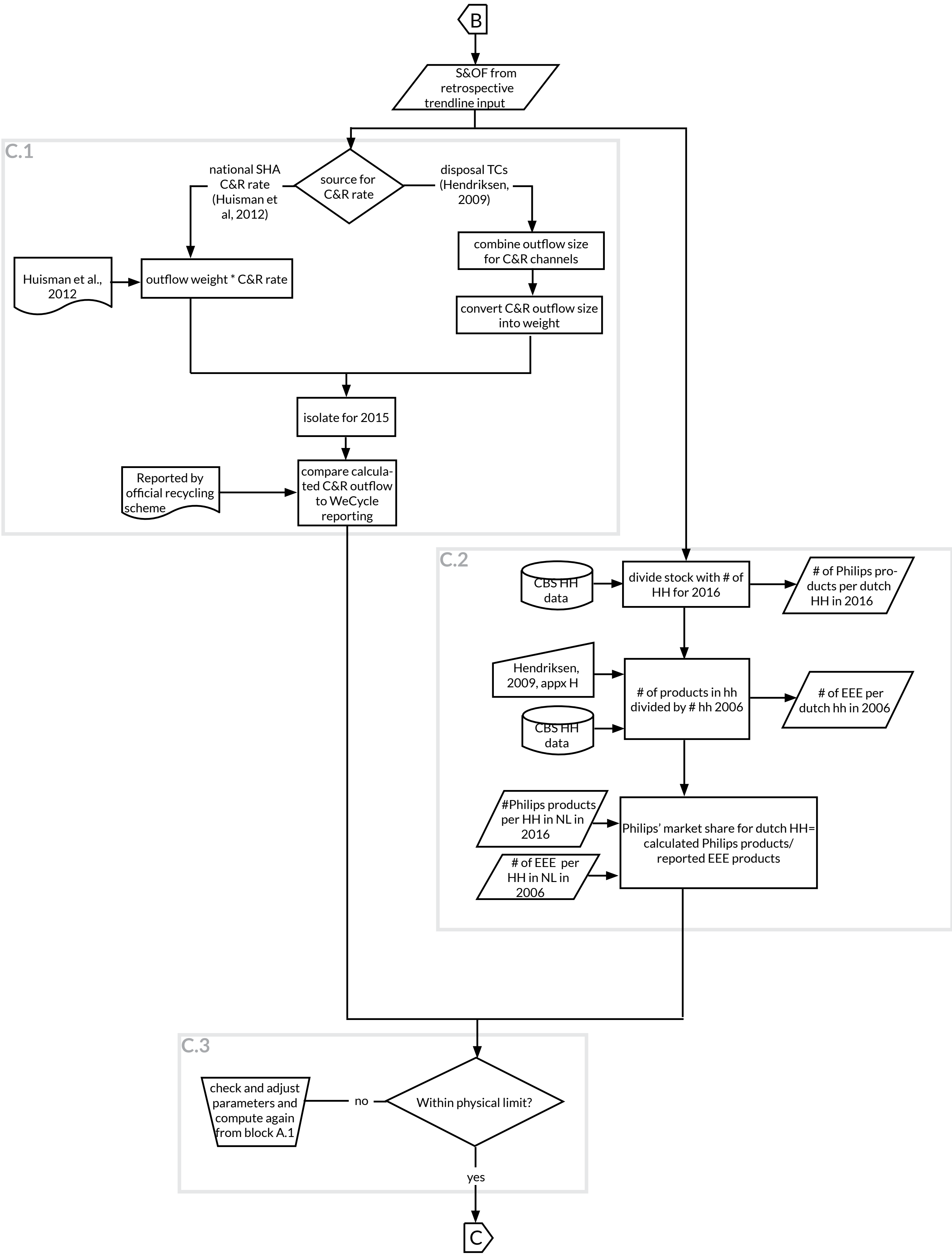
Depending on preferences of the user, the C&R outflow weight can be checked by using one of the two C&R rate sources. The C&R outflow for 2015 can then be compared with the reported C&R weight by WeCycle for 2015.

Block C.2 - Stock size consistency check

The study by Hendriksen (2009) provides detailed stock information (see appendix H). The results are accounted as total units in-stock in the Netherlands in 2006. To make the data comparable to the stock size calculated by this project's model, it is necessary to conform both stock data to the number of households (i.e. the product diffusion) for the corresponding years. The market share of Philips' products can then be calculated by dividing the Philips' product diffusion figure by the product diffusion figure for EEE of all brands,

Block C.3 - Consistency check evaluation

The model and the further future projections of the model can only be useful if both the stock and flow are considered consistent with reality. The criteria within the scope of the case study is that the results computed by the model must fall within the physical limits of the real-world data for the C&R outflow and product diffusion. Should the outcomes be deemed inconsistent with real world data, it is advised to revisit the input, parameters and/or change the source for calculating the scales and run entire model again until the result at the consistency check will be satisfactory.


B
S&OF from retrospective trendline input
C.1
national SHA C&R rate (Huisman et al, 2012)
source for C&R rate
disposal TCs (Hendriksen, 2009)
combine outflow size for C&R channels
Huisman et al., 2012
outflow weight * C&R rate
convert C&R outflow size into weight
isolate for 2015
Reported by official recycling scheme
compare calculated C&R outflow to WeCycle reporting
C.2
CBS HH data
divide stock with # of HH for 2016
# of Philips products per dutch HH in 2016
Hendriksen, 2009, appx H
# of products in hh divided by # hh 2006
# of EEE per dutch hh in 2006
CBS HH data
#Philips products per HH in NL in 2016
Philips' market share for dutch HH= calculated Philips products/ reported EEE products
# of EEE per HH in NL in 2006
C.3
check and adjust parameters and compute again from block A.1
no
Within physical limit?
yes
C

3.2.2.4 *Stage D - Modelling S&OF BAU 1995-2030*

This stage involves the preparation of the future sales until 2030 for the BAU simulation and the calculation of the stock and outflow from the simulation.

Block D.1 - Prospective extrapolation of POM data

As described in the case study scope, the model will initially provide the outcomes for the conservative'2016-level' sales projection, but the outcomes are going to be checked with the optimistic 'trendline' sales projection. The extrapolation for the two sales projections are made in the same fashion as the retrospective extrapolation in block A.3. The main sales projection, the 'future 2016-level sales'-input, is made through duplicating the 2016 POM quantity for the years 2017-2030. The scenario for the sensitivity analysis, the 'future sales trendline'-input, uses the same trendline as used in block A.3 to calculate the future POM quantity for 2017-2030. For both scenarios, it is assumed that no products will be discontinued after 2016, although this is unlikely to happen in reality. The results of the prospective extrapolations can be seen in appendix M.4 and M.5

Block D.2 - Computing stock and outflow (S&OF)

With the same operations used in block B.1, the S&OF sizes (in weight and unit quantity) will be calculated for 1995-2030.

3.2.2.5 *Stage E - RL modelling preparation*

This stage involves the preparation of the input data and S&OF data that will be used for the 3 RL scenario modelling.

Block E.1 - Calculating aggregated stock size for lease

First, the BAU S&OF will be filtered for high-end products sold from 2016 on. Second, when leasing products, it is in theory not possible to produce hibernating stock (i.e. unused products or defect stored products). Therefore, the share of stored and defect products (see appendix C) have to be subtracted from the calculated aggregated stock for the high-end products for BAU (demonstrated in figure 13). This is the stock size (in unit quantity) that needs to be satisfied with leased products.

Block E.2 - Preparing input for lease

In this block, the initial input for the RL scenarios is prepared. The BAU input is filtered for high-end products and for year POM=2016. We will need only the 2016 input, as the lease inputs for following years will be calculated with the stock size in the RL modelling. Lastly, the lease duration will be determined by the Philips lifespan times *x*, *x* being a variable that can be determined by the user. For example, when the products will be leased, the lease duration will be 130% of the Philips lifespan. The 130% will then be used as the input for x. Since the time series is based on whole years, the lease durations will always be rounded down to a whole number.

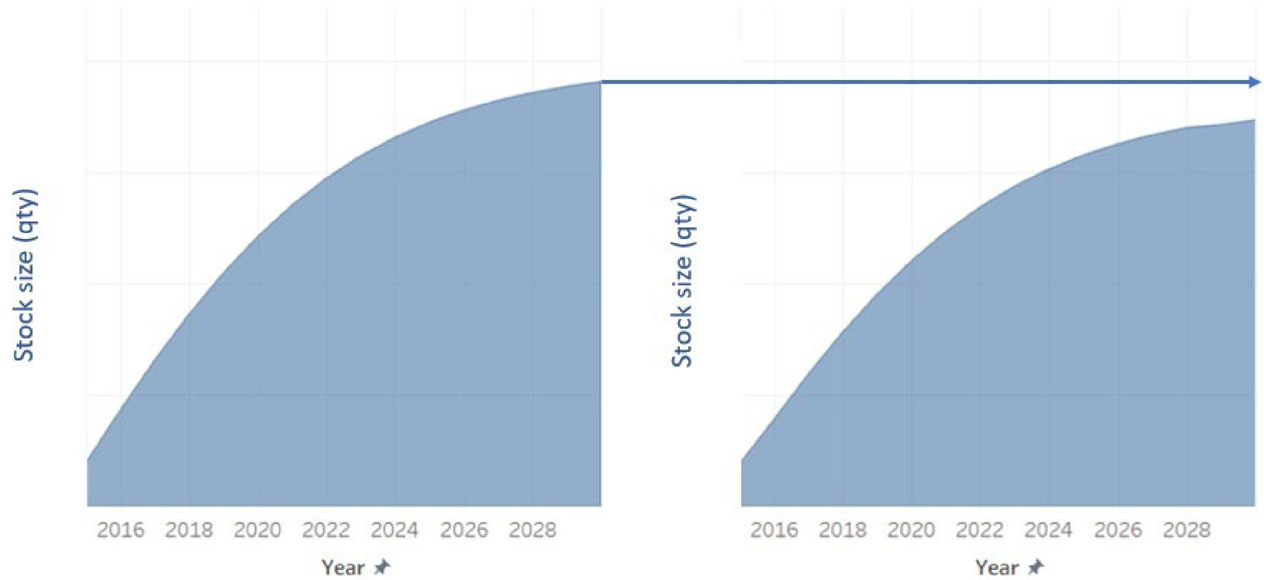
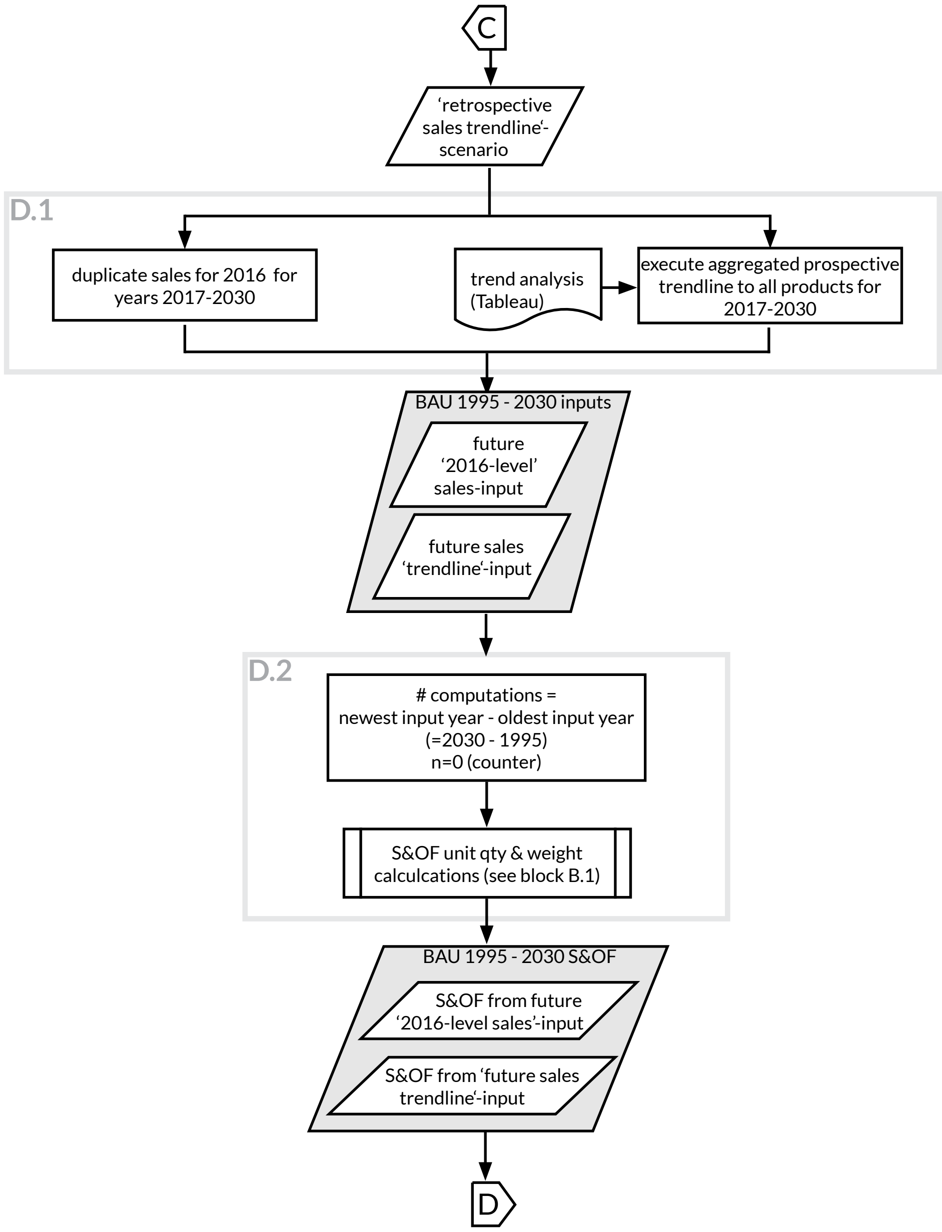
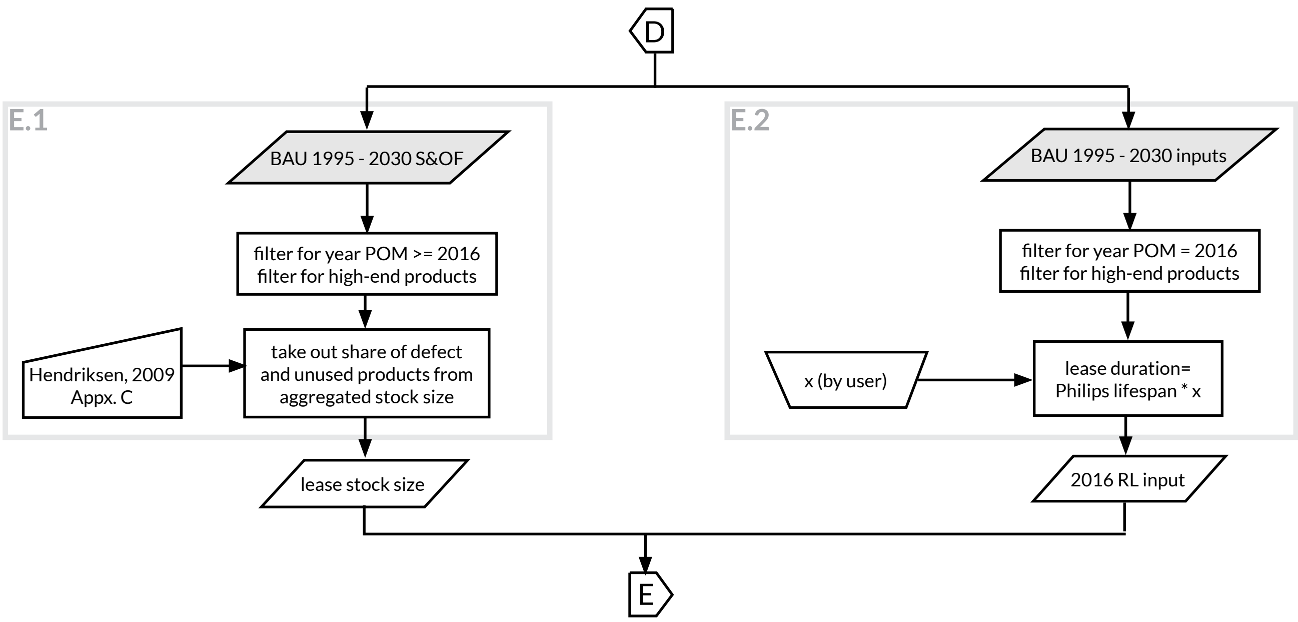


Figure 13: Illustration of the aggregated stock size for BAU (left) and the aggregated stock size for leased products, where the share of hibernating products is removed


C
'retrospective sales trendline'-scenario
D.1
duplicate sales for 2016 for years 2017-2030
trend analysis (Tableau)
execute aggregated prospective trendline to all products for 2017-2030
BAU 1995 - 2030 inputs
future '2016-level' sales-input
future sales 'trendline'-input
D.2
computations = newest input year - oldest input year (=2030 - 1995) n=0 (counter)
S&OF unit qty & weight calculcations (see block B.1)
BAU 1995 - 2030 S&OF
S&OF from future '2016-level sales'-input
S&OF from 'future sales trendline'-input
D


D
E.1
BAU 1995 - 2030 S&OF
filter for year POM >= 2016 filter for high-end products
Hendriksen, 2009 Appx. C
take out share of defect and unused products from aggregated stock size
lease stock size
E.2
BAU 1995 - 2030 inputs
filter for year POM = 2016 filter for high-end products
x (by user)
lease duration= Philips lifespan * x
2016 RL input
E

3.2.2.6 *Stage F - RL scenario 1 - lease once (L)*

This stage will cover the RL scenario where the products are leased for the provided lease duration with the goal of satisfying the BAU in-use stock size through a stock-driven input model (illustrated in figure 14). Block F.1 is the input driven sub-model, that, similar to block B.1, calculates the stock and outflow of the lease products. In block F.2, the new lease input for the following year is calculated by comparing the BAU in-use stock size with the lease stock size until 2030 is reached. The output of this stage will be the lease inputs for 2016-2030 and the lease S&OF for 2016-2030.

<u>Block F.1 - lease S&OF computations</u>

Block F.1 is similar to block B.1 from the BAU S&OF modelling stage. Instead of calculating the S&OF based on the discarding PDF, the size of the S&OF will be calculated based on the assigned Lease Duration (LD). According to the model, all products will stay in use (stock =100% size of POM input) until the lease duration end (=LD) is reached. In the year the lease duration ends, the products will be returned (outflow = 100% size of POM input). The years after the end of the lease duration, the products will be neither in the stock, neither in the outflow. The initial input used for block F.1 is the '2016 RL input' prepared in block E.2. After the initial input (2016 RL input), the 'lease input' (the output of block F.2) will be used.

<u>Block F.2 - calculating lease input for following year</u>

The output from block F.1 will be used to calculate the new input required for the following year. Per illustration, the lease stock for 2017 produced from the '2016 RL input' will not satisfy the BAU in-use stock for 2017 (see figure 14). The gap between the stock for 2017 produced from the leased input of 2016 and the in-use BAU stock for 2017 must be filled by additional lease input for 2017. This 2017 lease input will be added to the '2016 RL input' as the 'lease input', and will be fed as an input to block F.1. The 2018 stock of lease input of 2016+2017 will then be compared with the 2018 in-use BAU stock to get to the additional lease input for 2018, and so on. This process is stopped when the input is calculated for 2030.

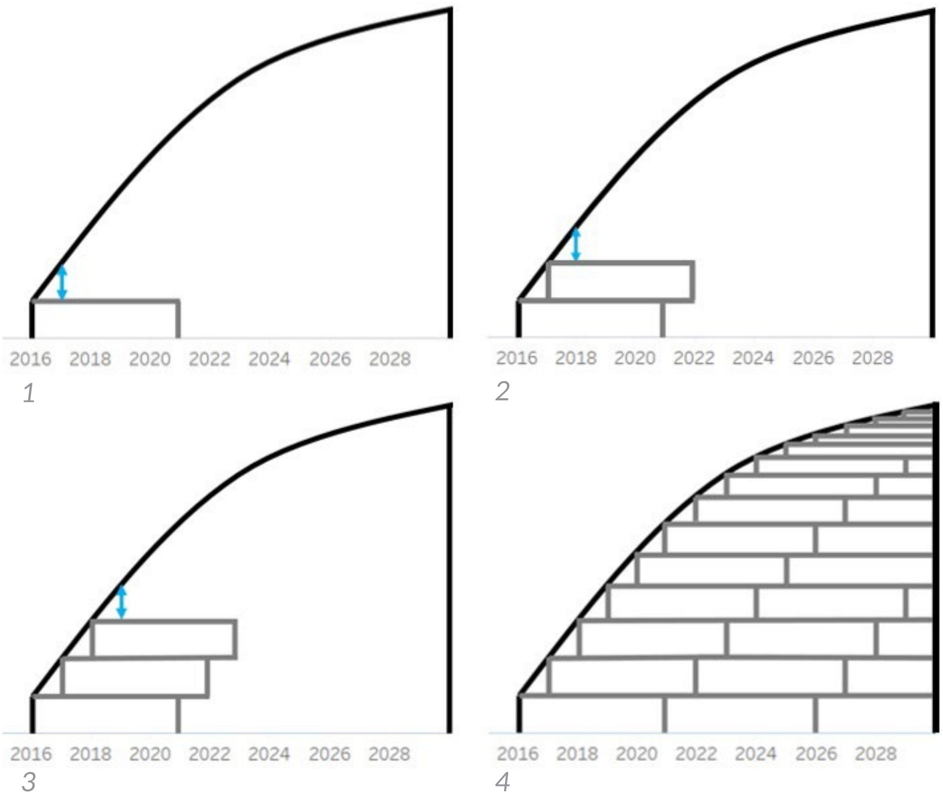
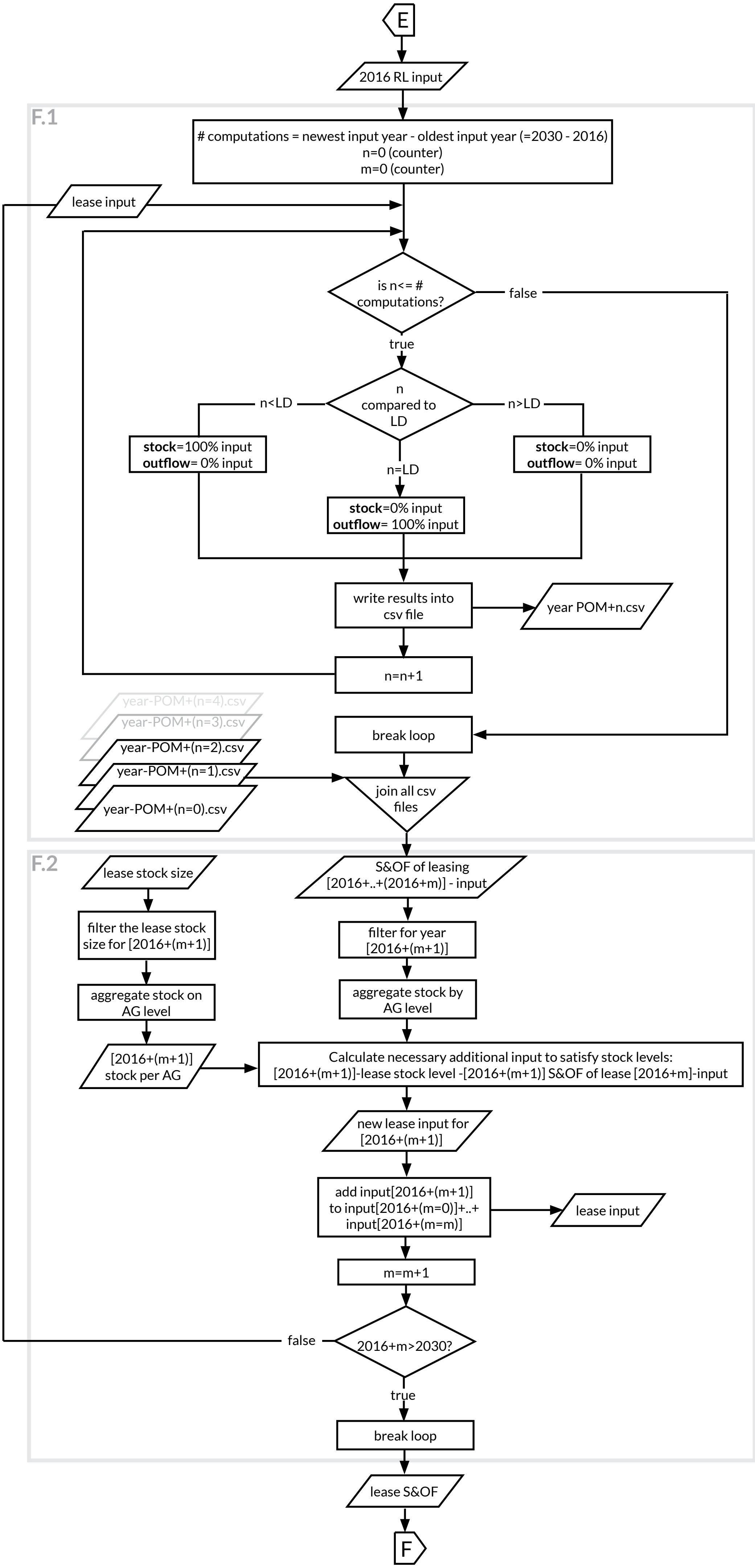


Figure 14: Illutration of the progression of the stock driven input model. The outline of the in-use stock size is provided in black, which needs to be filled with stock from leased products. For each year, the gap between the stock produced by leased products and the required BAU in-use stock needs to be filled with new leased inputs (blue arrows; see 1-3). Figure 4 shows a simplified illustration of how the stocks from lease can satisfy the 2016-2030 BAU in-use stock size.



E
2016 RL input
F.1
# computations = newest input year - oldest input year (=2030 - 2016)
n=0 (counter)
m=0 (counter)
lease input
is n<= # computations?
false
true
n compared to LD
n<LD
n>LD
stock=100% input
outflow= 0% input
stock=0% input
outflow= 0% input
n=LD
stock=0% input
outflow= 100% input
write results into csv file
year POM+n.csv
n=n+1
year-POM+(n=4).csv
year-POM+(n=3).csv
year-POM+(n=2).csv
year-POM+(n=1).csv
year-POM+(n=0).csv
break loop
join all csv files
F.2
lease stock size
filter the lease stock size for [2016+(m+1)]
aggregate stock on AG level
[2016+(m+1)] stock per AG
S&OF of leasing [2016+..+(2016+m)] - input
filter for year [2016+(m+1)]
aggregate stock by AG level
Calculate necessary additional input to satisfy stock levels:
[2016+(m+1)]-lease stock level -[2016+(m+1)] S&OF of lease [2016+m]-input
new lease input for [2016+(m+1)]
add input[2016+(m+1)] to input[2016+(m=0)]+..+ input[2016+(m=m)]
lease input
m=m+1
2016+m>2030?
false
true
break loop
lease S&OF
F

3.2.2.7 Stage G - RL scenario 2 - lease-refurbish-lease (LRL)

This stage will cover the RL scenario where the products are leased for the given lease duration, then refurbished and leased again, with the goal of satisfying the BAU in-use stock size with a stock-driven input model (as illustrated in figure 14). Block G.1 sets conditions specific to this RL scenario. Block G.2 is the input driven sub-model, similar to block F.1, that calculates the stock and outflow of the new and refurbished lease products. In block G.3, the new lease input for the following year is calculated by comparing the BAU in-use stock size with the lease stock size until 2030 is reached. The output of this stage will be the LRL inputs for 2016-2030 and the LRL S&OF for 2016-2030.

Block G.1 - LRL scenario conditions

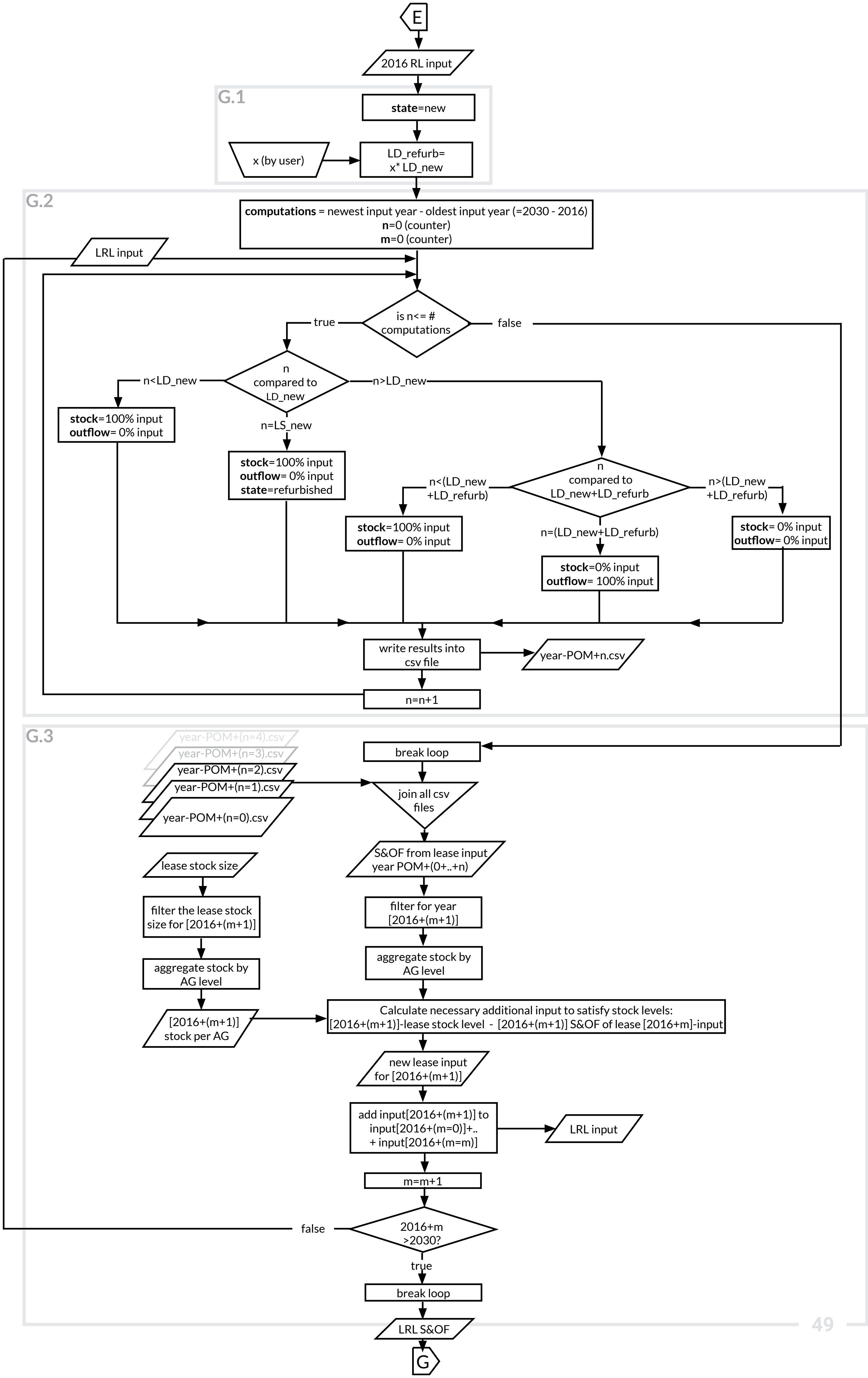
New products and refurbished products can get different values for certain variables (e.g. lease durations, costs and revenues), and therefore the 'state'-dimension is added to label the product as new or refurbished. Furthermore, similar to block E.2, the user will determine what the lease duration for refurbished products (LD_refurb) are compared to new product lease durations (LD_new). For example, the lease duration will be (x =)70% of the new product leases. Again, since the time series is based on whole years, the lease durations for refurbished products will be rounded down to a whole number.

Block G.2 - lease and refurbished lease S&OF computations

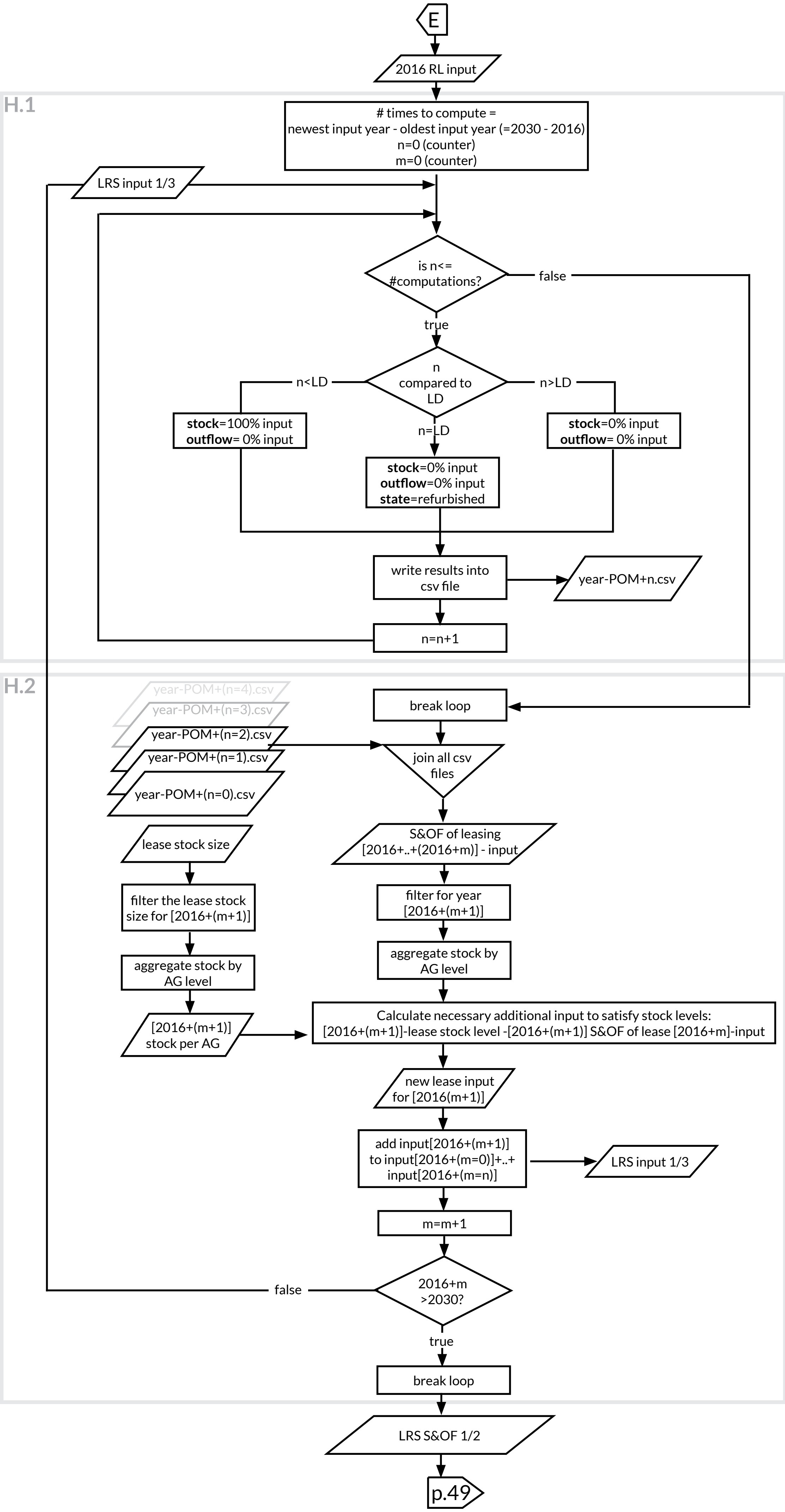
In block G.2, the same S&OF modelling technique is applied, but adds the lease duration of the refurbished products (LD_refurb). According to the model, all products will stay in use as a new product(stock =100% size of POM input) until the maximum lease duration end (=LD_new) is reached. Then, the product is reintroduced as 'state=refurbished' and leased again for the given lease duration for refurbished products (=LD_refurb). When the lease duration for refurbished products expires, the products will be returned once again, but now the outflow is considered WEEE (outflow = 100% size of POM input). The initial input used for block G.2 is the '2016 RL input' prepared in block G.1 After this initial input, the 'LRL input', the output of block G.3, will be used.

Block G.3 - calculating lease input for following year

Block G.3 incorporates the same operational steps as block F.3 and produces the 'LRL input'.

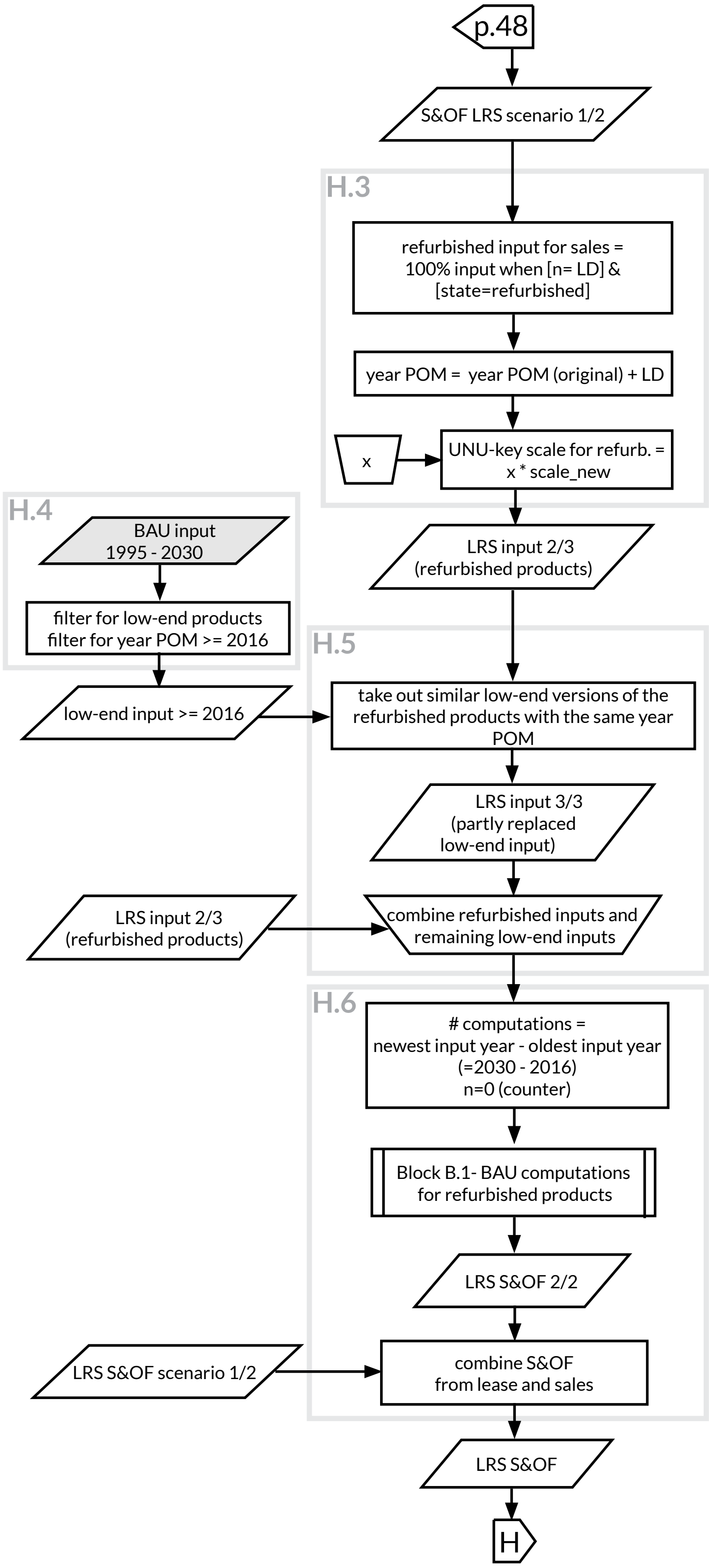


E
2016 RL input
G.1
state=new
x (by user)
LD_refurb=
x* LD_new
G.2
computations = newest input year - oldest input year (=2030 - 2016)
n=0 (counter)
m=0 (counter)
LRL input
is n<= #
computations
true
false
n
compared to
LD_new
n<LD_new
n>LD_new
n=LS_new
stock=100% input
outflow= 0% input
stock=100% input
outflow= 0% input
state=refurbished
n
compared to
LD_new+LD_refurb
n<(LD_new
+LD_refurb)
n>(LD_new
+LD_refurb)
n=(LD_new+LD_refurb)
stock=100% input
outflow= 0% input
stock=0% input
outflow= 100% input
stock= 0% input
outflow= 0% input
write results into
csv file
year-POM+n.csv
n=n+1
G.3
break loop
year-POM+(n=4).csv
year-POM+(n=3).csv
year-POM+(n=2).csv
year-POM+(n=1).csv
year-POM+(n=0).csv
join all csv
files
S&OF from lease input
year POM+(0+..+n)
lease stock size
filter the lease stock
size for [2016+(m+1)]
filter for year
[2016+(m+1)]
aggregate stock by
AG level
aggregate stock by
AG level
[2016+(m+1)]
stock per AG
Calculate necessary additional input to satisfy stock levels:
[2016+(m+1)]-lease stock level - [2016+(m+1)] S&OF of lease [2016+m]-input
new lease input
for [2016+(m+1)]
add input[2016+(m+1)] to
input[2016+(m=0)]+..
+ input[2016+(m=m)]
LRL input
m=m+1
2016+m
>2030?
false
true
break loop
LRL S&OF
G


E
2016 RL input
H.1
times to compute =
newest input year - oldest input year (=2030 - 2016)
n=0 (counter)
m=0 (counter)
LRS input 1/3
is n<= #computations?
false
true
n compared to LD
n<LD
n>LD
n=LD
stock=100% input **outflow**= 0% input
stock=0% input **outflow**= 0% input
stock=0% input **outflow**=0% input **state**=refurbished
write results into csv file
year-POM+n.csv
n=n+1
H.2
year-POM+(n=4).csv
year-POM+(n=3).csv
year-POM+(n=2).csv
year-POM+(n=1).csv
year-POM+(n=0).csv
break loop
join all csv files
lease stock size
S&OF of leasing [2016+..+(2016+m)] - input
filter the lease stock size for [2016+(m+1)]
filter for year [2016+(m+1)]
aggregate stock by AG level
aggregate stock by AG level
[2016+(m+1)] stock per AG
Calculate necessary additional input to satisfy stock levels: [2016+(m+1)]-lease stock level -[2016+(m+1)] S&OF of lease [2016+m]-input
new lease input for [2016(m+1)]
add input[2016+(m+1)] to input[2016+(m=0)]+..+ input[2016+(m=n)]
LRS input 1/3
m=m+1
2016+m >2030?
false
true
break loop
LRS S&OF 1/2
p.49

3.2.2.8 *Stage H -RL scenario 3 - lease-refurbish-sell (LRS)*

This stage involves operational steps for leasing the products once, refurbishing the returned product and selling as refurbished on the low-end market, while considering the replacement effect that might happen for some low-end products. Since this model considers both the high-end market and the low-end market, separate steps need to be made to calculate the input and S&OF from leasing high-end products ('LRS input 1/3' and 'S&OF LRS 1/2' respectively). The refurbished input for the low-end market ('LRS input 2/3') will compete with some new products on the low-end market, resulting into partly replaced new low-end input ('LRS input 3/3'). 'LRS input 2/3' and 'LRS input 3/3' will be used to calculate 'S&OF LRS 2/2' with BAU modelling.



<u>Block H.1 - Lease S&OF computations</u>

Similar to block F.1, according to these operational steps, all products will stay in use until the maximum lease duration (LD). However, when the lease duration is reached, the stock becomes 0% of the original input and no outflow is produced; instead, the product gets the label 'refurbished.'

<u>Block H.2 - calculating lease input for following year</u>

Block H.2 incorporates the same operational steps as block F.2 and produces 'LRS input 1/3', which is fed back to H.1.

<u>Block H.3 - Preparing lease returns as refurbished input</u>

The lease returns are refurbished and are put on the market again. Since the refurbished products might not have the same Weibull distribution shape as their newly produced counterpart, the option is given for the user to lower the scale by *x*.

<u>Block H.4 - Retrieving possible competing low-end market</u>

The BAU input for 1995-2030 will be filtered for low-end product POM from 2016.

<u>Block H.5 - Low-end replacement</u>

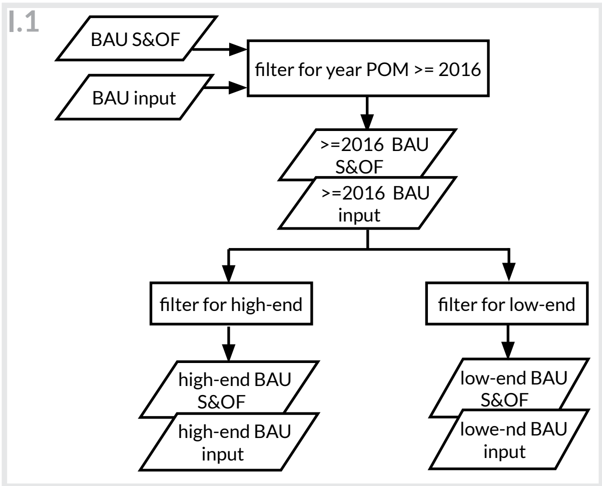
The refurbished products will take out similar new low-end products sold in the same year by comparing the output from block H3 and block H.4. This step requires manual intervention for deciding which refurbished products can replace the low-end products based on functionality. Block H.5 produces the input of refurbished products and partly replace sales of low-end products.

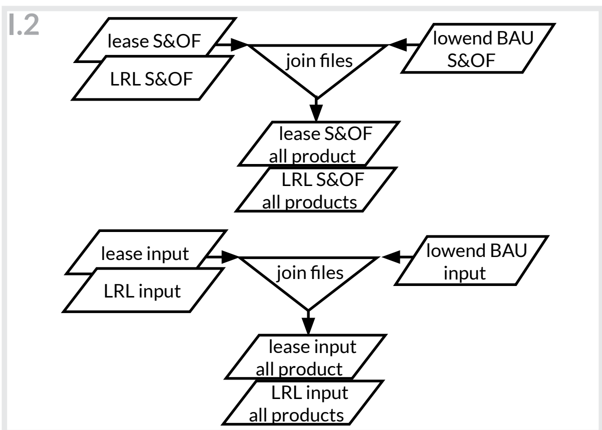
<u>Block H.6 - S&OF computation for all low-end products</u>

The S&OF from the refurbished products input and the partly replaced new product input will be calculated based on the discarding PDF - in the same fashion as block B.1. Finally, the S&OF from the leased high-end products and sold low-end (new and refurbished) products sold after 2016 will be combined to form the 'LRS S&OF'.

3.2.2.9 Stage I - Consolidating data for assessment

The simulations for the BAU and 3 RL scenarios have provided us with the S&OF and input for the high-end products sold from 2016 on. However, we have seen that in the LRS scenario also the low-end products sold after 2016 is impacted. To allow proper comparison of all four scenarios, the S&OF and input from the low-end products sold from 2016 on are added to the other three scenarios as well. In block I.1, the S&OF and input from the BAU simulation are filtered on year POM and low-end/high-end. The high-end S&OF and inputs are used to compare the BAU simulation outputs to those of the other scenarios on high-end products only. These filtered low-end S&OF and input are added to the computed S&OF and inputs for the lease and LRL scenario in block I.2. Block 1.3 shows the collection of S&OF and inputs for all 4 simulations divided in 4 categories. This grouping is made to make the flowchart for the last stage, the assessment, less convoluted.





3.2.2.10 Stage J - Assessments on performance indicators

This is the final stage of the model. The S&OF and inputs computed for the BAU and the 3 RL scenarios will be assessed on the necessary input from new products (in unit quantity), the waste generated (in weight), the C&R rate (in weight) and profitability. The performances from the RL scenarios will be compared to BAU simulation results as a baseline for 2016 to 2030.

Block J.1 - New product input growth

In this block, the 3 scenarios will be compared to the BAU simulation on the size of the new input and displayed in relative change of the unit quantity. The bigger the negative growth, the better the scenario performs.

Block J.2 - WG growth

In this block, the EoL-product, outflow for the 3 scenarios will be compared to the BAU simulation on the size of the total outflow (i.e. WG) and displayed in relative change of the WG weight. The bigger the negative growth, the better the scenario performs.

Block J.3 - C&R rate change

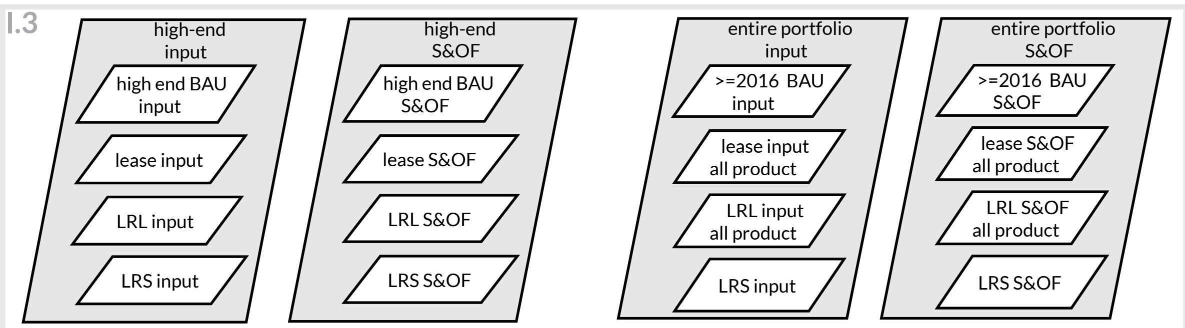
In this block, the overall C&R rate will be calculated for all four simulations, which can be done either on the weight-based national SHA C&R rate by Huisman et al. (2012), or according to the TCs for the C&R channels by Hendriksen (2009). Then, the RL scenarios C&R rate will be compared with the C&R rate for the BAU simulation. The bigger the positive C&R rate change, the better the scenario performs.

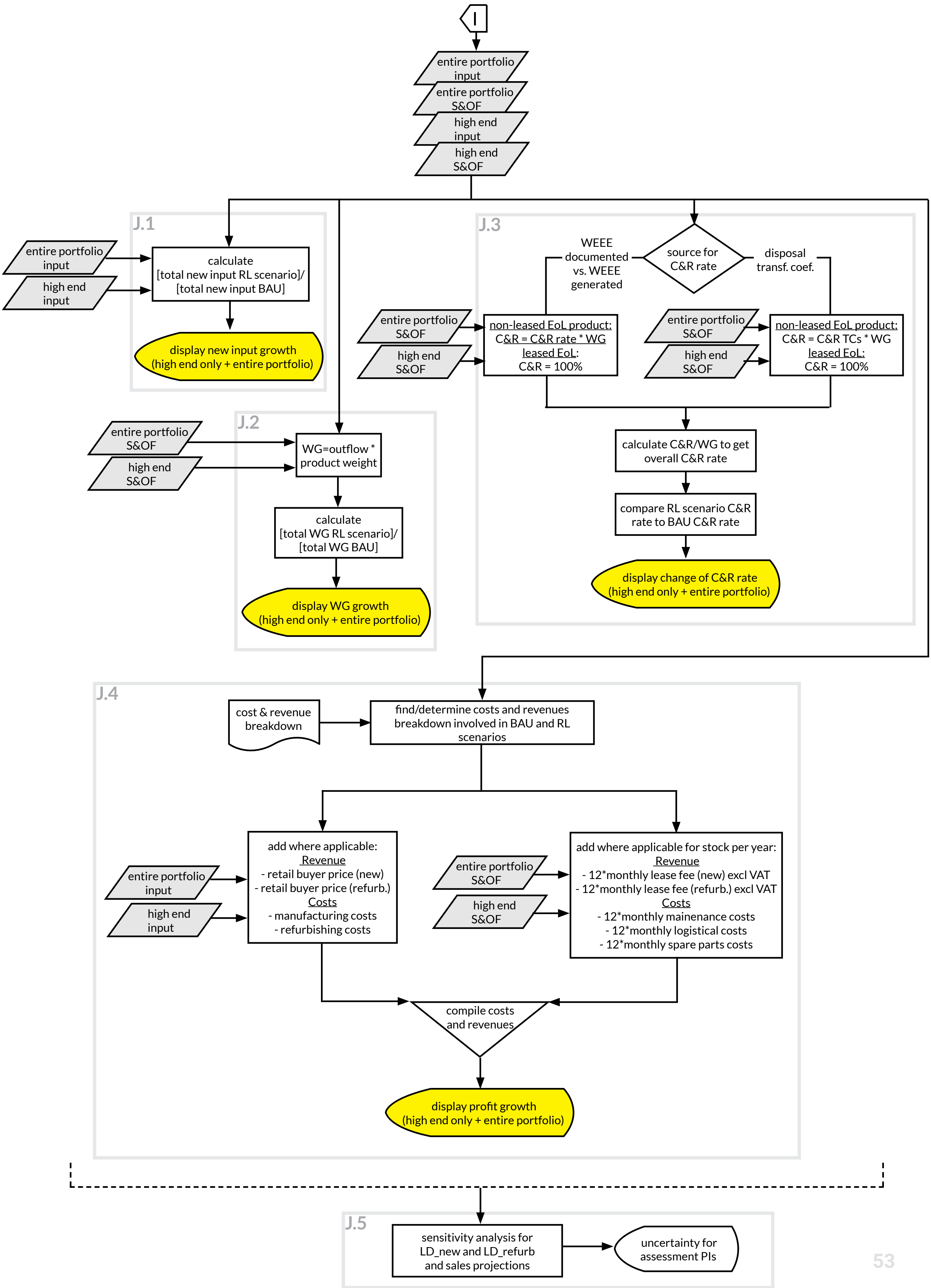
Block J.4 - Profitability growth

In this block, all costs and revenues associated with the input, stocks and flows will be added to all the scenario inputs and S&OF data. With the incorporation of this data, it is possible to compare the RL scenarios with the BAU simulation for profitability on relative change. The bigger the positive growth, the better the scenario performs.

Block J.5 - Sensitivity analysis

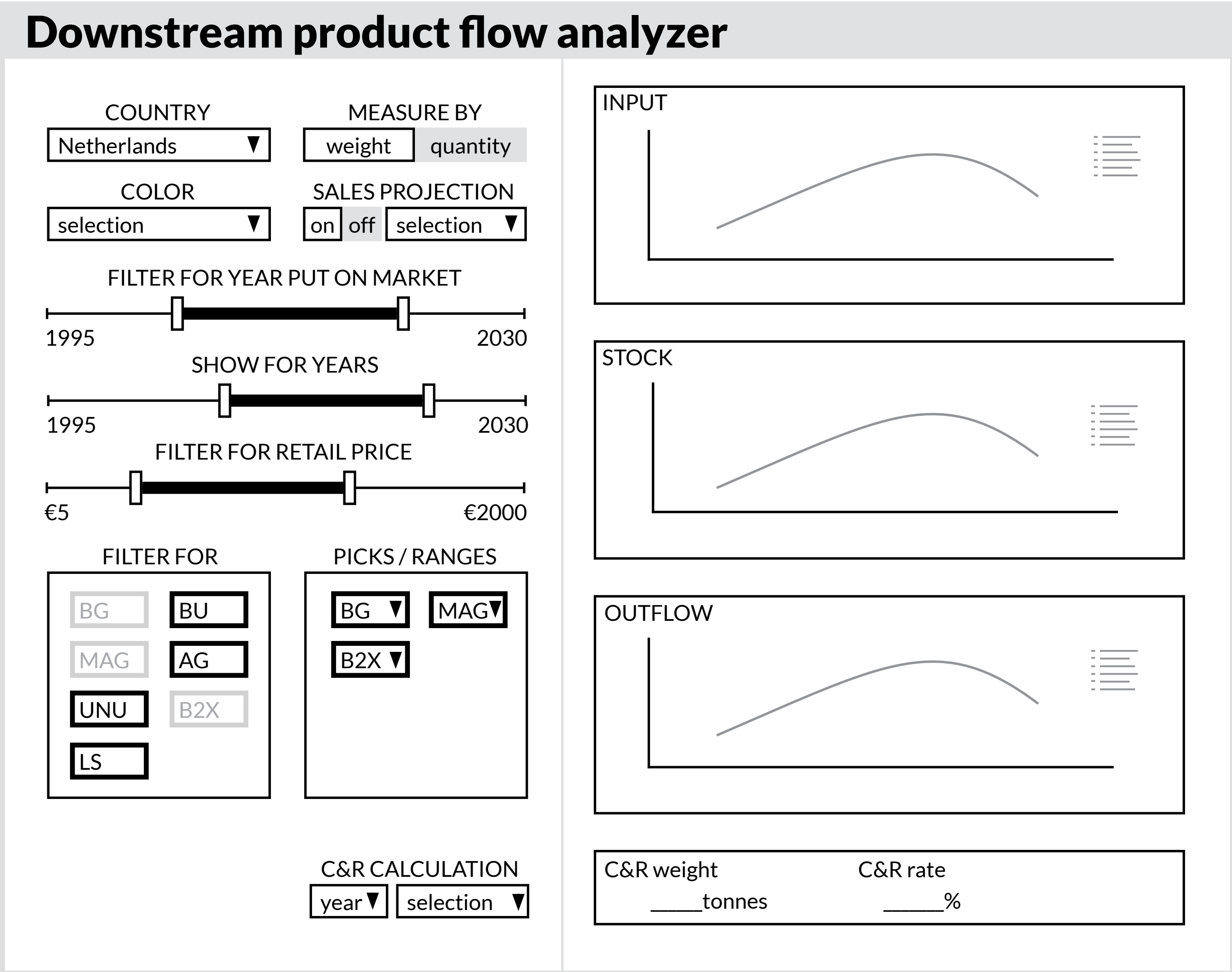
In the sensitivity analysis, the differences in the assessment outcomes under the two different sales projections ('2016-level' sales and 'trendline' sales) will be calculated and displayed.





I
entire portfolio input
entire portfolio S&OF
high end input
high end S&OF
J.1
entire portfolio input
high end input
calculate [total new input RL scenario]/ [total new input BAU]
display new input growth (high end only + entire portfolio)
J.2
entire portfolio S&OF
high end S&OF
WG=outflow * product weight
calculate [total WG RL scenario]/ [total WG BAU]
display WG growth (high end only + entire portfolio)
J.3
source for C&R rate
WEEE documented vs. WEEE generated
disposal transf. coef.
entire portfolio S&OF
high end S&OF
non-leased EoL product: C&R = C&R rate * WG
leased EoL: C&R = 100%
entire portfolio S&OF
high end S&OF
non-leased EoL product: C&R = C&R TCs * WG
leased EoL: C&R = 100%
calculate C&R/WG to get overall C&R rate
compare RL scenario C&R rate to BAU C&R rate
display change of C&R rate (high end only + entire portfolio)
J.4
cost & revenue breakdown
find/determine costs and revenues breakdown involved in BAU and RL scenarios
entire portfolio input
high end input
add where applicable:
Revenue
- retail buyer price (new)
- retail buyer price (refurb.)
Costs
- manufacturing costs
- refurbishing costs
entire portfolio S&OF
high end S&OF
add where applicable for stock per year:
Revenue
- 12*monthly lease fee (new) excl VAT
- 12*monthly lease fee (refurb.) excl VAT
Costs
- 12*monthly mainenance costs
- 12*monthly logistical costs
- 12*monthly spare parts costs
compile costs and revenues
display profit growth (high end only + entire portfolio)
J.5
sensitivity analysis for LD_new and LD_refurb and sales projections
uncertainty for assessment PIs

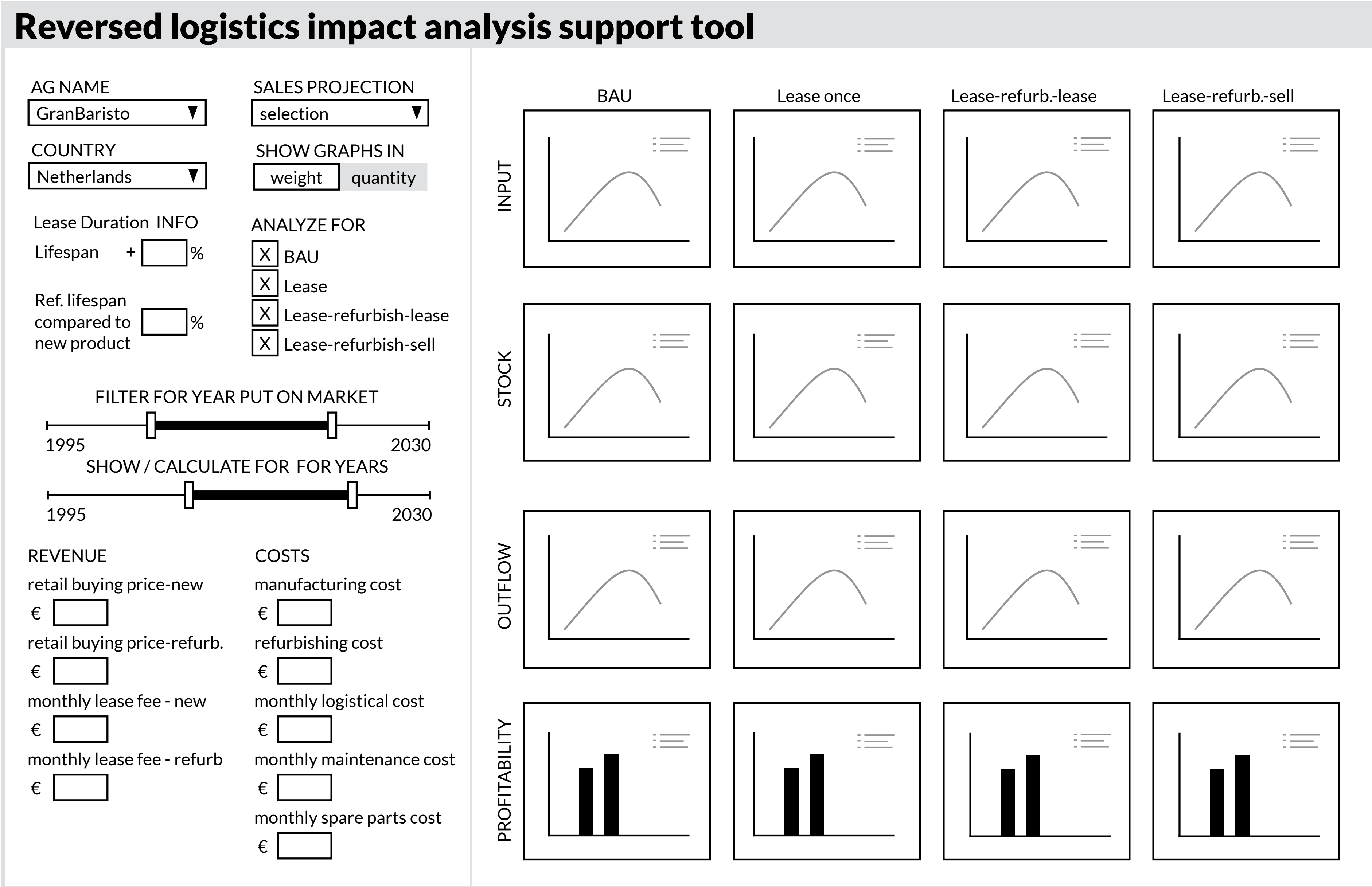
3.2.3 Wireframe concepts



Two wireframes are made to suggest the options that can be incorporated in the user interface of the pilot tool. All options, sliders, toggles and dropdown menus (except for 'country') can already be built upon the data output from the built model.

Description wireframe left (p.54):
This wireframe displays the options for the analysis of the input, stock and outflow of the downstream product flows for the current situation (i..e BAU simulation). This wireframe also suggests the option to choose different sales projections and calculate the C&R weight according to 2 or more methods. Dashboarding can be done for weight or for unit quantity.

Description wireframe right (p.55):
This wireframe gives an idea of what a pilot tool regarding the RL strategic decision making tool could look like with the currently built model. This wireframe focuses on the environmental and economic assessment of one product on AG level. The user must enter the lease duration information (for new products and refurbished products) or will be set to a default to the Philips lifespan. Other entries are the revenues and costs associated with the different selected scenarios. This way this tool can be also used as a pricing tool. This wireframe also suggests the option to choose different sales projections and can display the results in weight and unit quantity,


Reversed logistics impact analysis support tool
AG NAME
GranBaristo
SALES PROJECTION
selection
COUNTRY
Netherlands
SHOW GRAPHS IN
weight
quantity
Lease Duration INFO
Lifespan + %
Ref. lifespan compared to new product %
ANALYZE FOR
X BAU
X Lease
X Lease-refurbish-lease
X Lease-refurbish-sell
FILTER FOR YEAR PUT ON MARKET
1995
2030
SHOW / CALCULATE FOR FOR YEARS
1995
2030
REVENUE
retail buying price-new
€
retail buying price-refurb.
€
monthly lease fee - new
€
monthly lease fee - refurb
€
COSTS
manufacturing cost
€
refurbishing cost
€
monthly logistical cost
€
monthly maintenance cost
€
monthly spare parts cost
€
BAU
Lease once
Lease-refurb.-lease
Lease-refurb.-sell
INPUT
STOCK
OUTFLOW
PROFITABILITY

3.3 Results

In this section, the output for the model will be described and analyzed. First, the output for the BAU simulation for 1995-2016 will be described, followed by the output from the 2016-2030 RL scenarios comparison model for all high-end products and for one product specifically. After the describing and analyzing the simulation result, the BAU simulation will be checked for consistency with real-world data and the sales extrapolations undergo a sensitivity analysis.

3.3.1 *Simulation results*

3.3.1.1 1995-2016 - BAU stock and outflow

The sizes of the stock and outflow from the BAU simulation can be seen in figure 15. The results are presented in unit quantity on the left and in weight on the right, where the top graphs show the accumulated stock and the bottom graphs show the yearly outflow. The blue field in the graph is the size of the extrapolated data. As can be seen from the graphs, the extrapolated input will have a relatively small share of the stock and outflow in 2016. The share of the

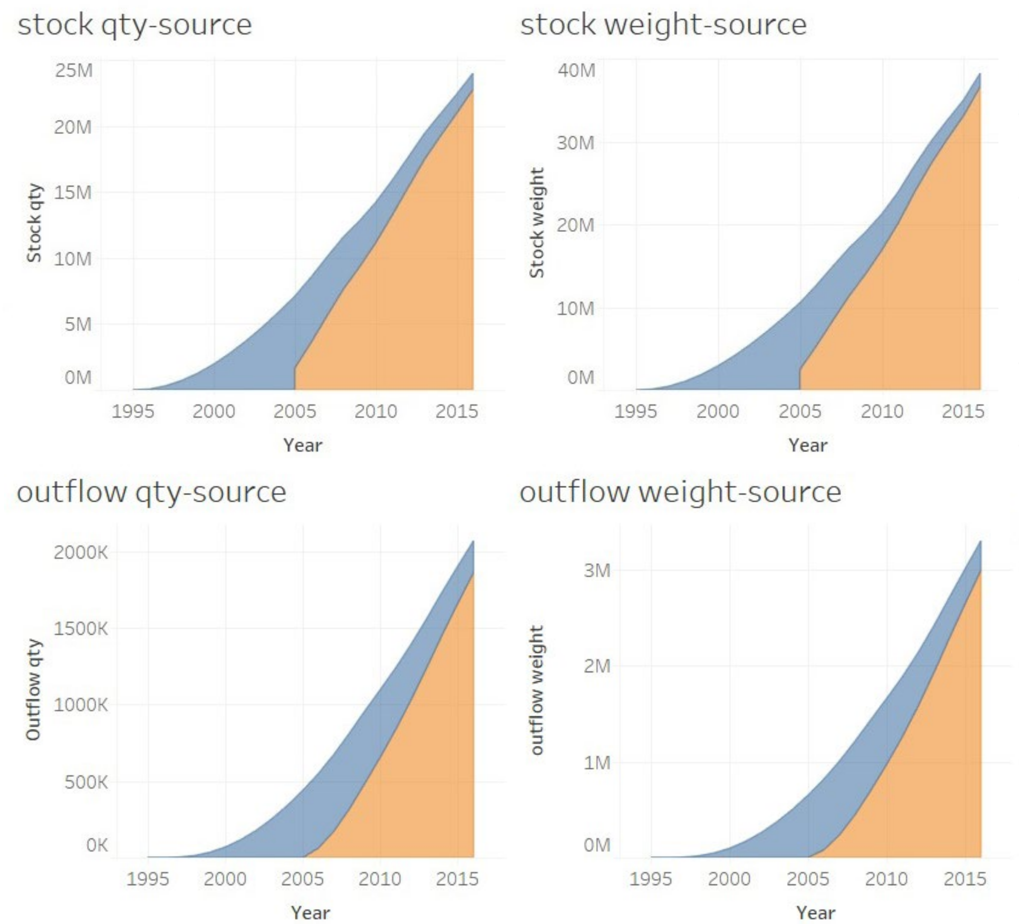


Figure 15: graphs of the stock (top) and outflow (bottom) in unit quantity (left) and weight (right), broken down on the sales data source; extrapolated (blue) and reported (orange). Qty=unit quantity

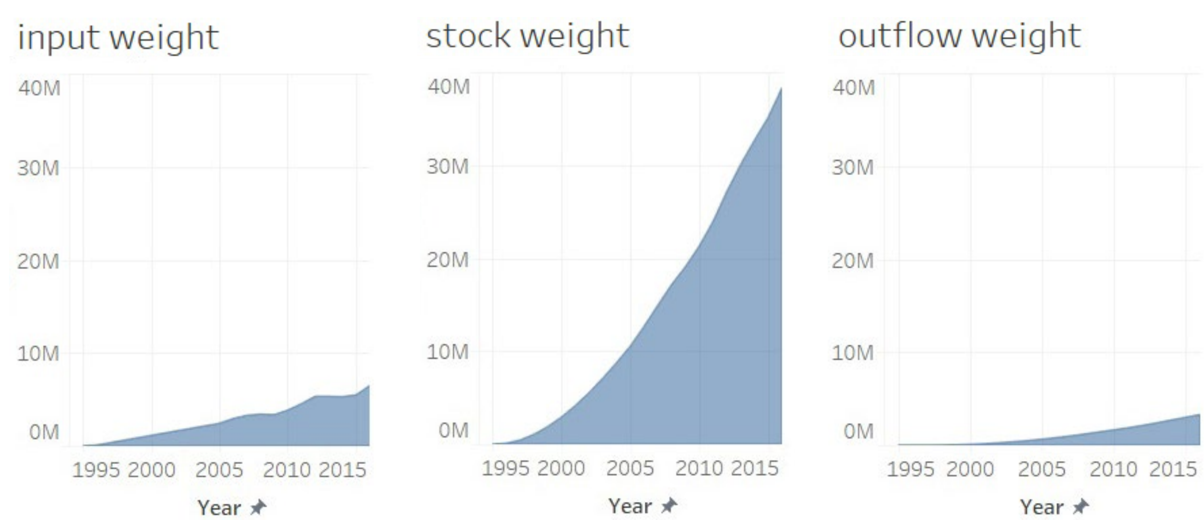


Figure 17: Overview of the input weight per year, accumulated stock weight and outflow weight per year for 1995-2016

extrapolated data for the stock in 2016 is 5.2% in quantity and 4.3% in weight. The share of the extrapolated data for the outflow in 2016 is 10.1% in quantity and 9.4% in weight. The share of the results for the extrapolated data input is bigger for the outflow than the stock due to the delay model.

Figure 16 provides the insight to the EoL destinations of the product (left) and how this relates to weight (right). As can be seen from the graphs. Personal Care products are more likely to be unable to recover (in the 'residual waste' or 'other' channel), probably due to the small size of the products in the Personal Care portfolio, which are e.g. electrical toothbrushes and grooming devices. However, these types of products have a relatively small mass and are therefore not the biggest contributors to the unrecoverable waste stream in weight. Based on the weight-based stream to the 3 C&R channels (i.e. recycling scheme, pick-up and retailer) it is calculated that the C&R rate for 2016 is 64.2%.

Figure 17 shows the relation of the yearly input, accumulated stock and yearly outflow in weight. As a top-down mass balance check, the total input for 1995-2016 minus the total outflow for 1995-2016 should equal the stock weight for 2016.

More visualized breakdowns are provided in appendix N for the input, stock and outflow for quantity and weight.

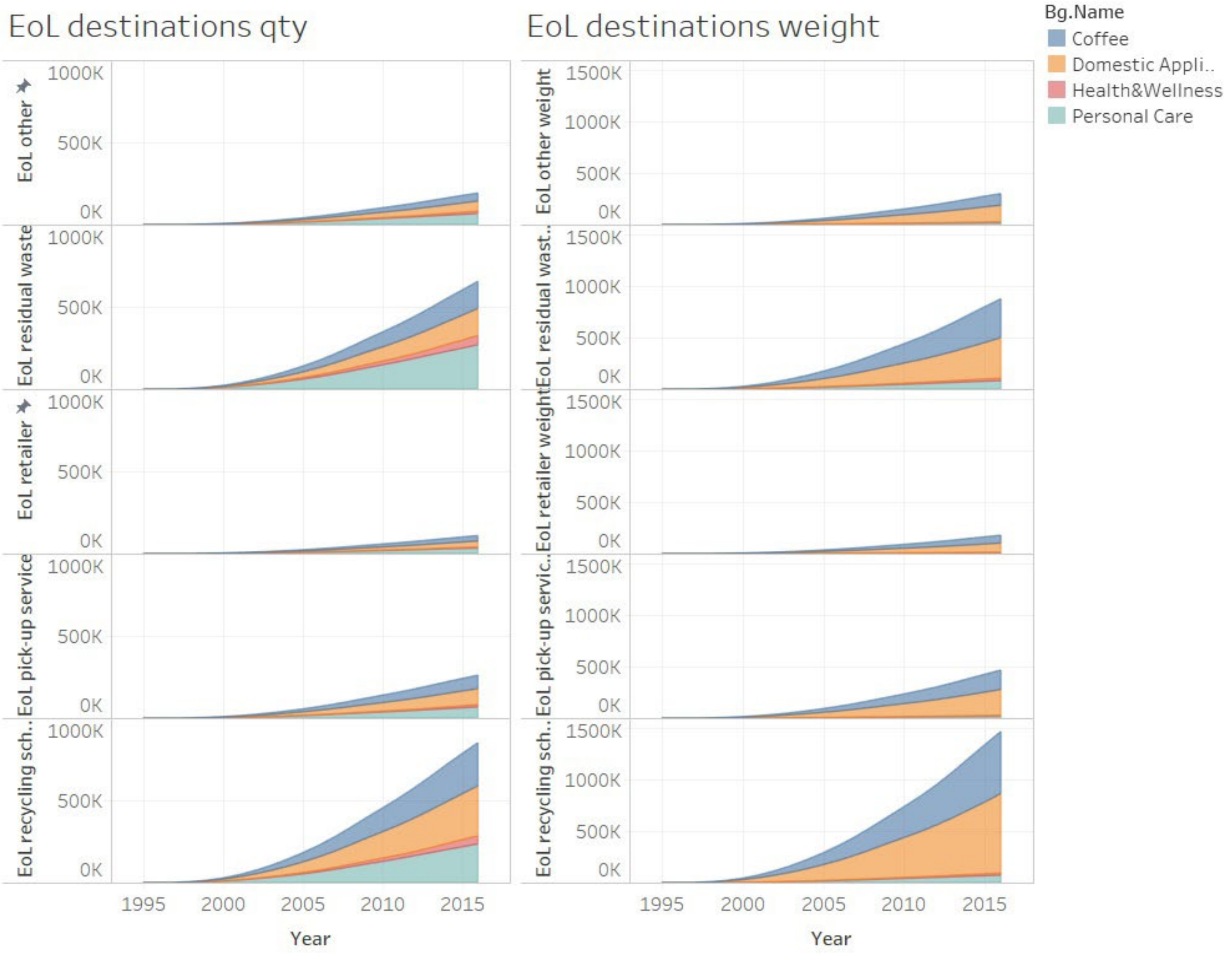


Figure 16: Outflow sizes to the different EoL destinations in unit quantity (left) and weight (right), broken down on Business Group. EoL channels (from top to bottom): other, residual waste, return to retailer, pick-up service, recycling scheme. Qty=quantity

3.3.1.2 *1995-2030 - BAU stock and outflow*

The extension of the stock and outflow calculations of the BAU simulation towards 2030 has two main functions. First, it provides insight on how the products recently put on the market influence the stock and outflow beyond 2017. Secondly, it provides the base to build the RL scenarios on and, furthermore, serves as the baseline for the RL scenario comparisons.

BAU stock and outflow development

The top graphs in figure 18 show the development of the stock until 2030 for the 2016-level sales projection. With this sales projection, the stock from input before 2017 account for a share of 11.6% in unit quantity and 8.4% in weight in 2030. The bottom two graphs in figure 18 show the development of the outflow. The results for the outflow indicate that in 2030 the share from products sold before 2017 is 17.3% in unit quantity and 14.8% in weight. The size of the outflow from products sold before 2017 will peak in 2018 and will remain the major outflow source until 2024.

Figure 19 shows the relation between the input per year, accumulated stock and outflow per year over time. While the input data is stable from 2016, it is expected that the stock level will stabilize around 2033 and that the outflow is stabilized around 2039 (23 years after the input stabilization).

Additional breakdowns of the input, stock and outflow for different product categories can be found in appendix O.

High-end products in BAU

The share of high-end products in the input from 2016 on are 5.7% in unit quantity and 15.2% in weight (see graph in appendix O.1). This discrepancy between unit quantity and weight is likely due to the fact that a large portion of the high-end products are FAEM that are rather heavy. The total input produces a stock of which the high-end products account for roughly 6% in unit quantity and 15% in weight throughout the years (see figure 20).

From the statistics provided by Hendrikson (2009) on SHA storage in Dutch households (appendix C), it was found that the shares for hibernating products are the following: 8.3% for kitchen appliances, 10.9% for personal care product and 8.6% for others. Figure 21 shows the calculated share of the hibernating stock for the high-end products, which is roughly 9% througout the years.

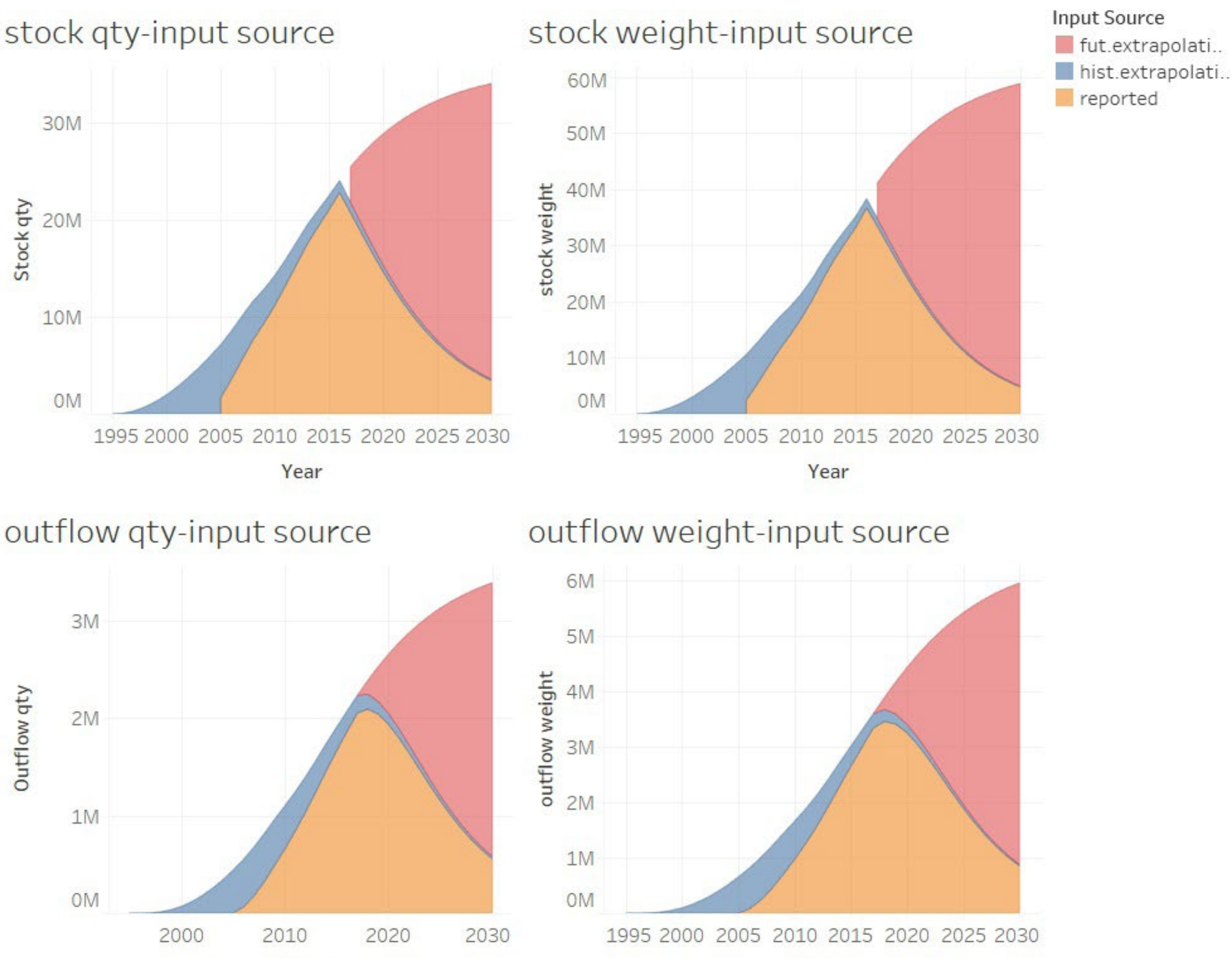


Figure 18: Graphs of the stock (top) and outflow (bottom) in unit quantity (left) and weight (right), broken down on the sales data source; retrospective extrapolated (blue), reported (orange) and prospective extrapolation (red). Qty=quantity.

Figure 19: Overview of the input weight per year, accumulated stock weight and outflow weight per year for 1995-2030

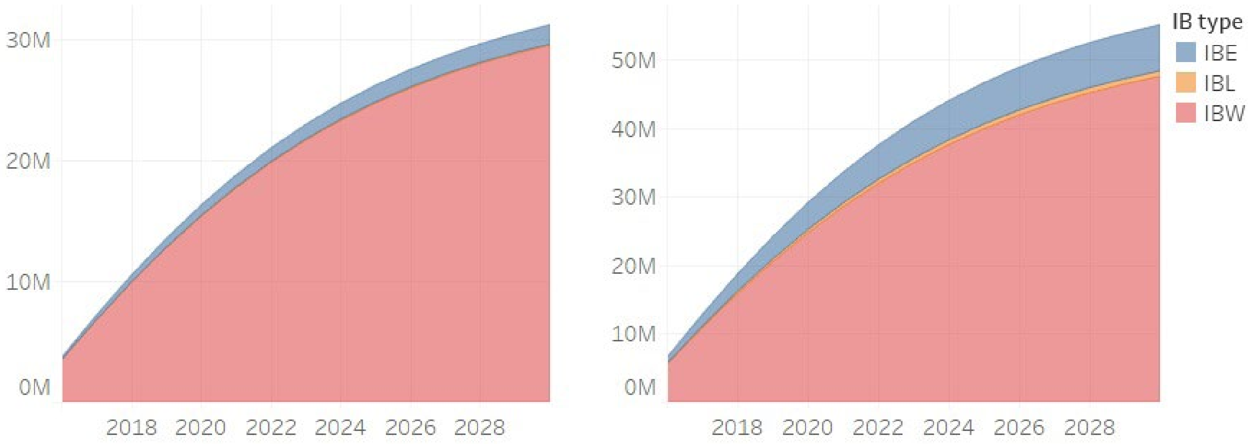


Figure 20: break down of the high-end (IBL+IBE) products and the low-end (IBW) for products sold from 2016

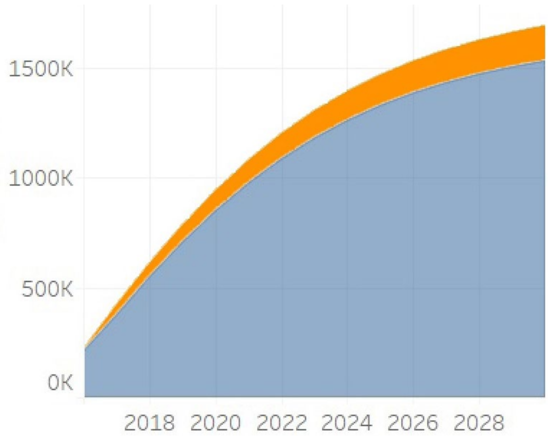


Figure 21: the high-end stock in quantity broken down for the hibernating stock (orange) and in-use products (blue)

3.3.1.3 RL modelling - results for high-end portfolio

This section will present the results for the performance throughout 2016-2030 of the RL scenarios compared to the BAU simulation for high-end products sold from 2016.

The products that fall under the high-end category are shown in the table in appendix P. Since the main input variable for this model is the lease duration, the model is run for two conditions; the lease duration for new products is 1) 100% Philips lifespan and 2) 130% Philips lifespan. The lease durations will be rounded down, because model is built on yearly time series steps. Since most lifetimes are set to on 4,5 and 7, the second condition increases the lifetimes to 5, 6 and 9 respectively. In addition, for this assessment, the refurbished lifespan and scale parameter is set as 70% of the new product lifespan and scale parameter, corresponding to the value used in the Health System refurbishment program.

In appendix R, you can find the graphs for the yearly developments of the input, stock and outflow for the BAU and the three RL scenarios for lease duration=100% Philips lifespan (appendix R.1) and for lease duration=130% Philips lifespan (appendix R.2), provided in unit quantity.

The impact on the three performance indicators for the period 2016-2030 are shown in figure 22 for condition lease duration=100% Philips lifespan and in figure 23 for condition lease duration=130% Philips lifespan. For the input quantity (left) and WG weight (middle), it shows the relative change compared to the BAU input and stock size. The chart on the right shows the C&R rates for all simulations. The input quantity, WG and the C&R rate results are provided for high-end products (when only considering the impact on the high-end products) and for all products (when considering the impact on the entire Philips portfolio).

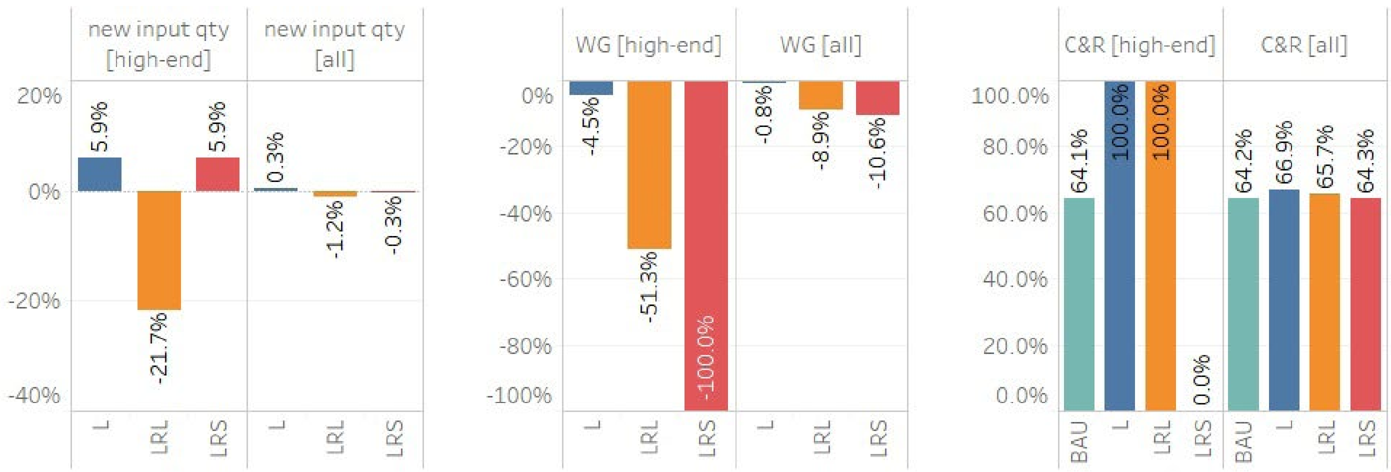


Figure 22.1 *Figure 22.2* *Figure 22.3*

Figure 22: Results for the performance indicators compared to the BAU simulation for high-end products for lease duration=100% Philips lifespan. '[high-end]' and '[new]' refer to the impact on the high-end and entire portfolio respectively; WG=WEEE generation; C&R=Collection&Recycling rate; L= lease scenario; LRL=lease - refurbish - lease scenario; LRS = lease - refurbish - sell scenario.

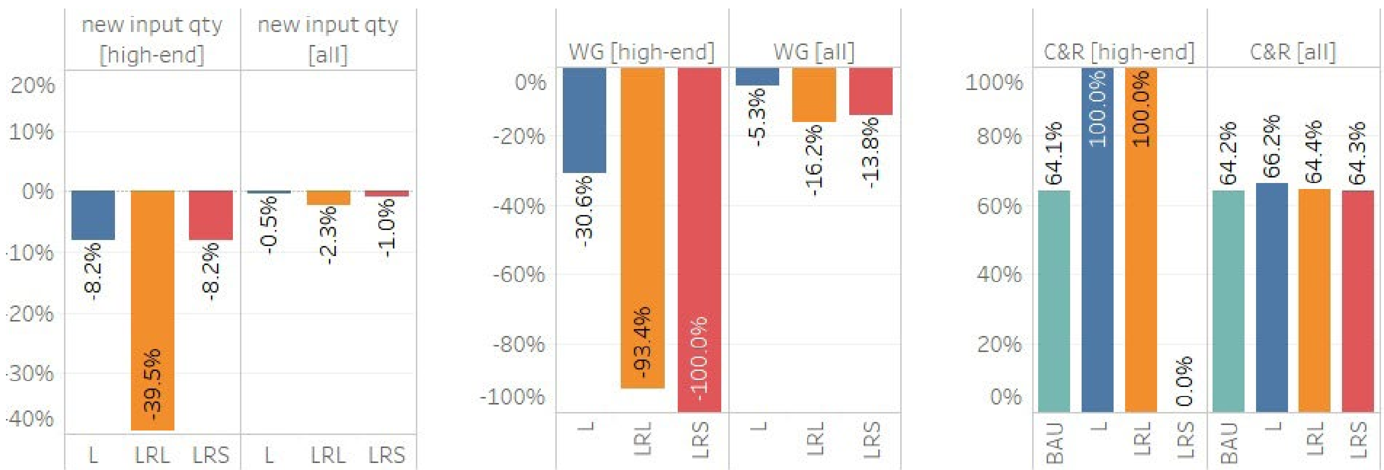


Figure 23.1 *Figure 23.2* *Figure 23.3*

Figure 23: Results for the performance indicators compared to the BAU simulation for high-end products for lease duration=130% Philips lifespan. '[high-end]' and '[new]' refer to the impact on the high-end and entire portfolio respectively; WG=WEEE generation; C&R=Collection&Recycling rate; L= lease scenario; LRL=lease - refurbish - lease scenario; LRS = lease - refurbish - sell scenario.

Results for input quantity - in figure 22.1, it is seen that leasing products once can have a negative effect on the required input. Leasing the products for the current Philips lifespan would result in a negative impact (fig. 22.1), but can be negated by increasing the lease duration (fig 23.1). In the LRS scenario, the impact for the entire portfolio is positive because a significant number of the leased products, which will be refurbished and sold, will replace new low-end products. When considering both the high-end products and the entire portfolio, the LRL scenario has the most positive high-level environmental impact.

Results for WG - Figure 22.2 and 23.2 show the weight-based results for the WG delay and/or decrease. There are positive results accross the board for both lease duration conditions. Regarding the WG for the LRS scenario when considering only the high-end portfolio, there is no waste generated since the products will not be considered high-end when the lease duration ends. The effect of the LRS scenario on WG should therefore be reviewed for the entire portfolio. Thusly, when considering WG for the entire portfolio for 2016-2030; 1) the condition lease duration = 100% Philips lifespan, the LRS performs the best, and 2) for the condition lease duration=130% Philips lifespan, the LRL scenario performs the best.

Results for C&R - Figure 22.3 and 23.3 show the average C&R rate for the years 2016-2030. The C&R rate for high-end products is 64.1% in the BAU simulation, is 100% in both the L and LRL scenarios (since all returned products are scrapped) and does not apply to the LRS scenario. When considering the C&R rate for the entire portfolio, the RL scenarios generally has little effect due to the much larger waste streams from the low-end segment. The L scenario scores the highest C&R rate, but this is due to the faster circulation of products and thereby producing relatively more WEEE than the other two scenarios. For the LRL and LRS scenario, the increase of the C&R rate is likely low due to the small share of high-end product of the entire portfolio and for which even fewer WEEE is generated due to the RL strategies. The C&R rates for the lower lease duration condition are higher than for the higher lease duration conditions for the same reason of having fewer WEEE generated.

For the LRS scenario, the replacement of new low-end product sales with refurbished products has an positive effect on input quantity. Figure 24 shows graphs for the replacement effect for the condition lease duration=100% Philips lifespan; figure 24.1 shows the total size of the input quantities over the year, figure 24.2 shows the input quantity for BU Coffee and 24.3 shows the input for BU Air. Figure 24.1 shows an overall increase of low-end products, although, the 'new' share of the low-end products slightly decrease after the introduction of refurbished products. For some product categories, complete replacement takes place, such as can be seen in 24.2; for this BU, the refurbished FAEM compete with cheaper coffee machines. Figure 24.3 illustrates another effect of the introduction of refurbished products, using 'Air' products as an example. The low-end products in 'Air' are humidifiers only, whereas the high-end products in 'Air' are air cleaners. There is no direct substitute for the humidifiers as the air cleaners fulfill a different need, so the introduction of refurbished air cleaners will add to the low-end market rather than replace the sales of low-end products.

Figure 24.1 *Figure 24.2* *Figure 24.3*

Figure 24: Demonstration of the effects of the replacement effect in unit quantity (measures not included for confidential reasons) for certain BUs for the 2016-level sales projection

3.3.1.4 RL modelling - results GranBaristo

This section contains the results for the performance indicators for the RL scenarios compared to the BAU simulation for the GranBaristo specifically. Additionally to the 3 high-level environmental indicators, this assessment also provides the results for a profitability analysis. To reiterate, the financial data is not backed by experts (apart for the BAU), and is used as an illustration for future development and use with accurate data. A limitation of the single product assessment is that the sales replacement of similar low-end products is not considered for the LRS scenario.

Equal to the assessment done for the high-end portfolio in the previous section, the stocks and flows are computed for 2016-2030 for two conditions where the lease duration for new products is; 1) 100% Philips lifespan and 2) 130% Philips lifespan. The Phlips lifespan for the GranBaristo is 7 years, so the lease duration for the second condition will be 9 years rounded down. Just like the high-end product assessment, the refurbished lifespan and scale parameter is set as 70% of that of the new product. In appendix S, one can find the graphs for the development of the input, stock and outflow for the BAU simulation and the three RL scenarios for lease duration=7 (appendix S.1) and for lease duration=9 (appendix S.2), provided in unit quantity.

The impact on the four performance indicators for 2016 to 2030 are shown in figure 25 for the lease duration=7 and in figure 26 for lease duration=9. For the input quantity, and WG weight and the profitability, the charts show the relative change compared to the BAU simulation results for 2016-2030. The C&R chart shows the C&R rates for all four simulations.

Figure 25.1

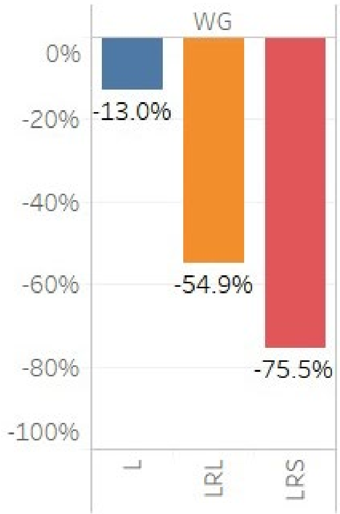


Figure 25.2

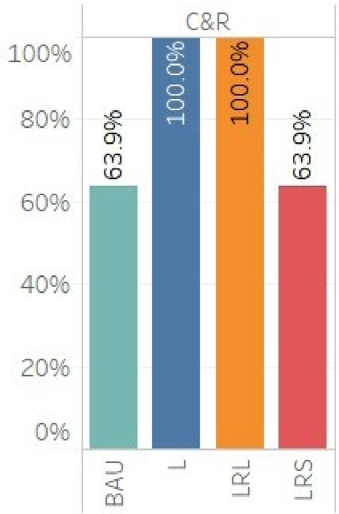


Figure 25.3

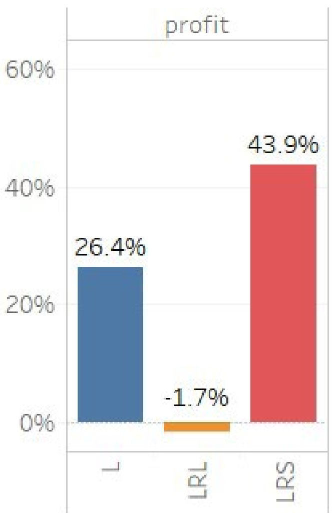


Figure 25.4

Figure 25.5

Figure 25: Results for the performance indicators compared to the BAU simulation for the GranBaristo for lease duration= 100% Philips lifespan. '[high-end]' and '[new]' refer to the impact on the high-end and entire portfolio respectively; WG=WEEE generation; C&R=Collection&Recycling rate; L= lease scenario; LRL=lease - refurbish - lease scenario; LRS = lease - refurbish - sell scenario.

Results for input quantity - Since the GranBaristo has a relatively high Philips lifespan, all scenarios have a positive impact on the total input (see figure 25.1). The 2-year increase of the lease duration roughly doubles the decrease rate for the input (see figure 26.1). Similar to the high-end portfolio assessment, the preferable scenario regarding the input performance indicator is the LRL scenario.

Results for WG - The WG is reduced in all scenarios for condition lease duration=7 (see figure 25.2) and even delayed beyond 2030 for the LRL scenario when the lease duration=9 (see figure 26.2). With a relatively short lease duration, the LRS scenario can outperform the otherwise better performing LRL scenario. Although the L scenario reduces the WG significantly, it falls far behind the results of the other RL scenarios

Results for C&R - The results for the LRS scenario and BAU are the same because the products are all discarded by the consumer in the same fashion (see figure 25.3 and 26.3)

Results for profitability - The charts in 25.4 and 26.4 show the comparative growth compared to the BAU simulation results and the charts in 25.5 and 26.5 shows the proportional cost breakdown for all simulations (no units for confidentiality). The most notable result is that the LRL is the least economically attractive concept, especially for a relatively low lease duration, since the low lease fees for the refurbished products do not make up much for the RL network costs. Furthermore, the most financially attractive scenario is the LRS scenario (not taking the replacement effect into consideration).

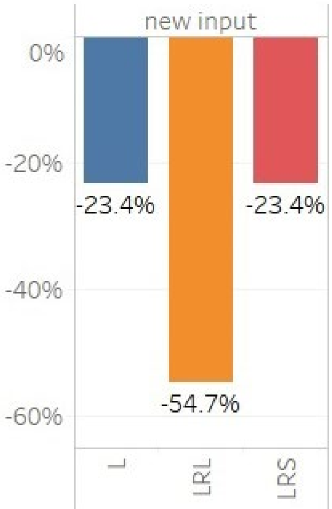


Figure 26.1

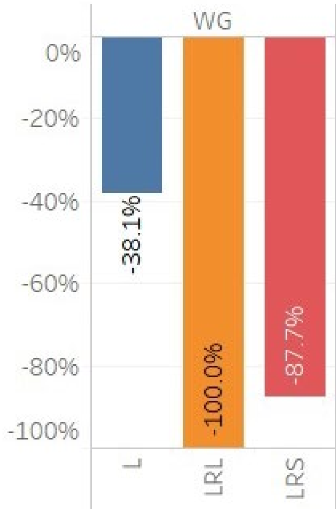


Figure 26.2

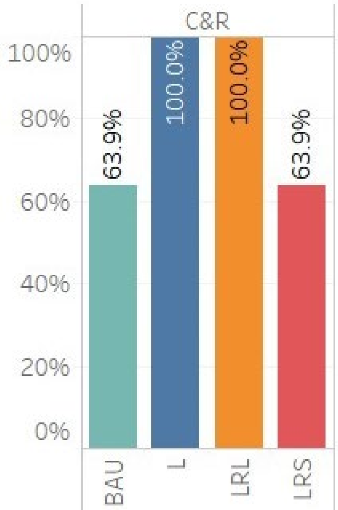


Figure 26.3

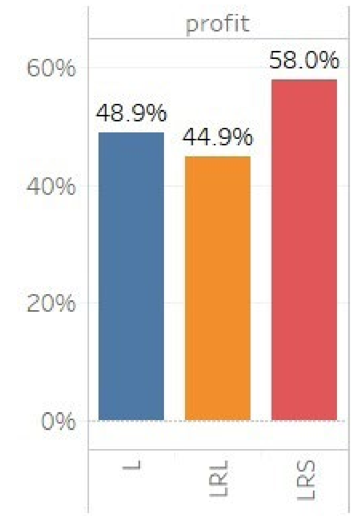


Figure 26.4

Figure 26.5

Figure 26: Results for the performance indicators compared to the BAU simulation for the GranBaristo for lease duration= 130% Philips lifespan. '[high-end]' and '[new]' refer to the impact on the high-end and entire portfolio respectively; WG=WEEE generation; C&R=Collection&Recycling rate; L= lease scenario; LRL=lease - refurbish - lease scenario; LRS = lease - refurbish - sell scenario.

3.3.2 Consistency check

In this section, the results for the stock and outflow modelling of the BAU is compared with real-world data.

3.3.2.1 C&R outflow

As can be seen in appendix G, WeCycle has collected and recycled 6,839 T of WEEE in 2015. Philips' weight-based market share for 2015 (18.2%) dictates WeCycle recycled 1,244 T on behalf of Philips. According to the transfer coefficients to EoL disposal channels provided by Hendriksen (2009), 1929 T goes to C&R in 2015 (28.2% of total WEEE). This is 55% more than WeCycle reported, while remaining in the physical limit.

According to the SHA national C&R rate by the official C&R schemes by Huisman et al. (2012), which was 26.8% for 2010, 805 T goes to C&R in 2015; 35 % less than WeCycle reported. It is likely that the complementary recycling for SHA is nowadays more overtaken by WeCycle and WEEE NL and that therefore the C&R rate for 2010 is lower.

Overall, the results for both C&R calculations do not exactly match the 1,244T reported by WeCycle. However, since WeCycle also uses a calculation on the current weight-based market share rather than using observed data, rendering it also an uncertain measurement. Within the scope of this project, the C&R outcomes of the model are deemed satisfactory.

3.3.2.1 Stock size

The quantified results are found in the appendix due to the confidential nature of the data. The data on consumer EEE in stock in Dutch households in 2006, provided by Hendriksen (2009), see appendix H, is processed into a table in appendix T.1, showing the diffusion of products per households. Where relevant, the Philips BU has been attributed to the product types. When aggregating the product diffusion per household data on the BU, it can be more easily compared with the computed stock data. In appendix T.2 you can find the results for the aggregated Hendriksen (2009) data per BU ('per hh stock'. In the column 'per hh', you will find the aggregated Philips stock data for 2016 divided by the number of Dutch households in 2016. It is chosen to work with 2016 data due to the highest stock size certainty from reported data (see figure 15). With the data of Philips stock diffusion and all SHA stock diffusion, it is possible to calculate the Philips market share of in-stock products. All market shares are realistically below 100%, therefore not crossing the physical limit (although the comparable data is outdated).Therefore, all market shares fall within an acceptable range according to the criteria and thus the results for the stock modelling are satisfactory.

3.3.3 Sensitivity analysis

The uncertainties propogated by the sales quantity extrapolations are analyzed in this section. First, the retrospective sales extrapolation is examined and, second, the prospective sales extrapolation is examined.

3.3.3.1 Retrospective extrapolation 1995-2004

The retrospectve extrapolation follows the sales quantity trendline, but is compared to a scenario where no sales happen before 2005 and where the level of sales of 2005 is applied to all years towards 1995. In table 7 you will find the deviation for the stock and outflow on weight and quantity from the trendline anaysis when compared with the two extreme other scenarios.

The deviation for the outflow weight for 2015, i.e. -12.1% and +9.5%, results in C&R weight changes to; 1) 1,695 T and 2,112 T respectively when using Hendriksen (2009) data, and 2) 707 T and 882 T respectively using Huisman et al. (2012) data. Regarding the consistency check of the results for extreme scenarios, the C&R size does not hit a physical limit or grows too far out of proportion. Therefore the uncertainty from the historical extrapolation has no detrimental effect on the outflow sizes for 2015.

The effect of the extreme historical scenarios on the stock data can be tested by applying the deviations for 2016 on the stock unit quantity, i.e. -5.7% and 4.3% to the results of the stock size consistency check. The deviations are too low to make a significant impact on the Philips market share, which is roughly a +/-1% change for the smallest market share and a +/- 4% change for the largest market share. Therefore, the uncertainty of the historical extrapolation also has no detrimental effect on the stock size for 2016.

3.3.3.2 Prospective extrapolation 2017-2030

For the sensitivity analysis of the prospective extrapolation, the modelling results for the 2016-level sales extrapolation will be compared to the results from the continues trendline extrapolation. The results for increase of the stock and flow sizes compared to the 2016-level in 2030 in unit quantity and weight are laid out in table 9, which shows a significant increase for the stock and a lower, yet significant increase, for the outflow. The share of the stock and outflow for product sold before 2017 will therefore also decrease by a similar ratio. For any sales eventuality between the two extreme projections, the share of the stock and outflow from input before 2017 of the total will be ranging between 7.2%-11.6% in unit quantity and 5.8%-8.4% in weight for the stock, and 12.8%-17.3% in unit quantity and 11.0%-14.8% in weight for the outflow.

Table 10 (for the high-end portfolio) and table 11 (for the GranBaristo) show the percentage points (i.e. the differences between the two percentages) when comparing results for the performance indicators based on the trendline input to the results of the performance indicators based on the 2016-level input. Considering the 2 compared inputs are very conservative and very optimistic, it can be concluded that the sales projections only slightly affect the output for the high-level environmental performance indicators. In table 11, the results for the economic calculation show much higher uncertainties. With the correct financial data, the sensitivity analysis has to be applied once more to determine whether the uncertainty remains equally high. Lastly. it shows that a more optimistic sales projection leads to a relatively lower profitability for all three scenarios for both lease duration conditions.

The full comparisons can be found in appendix U. Furthermore, a set of graphs on the results for the trendline input is provided in appendix V to appendix X.

	2015				2016			
	stock		outflow		stock		outflow	
	min	max	min	max	min	max	min	max
quantity	-6.5%	5.4%	-12.8%	10.6%	-5.2%	4.3%	-10.1%	8.3%
weight	-5.5%	4.3%	-12.1%	9.5%	-4.3%	3.4%	-9.4%	7.3%

Table 7: The deviations of the stock and outflow sizes for 2015 and 2016 with the output from the trendline sales input as baseline

	2030	
	stock	outflow
quantity	39.8%	29.4%
weight	41.0%	29.9%

Table 9: Increase of the stock and outflow size of the trendline sales projection compared to the 2016-level sales projection

	2016-level		trendline	
	stock	outflow	stock	outflow
quantity	11.6%	17.3%	7.2%	12.8%
weight	8.4%	14.8%	5.8%	11.0%

Table 9: The share of the products sold before 2017 for 2030 for the two sales projections.

	100% LS			130% LS		
	L	LRL	LRS	L	LRL	LRS
new input qty [high-end]	-2.6%	-0.7%	-2.6%	-1.7%	2.1%	-1.7%
new input qty [all]	-0.1%	0.0%	0.5%	-0.1%	0.1%	0.4%
WG [high-end]	-2.8%	-4.8%	0.0%	-3.7%	-0.7%	0.0%
WG [all]	-0.5%	-0.8%	0.3%	-0.6%	-0.1%	0.2%
C&R [high-end]	0.0%	0.0%	-	0.0%	0.0%	-
C&R [all]	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%

Table 10: Percentage point difference between the 2016-level and trendline sales input results for the high-end products. LS= lifespan.

	100% LS			130% LS		
	L	LRL	LRS	L	LRL	LRS
new input qty	-1.0%	0.2%	-1.0%	-0.1%	4.7%	-0.1%
WG	-2.7%	-4.8%	-2.4%	-3.7%	0.0%	-1.5%
C&R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
profit	-14.2%	-8.6%	-17.2%	-15.6%	-14.8%	-18.1%

Table 11: Percentage point difference between the 2016-level and trendline sales input results for the GranBaristo. LS= lifespan.

3.3.3 Summary and conclusions

The BAU simulation for 1995-2016 provides the insight that there is a steady growth for the inflow, outflow and the stock size. Furthermore, it can be extracted that a large number of products that are unrecoverable due to undesirable discarding behavior are Personal Health products. However, due to the relatively low weight of these products, the weight-based impact from Personal Health products is rather low. Instead, the overall heavier products in the Domestic Appliances BG are responsible for the majority of the unrecovered WEEE.

The BAU simulation results for 1995-2016 have passed the consistency criteria on the C&R outflow for 2015 and the product diffusion outcomes for 2016. Therefore, the model is deemed consistent with the real-world for this case study. The results for the BAU simulation show that the stock and outflow for the retrospectively extrapolated input has a relatively small share of the results for the entire input. It is also the case that the uncertainty in the stock and flow size due to extrapolation is decreasing with each year closer to 2016. Furthermore, the uncertainty for the outflow is larger than for the uncertainty for the stock size for a given year due to the delay effect of the discarding probability distribution function. From the sensitivity analysis of the historical projection, it is also found that share of the stock and flow size from the extrapolated input is too small to affect the verdict for the consistency check.

From the results for the BAU simulation extended towards 2030, the main things that can be deduced are, firstly, that the output from sales before 2017 will peak at 2018. And secondly, the effect of the stabilization of the input at 2016 will only be reflected in the output around roughly 2039 with using the current parameters. This determines that finishing one entire cycle in the BAU simulation (i.e. all products in the same POM year have all been discarded) for this product portfolio takes roughly 23 years. The BAU extension also serves as the basis for building the RL scenarios. The high-end products account for a 6% share in unit quantity and accounts for 15% of the average stock weight (due to heavier products) for the upcoming years. 9% of the stock produced by high-end products is hibernating and therefore is subtracted from the total stock to generate the stock size as the performance requirement for the product leases.

The main take-aways from the results for the performance indicators are, firstly, that all scenarios consist of trade-off when considering all performance indicators. Secondly, it shows an overall increase in positive impacts on all performance indicators when increasing the lease duration. Thirdly, it shows that the replacement effect takes place to generate a netto postive environmental impact.. The results for the performance indicators will be further discussed in section 4.1 ‘Interpretation of results‘. The outcome of the sensitivity analysis for the prospective sales extrapolation demonstrates that there is a low sensitivity for the environmental performance indicators. However, the outcome for the profitability analysis reveals a considerable sensitivity. The profitability will need to be assessed on sensitivity again in future research when applying the correct underlying financial data.

3.4 Evaluation

The model and the modelling results have been presented to the target group, which consisted of staff members that are involved with the CE developments for SHA appliances. The evaluation resulted in the following feedback on the modelling decisions and recommendations for improvement.

3.4.1 Feedback

Regarding the sales extrapolation - It is unlikely that a large share of products on AG-level that were sold in 2005, were also sold from 1995 on. From an innovation perspective, Philips strives to replace the sales of a product with a new products every 4-5 years or so.

Regarding the high-end selection - Currently, it would only be likely that the products with with the highest price range according to the UNETO-VNI chart (appendix J) would be considered for lease. A large share of the current ‘high-end‘ product selection contains FAEM products with mid-range prices, although they would not be financially interesting at this point for lease.

Regarding the lease duration - It is rather unlikely for products to be repaired after the initial warranty period according to the UNETO-VNI chart (appendix J). For occuring failure after the 2-4 year warranty time, the product will likely be replaced and the same would probably happen to leased products as well. The only consumer appliance that would get repaired long after the initial warranty time has passed would be large domestic appliances, such as refrigerators. Overall, Philips is currently more interested in leasing the products within the 2-4 years of warranty for the lower technical and financial risk.

Regarding the consistency check - The approach towards the consistency check on the calculated C&R outflow weight was accepted, however doubt was cast on the stock consistency check. Although the market shares did not cross any physical limit (i.e. >100%), some outcomes are still deemed rather improbable. This can be due due to the the probably outdated consumer survey data by Hendriksen (2009), the aggregated nature of the UNU-key parameters or the fact that there could be a rather high hibernation rate for Philips products sold in a time with a relatively higher market share.

3.4.2 Recommendations

Incorporate the replacement rate - Within the innovation groups for the different businesses within Philips, there is ongoing research on the *replacement rate* of products. This replacement rate is used to indicate when or how often businesses should start putting new products on the market. It could be interesting to incorporate this replacement rate into the model, since it will probably be more accurate for the company than using the UNU-key parameters (that are based on all brands and all price categories).

Include dynamic manufacturing costs - Since the model provides information on how many fewer products need to be produced, it can be argued that it could possibly save money on (the number of) manufacturing tools and manufacturing sites. The economy of scale still has to be considered with such an claim.

Consistency check with economic models - Although the data that is currently used is not correct, with the right underlying data this financial modelling approach can become very interesting. First of all, it would be necessary to compare the results with other RL financial models when using the same variables to check for the consistency and/or accuracy. It needs to be mentioned that the RL econometric models are also not be-all and end-all models and also deal with considerable uncertainties. When the outcomes of this model is in a comparable range to the outcomes of the existing RL models, the model would be likely to be developed further.

3.4.3 Conclusions

From the evaluation, it can be concluded that a more realistic simulation for the BAU conditions would include a market presence of the products for maximum 4-5 years instead of the retrospective extrapolation of sales in 2005 to 1995. Furthermore, the high-end product selection should exclude products that could also be categorized as mid-range products. Also, the products selected for lease would be leased for the 2-4 year warranty time according to the UNETO-VNI chart. For enhancing the accuracy of the results, the replacement rate (available in-house) could be incorporated in the model, as well as dynamic manufacturing costs. The consistency check for the BAU simulation on the market share will need to be improved on more modern and disaggregated stock data to check the accuracy of the stock data by Hendriksen (2009). Lastly, the model deliverable can be interesting for the company, but needs to be compared for reliability with existing in-house econometric models.

4. DISCUSSION

This chapter will lay out the new insights from the simulation results and evaluation. Furthermore, the data and the modelling approach will be critically reflected on, thereby acknowledging the limitations. Based on the limitations, recommendations are provided to further developing the model, along with recommended research topics for future work that arose from this research.

4.1 Interpretation of results

Through the consistency check and sensitivity check, it is acknowledged that the BAU model simulates the real world to an satisfactory degree according to the predefined criteria and can therefore be used to provide insight on the current downstream product flows.

The accuracy for the RL scenario outcomes still needs to be tested for correct financial data, however, with the current set-up of the model, it is possible to make longterm RL strategic recommendations. The suggested strategies applied in the 3 scenarios (L, LRL, LRS) all have negative and positive aspects and will be discussed in this section.

First, the L scenario is a rather safe option from a consumer acceptance perspective and does not require design for refurbishment or the set-up of a refurbishment program. However, from the results it is inferred that leasing products for the Philips lifetime can result in a higher required input compared to BAU conditions. Furthermore, the L scenario scores the lowest on WG decrease, although all WEEE ends up in C&R.

Second, the LRL scenario performs the best on the input performance indicator by far, reduces WG significantly and will account for 100% C&R of the WG. However, this scenario will be technically challenging for a product to guarantee full functionality for 2 consecutive lease durations. Furthermore, it is likely to perform poorly on profitability, since the fixed costs of the lease (maintenance, logistics) will likely be close to the revenue from lease fees for a refurbished product (lease fees which will be lower compared to those of a new product).

Thirdly, the LRS scenario performs well on the WG indicator and can perform well on the input performance indicators for relatively long lease durations and/or when the refurbished products substitute low-end products. The LRS scenario is technically less risky than the LRL scenario while still decreasing WG significantly. Most importantly, the scenario will likely outperform the other scenarios on profitability. However, the C&R rate is dictated by consumer discarding behavior in the LRS scenario, which means that the LRS scenario cannot to close the loop entirely.

From the analysis of the results for the RL scenarios, it can be deduced that all suggested RL scenarios have trade- offs for the four performance indicator. Based on the RL model outputs for the variablr entries used in the assessments, the researcher recommends the implementation the strategy used in the LRS scenario. This strategy is recommended based on the high decrease of WG and high likelyhood of being profitable, and is therefore generally less risky for the business.

In the evaluation, it was learned that currently there is a focus on leasing products for a shorter period than is applied in the simulation. The simulation results for the Philips lifetime as lease duration and a longer lease duration, it can be inferred that a shorter lease duration will score poorer on the input and WG performance indicators. It needs to be assessed whether it is actually worth setting up a RL network when little environmental benefits can be reaped. This conflict can be avoided by designing products for a longer lifespan. Increasing the products lifespan through design will lead to more succesfull and fruitful implementation of RL strategies. Design strategies that can be applied for a generating longer lifespan in a CLSC can include 1) design for durability, 2) design for maintenance and repair, 3) design for adaptability and upgradability and finally, 4) design for disassembly and reassembly (Bakker et al., 2015).

4.2 Limitations

This research project holds several limitations. First, the main limitations are laid out and are followed by a list of other limitations faced in this project.

4.2.1 Main limitations

Single case study - The model is based on only a case study on one company for one country. No exploration is done on whether the model can be used to assess the stocks and flows for other companies or another country.

Outdated data use - The data regarding consumer behaviour for the UNU lifespan distribution and Hendriksen (2009) might be already outdated since the data apply to 2010 and 2006 respectively. The data provided by Hendriksen is used exhaustively modelling this case study and the outdated nature of the data will likely cause inaccuracy for simulating for modern times.

Consumer behavior - The decisions on from the performance requirement of the same in-use stock size of the BAU simulation does not take in consideration that the new consumer interaction construction might increase or decrease the stock demand. Since a lease contract can make a product more financially accessible to a larger audience and generally lowers the threshold for consumers by taking out the barrier of a high initial investment. This could also possibly lead to a negative effect, where the demand of expensive SHA products for the average households increases due to its increased financial accessibility. Similarly, the use of the 'push' model for introducing the refurbished products to the market is not supported by any data. It might as well be the case that consumer acceptance for refurbished SHA is lower than needed. In addition to regarding the consumer behavior, during the research process, other new insights were made that questions the validity or up-to-date status of the current discarding PDF used in for modelling. According to this model, it is likely that a significant share of the initial products POM are discarded withing the first 2-3 years. After having acquired knowledge of the current second-hand market trend and the strong Dutch consumer protection laws, it is rather unlikely a product is discarded within the first 2-3 years due to consumer perceived obsolescence. In the case of product failure, consumers have the right to repair or replacement and, furthermore, in the case of an obsolete functional product, the consumer can sell the product on the second hand markets.

CBA/profitabilty consistency check - While the BAU simulation output for 2015 and 2016 have been checked for consistency with real-world data, this is not done for the CBA in modelling the future scenarios. From all performance indicators, the profitability is the most importance in a business context, although it still needs to be checked with existing econometric models. So, whether MFA modelling can complement economic or econometric models is still unexplored

4.2.2 Other limitations

Regarding the uncertainty of data

Uncertainty in UNU-key lifespan data - The sensitivity analysis for the WG calculations for the Netherlands using UNU-key Weibull parameters by Magalini et al. (2016) show that there is a +/- 33-37% margin of error for the WEEE flow for +/- 30% longer and shorter average lifespan. In fact, the Netherlands ranks the 6th place of the EU28 for the margin of error size. Althought two extreme scenarios were taken to calculate the uncertainty, it indicates that the weight-based WEEE flow faces significant uncertainties regarding the used UNU-key average lifespan.

B2X market data inavailability - There is no sales information available regarding the customer market, i.e. B2B or B2C, while the lifespan and C&R rate can differ greatly. According to the outcome to Huisman et al. (2012), the weight-based size of the share of B2B SHA WEEE was around (0.23[kg/HH]/6.20[kg/HH]=) 3.7% (see appendix E). This implies that the around 3.7% of the WEEE outflow in this model would go to 100% to C&R, thereby increasing the overall C&R rate with a few percentage points.

Hibernating stock calculation - Due to lack of better data, removing the share of hibernating products from the stock produced by high-end products sold from 2016 on the basis of a figure for the share of hibernating data for the entire stock is somewhat simplistic. Unfortunately there is no data available on how far into the product lifespan the product will go into hibernation. Also hibernation rate is disproportional to the year-POM stock. This method implies that in 2017 the share of hibernating products from 2016 and 2017 is equal to the hibernating share in 2030 from a stock produced by products sold in 2016-2030.

Regarding modelling decisions

Unrealistic sales extrapolations - The retrospective and prospective extrapolation is done on an aggregated level. The use of this method implies that all products sold in 2005 have been told in the years back to 1995 and that all product sold in 2016 will be sold throughout 2017-2030. A more accurate model will extrapolate the data for based on the trendline for each products. This way, the products that are introduced later or that are declining in sales are not included for all years in either 1995-2004 or 2017-2030.

Static discarding PDF - The model uses the simplest form for the discarding PDF (eq. 6) for the BAU simulation for 1995 to 2030, while a more accurate result could be produced with the more dynamic discarding PDF (eq. 7).

High-end durability assumption - The fact that all high-end SHA products are repaired instead of replaced in case of failures (and therefore are in general more repairable) is an assumption and might not actually be the case.

Qualification for lease - From the evaluation, it is understood that many products considered high-end in the definition of this project are not considered eligible for leasing in reality. Instead, the project must have only focused on the upper price ranges according to the UNETO-VNI chart (appendix J). However, looking at appendix 6, the highest product categories ('IBL') make up an neglectible share of the total product input, both in weight and in quantity.

Isolated replacement effect - The replacement effect in the low-end market by the refurbished high-end products is an extreme scenario. It does not factor in other competing brands and therefore might experience much less replacement than expected in this model.

Other considerations

High-level environmental indicators - The environmental performance indicators in this project are not based on actual mid-points impact categories (e.g. climate change, ozone layer depletion, acidification, etc) or end-point impact categories (i.e. environmental impacts, resource depletion and health impact). Working with a more high-level way whether a strategy is less/more impactful than the other needs to still be proven with the mid-point or end-points with data of the associated emissions.

4.3 Recommendations

The recommendations made in this section are largely built on overcoming the limitations discussed in the previous section. First, the main recommendations, which are most interesting and actionable, are laid out and are followed by a list of additional recommendations. The additional recommendations are grouped on suggestions for the model (increasing accuracy and adding features), suggestions for future research work and recommendations for the company more specifically.

4.3.1 Main recommendations

Increasing reliability through reproducability - The reliability of the model can be tested on the reproducability of the model by applying it to similar domestic EEE (preferably SHA) companies, such as Braun, De'Longhi, Princess and Magimix. In addition, the reliability of the model can also be tested for multiple countries. For starters, it might be interesting to check the model for the current case study company for a country with a lowest sensitivity to lifespan changes, such as Macedonia, Turkey, Montenegro or Serbia (Magalini et al., 2016). Lastly, in order to examine the reliability of the MFA-based profitability analysis, the results for a scenario with certain parameters have to be compared to the results from an in-house RL econometric model

Carry out IB forecasting method - The accuracy of the MFA model can be tested by comparing the results with the stock and flows calculation results for the IB forecasting model proposal, as is shown in Table 3. It will require data collection on the survival distribution function parameters, repair costs for common failures and the depreciation rate. These are data that are expected to be found in-house, albeit dispersed over various departments. The accuracy could also be tested by comparing the results with the Carnegie-Mellon model, but this model requires data from close observation from possibly more than a decade.

Find discarding PDF based on price categories - Because in this research it was discovered that for stock and flow accounting in RL management products are primarily grouped in price categories rather than product type/ functionality, it could be interesting to determine the discarding PDF parameters based on price categories. This can be done as an alternative to IB forecasting, while applying the same grouping concept.

Finding technical optimum for lease duration - More in-house research is needed on the technically optimal lease duration for the products and how this optimal lease duration relates to the current minimum expected average lifetime. On the one hand, in a lease scenario there is more maintenance done and repair when needed, implying that a product will last longer. On the other hand, the utility the product might increase significantly through the redistribution of the product, which might decrease the technical lifespan. Furthermore, since the consumer does not bear ownership of the product, the product might not be handled with as much care and thereby also decreasing the technical lifespan.

4.3.2 Additional recommendations

Increased accuracy of the model

Add B2X market information - It is recommended to include B2B/B2C market information on the sales of the products to primarily increase the C&R projection more accurate. Secondly, the difference in lifespan for the same product in a B2B or B2C environment can be taken into consideration, although that information is currently still lacking.

Replace outdated data - The BAU model and all the EoL destination modelling is based upon data that is likely to be quite outdated. It is advised to update the data on the consumer behavior for SHA in the Netherlands once more recent data becomes available.

Include dynamic discarding PDF - Instead of using the static discarding PDF according to equation 6, pair the trend data on decreasing EEE lifetimes, which can be found in Bakker et al. (2014), and incorporate it into equation 7 for a more accurate representation of the stock and flows over the many years.

Include diffusion and saturation-level function - To make a more accurate extrapolation for future sales, the simple Gompertz function (as shown in equation 9) can be introduced. This will require PPP/capita projections for the Netherlands, the saturation rates for the products and lastly, the projection for the number of households in the Netherlands (the latter is provided in appendix I.2). Also, the other Gompertz functions described in the study by Diaoglou (2010) can also be explored as a potentially more suitable product diffusion and saturation rate.

Added features to the model

Incorporating replacement rates- As is suggested in the evaluation session, it would be interesting to explore the opportunities to incorporate the replacement rates that are available within the different business groups to develop a more accurate Philips-specific discarding PDF.

Coupling LCA data - If there are LCA data available for one or more SHA products, it can be coupled with the MFA. For an easy integration, the data has to be provided in a similar way as the financial data. With regard to the

BAU simulation, the total CO2-eq. for manufacturing has to be provided, together with the yearly average CO2-eq emissions related to the use of the product and finally the CO2-eq. impacts for a product per different EoL channel. In addition, for the RL scenarios, the total CO2-eq for refurbishing and (internal) scrapping is needed together with the potential emissions associated with maintenance and (spare part) logistics. The same concept applies to LCC data, which can be a helpful tool to calculate the external costs for all scenarios.

Possible spin-off research projects

Single product MFA - One suggestion as a spin-off project is to build a MFA just for one specific product only. This makes it easier to collect more exact data and negates the effects of the generalizations made in this current MFA. The only downside to this approach is the lack of C&R data on such a disaggregated level and thus a consistency check on the outflow might not be possible.

High/low-end in the CE - During the step of defining the different RL scenarios, it was brought up that the original definition of high-end and low-end might need a revision in the context of the CE. A follow-up discussion on whether recovered products can be viewed as high-end will probably lead to interesting positions on one practical issue in the CE.

Trend in reuse and repair claims - The effects of the Dutch consumer protection laws and the emerging consumer-run second-hand markets on the discarding PDF could be investigated. As is stated in the limitations, it is unlikely for a significant share of products to be discarded within the first 2-3 years and therefore the validity of the currently used Weibull distribution parameters can be questioned.

Replacement effect - Considering this research examined the replacement effect for new low-end products by similar refurbished products, it could also be an interesting business proposition to explore how a company can go in the direction where the low-end market can be entirely satisfied by refurbished high-end products. It would be a thought-provoking experiment to explore how many products must be initially produced for lease as high-end to satisfy the low-end demand and how could this system be gradually introduced. It could be a financially attractive proposition when the refurbishing and the costs of the RL network are overall smaller than the manufacturing of new products.

4.3.2 Recommendations for (companies like) Philips

Building the applications - It is suggested to Philips that two internal applications can be build; the first one providing insight on the current downstream product flows and the second one providing insight on the impact of the different RL scenarios compared to the BAU simulation. When the applications are built on the company-server, it can be easily used by whoever has access. The use of the applications can generate ample feedback and possibly ideas for a follow-up project. First, it is possible to build a rather simple model for the BAU simulation based on the data output. Since there are no specific modelling entries involved for the stock and flow output of this data, the application can just be a data visualizer. The application user interface could look like the wireframe presented on page 54. The second application, a BAU-RL 'comparison' tool requires modelling parameters entered by the user. Therefore, this tool will also have to compute the stocks and flows within the program and will require a more elaborate back-end. The user interface would require a similar data visualizer as the BAU simulation tool and could look like the wireframe presented on page 55.

Long-term focus - Although Philips embraces the CE principles on a high level, there is still a short term focus closer to the operational level. The introduction of RL into a business requires initial investments, such as the RL network, and will also require several years before before turning profitable. As is the case for most 'radical' transitions and changes, it will pay off in the long-term rather than in the short-term. In addition, the long-term benefits of reduced environmental impact will in turn also reduce risks through reduced environmental liability and can be a competitive advantage due to the greener image.

5. CONCLUSION

The thesis research project was set out to incorporate Reverse Logistics into the dynamic Material Flow Analysis (MFA) method to make it more useful to companies and was carried out through theoretical analysis and a case study.

Currently, dynamic MFAs have been successfully applied to track Waste of Electronic and Electrical Equipment ((W)EEE) on a national level. Within the case study, it is discovered that the current state-of-the-art dynamic MFA can also be applied to provide insight on the product stocks and flows for a company in the current production-consumption system. Additionally, it was found that Reverse Logistics stock and flow accounting methods can strengthen the accuracy and reliability of the dynamic MFA method. However, the stock and flow accounting methods from the different fields, i.e. Industrial Ecology and Supply Chain Management, have never been connected before. This is likely due to the fact that the objectives of the methods in the two fields are different. While the dynamic MFA is used to track products to make an overall mass balance and to eventually calculate the weight-based recycling rate, the Reverse Logistics stock and flow accounting methods focus solely on predicting the spare part production demand. Due to the time restriction of the project, it has not been possible to satisfy the data requirements for the Reverse Logistic stock and flow modelling, and therefore it was not possible to compare the outcome of the two different methods. It is recommended that this option will be explored in future research.

The shift towards a Circular Economy is achieved within companies through Reverse Logistics management within a Closed Loop Supply Chain. This project presents the first attempt to apply concepts from the Reverse Logistics field to the dynamic MFA method to build circular loops for assessing the impacts from the Reverse Logistics strategies on the stocks and flows. The concepts that are incorporated to make the Reverse Logistics modelling viable are focused on overcoming the three main supply constraints in Closed Loop Supply Chain management according to Geyer & Jackson (2004). This is done by creating scenarios where only high-end products are leased (assuming high-end are more durable and repairable) and where recovered products from lease returns are sold with a 'push' reuse market driver. By building the Reverse Logistics scenarios according to these conditions, while excluding any external influence, it was found that the main modelling variable is the lease duration. An increase of the lease duration will considerably change the outcomes for the performance indicators, while the sales projection has little effect on the outcomes. Additionally, financial information associated with the stocks and flows can be added, which enables a profitability analysis. Due to time restriction of the project, the profitability analysis has only been made possible for one product. However, it is assumed that products in similar price ranges will produce comparable results.

Based on the results for the RL scenarios for this case study, it can be deduced that introducing the circular loops within a Closed Loop Supply chain can be environmentally and economically attractive for a company from a certain minimum lease duration onward. From the several Reverse Logistics scenarios presented in this case study, the recommended strategy would be to refurbish the returned end-of-lease products and sell it to the low-end market. This strategy will likely be the most financially attractive and is not the most technically demanding, while decreasing WEEE production significantly. Furthermore, based on the results, it can be recommended to focus on designing products to last longer to guarantee a more successful implementation of Reversed Logistics strategies.

For the downstream product flow modelling of the current situation, a visualization tool can be made based on the stock and flow output. To test the current Reverse Logistics modelling, the model has to be tested with accurate financial data and compare it to existing in-house economic Supply Chain models for similar scenarios. Additionally, to make the model more generally applicable, the model needs to be applied to more companies and countries.

While the stock and outflow model results for the case study reflects real-world data in an accurate way for recent years, the model faces limitations for accurate predictions for the coming years, especially when introducing reversed flows to the MFA model. The model results can be used to provide the insights to the stocks and flow sizes of recent years when considering the current production-consumption system and thereby be able to e.g. connect reported collection and recycling data to the actual product flow sizes. For the future stock and flow size predictions, however, it can be concluded that the model is more useful for thought experiments. It will likely not be useful for accurately predicting stocks and flow sizes for RL scenarios, but it will provide insight on the underlying processes and the overall influence of changing a variable or parameter in the system. The outcomes of this thought experiment can likely be useful for making strategic decisions.

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7. APPENDICES

Appendix A

Weibull distribution parameters for UNU-keys in the NL, FR and BE (Balde et al, 2015a)

EEE Category	Lifespan distribution (Weibull) [2]	
	α (shape)	*β (scale)*
1. Large household appliance		
0101	1.8	15.8
0102	1.6	13.1
0103	2.5	18
0104	2.2	13.9
0105	2.6	16.5
0106	2	13.5
0108	2.2	16.5
0109	2.6	23.2
0111	2.8	12.3
0112	2.4	13.6
0113	2.5W	20.6
0114	0.8	14.7
2. Small household appliances		
0201	1.3	9.4
0202	1.3	12.3
0203	1.8	7.9
0204	1.5	10.3
0205	1.3	10.8
3. IT and telecom equipment		
0301	1.3	5.9
0302	2.1	9.6
0303	1.5	5.2
0304	1.7	10.1
0305	2.1	6.5
0306	0.7	7.6
0307	1.5	7.8
0308	2.2	8.5
0309	2.5	7.5
4. Consumer equipment		
0401	1.4	10.2
0402	0.8	8
0403	2.1	15.6
0404	1.7	10.5
0405	1.5	10.8
0406	1.4	8.2
0407	2	12.6
0408	2.1	12
5. Lighting equipment		
0501	1.4	8.72
0502	1.6	8.43
0503	1.9	8.43
0504	1.6	6.9
0505	1.2	4.57
0506	2.3	16.59
0507	2	11.84
6. Electrical and electronic tools		
0601	2	6.6
0602	1.9	11.6
7. Toys, leisure and sports equipment		
0701	2.6	15.7
0702	1.5	4.7
0703	1.2	5.6
8. Medical devices		
0801	2.4	11.6
0802	1.4	7.6
9. Monitoring and control instruments		
0901	2.6	19.2
0902	1.7	9.6
10. Automatic dispensers		
1001	1.9	11.6
1002	2	10.1

Appendix B

Transfer coeficcients for reuse or discarding of obsolete product - p. 41 (Hendriksen, 2009)

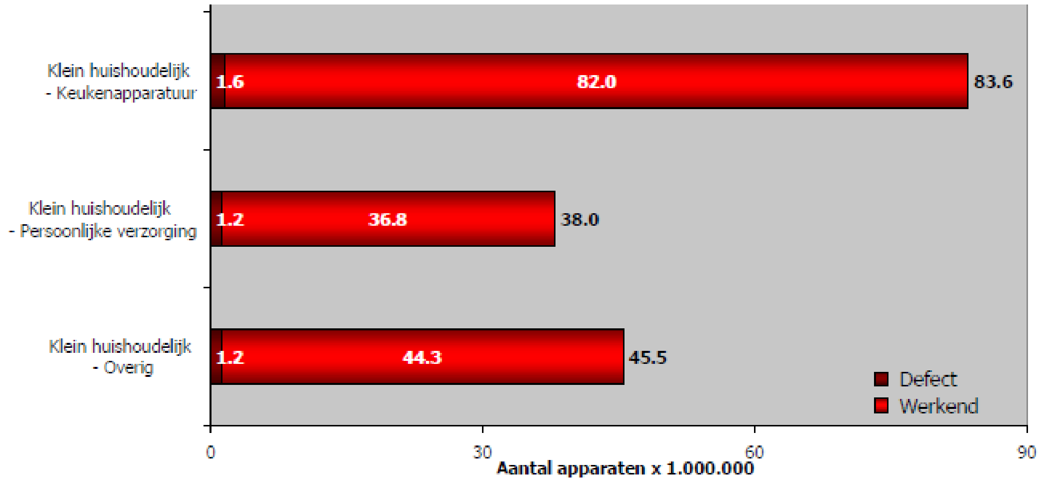
Tabel 3.1 Bestemming afgedankte witgoedapparaten in %

Percentage	Verwijderd	Hergebruik	Onbekend
Totaal Witgoed	69,2	28,7	2,1
Groot huishoudelijk	65,3	33,8	0,9
Klein huishoudelijk – Keukenapparatuur	67,0	30,6	2,4
Klein huishoudelijk – Persoonlijke verzorging	77,8	19,4	2,8
Klein huishoudelijk – Overig	70,8	26,9	2,3

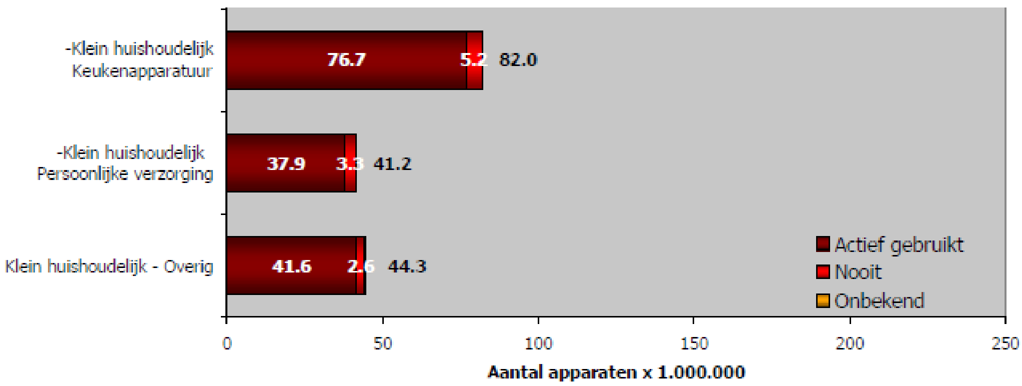
Appendix C

Statistics on (W)EEE storage in Dutch households in 2006 (Hendriksen , 2009)

Appendix C.1 **-** The share of defect products of all products in the households - p..35 ;

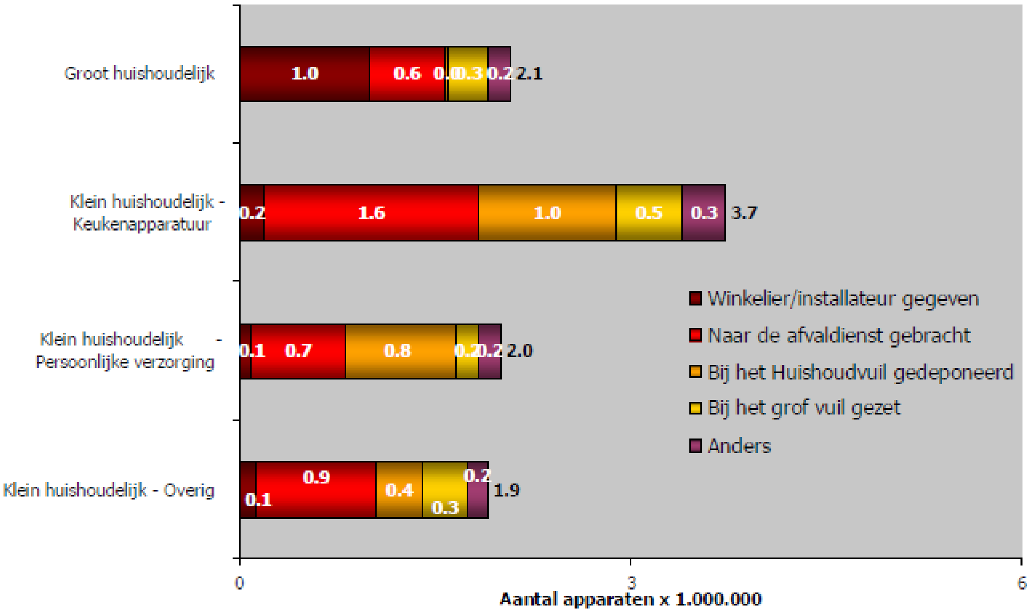


Appendix C.2 -The share of unused products of all working products in the households - p..36 (Hendriksen , 2009)



Appendix D

Statistics on WEEE EoL destination transfer coefficients (Hendriksen , 2009)



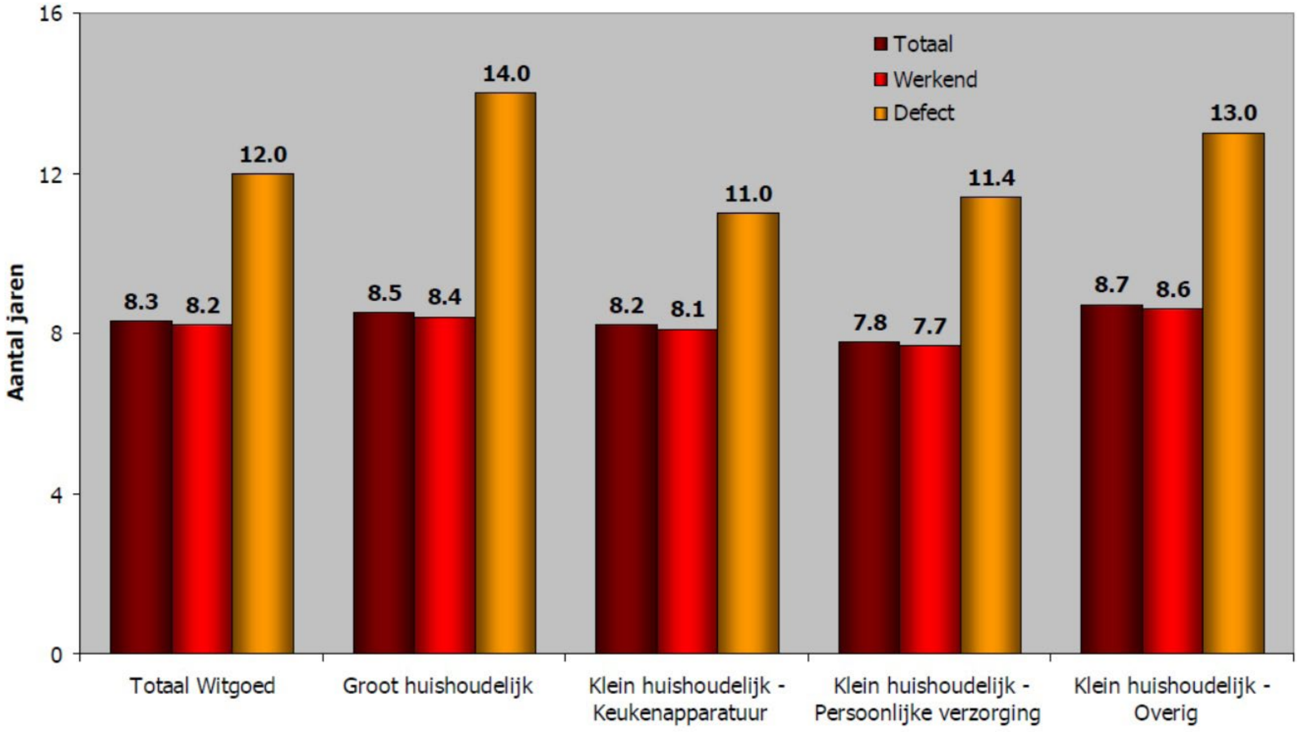
Appendix E

Statistics on EEE POM and WEEE generation in 2010 in the Netherlands(Huisman et al. , 2012)

2010 IN KG/INH	A LHA	B C&F	C SHA	D IT	E1 MON	E2 TV	F LAMPS	G PROF	TOTAL (KG/INH)	TOTAL (KTON)
EEE POM 2010	**7.88**	**3.88**	**7.50**	**3.03**	**0.76**	**1.74**	**0.27**	**1.46**	**26.5**	**440**
WEEE + used EEE Generated	**6.39**	**2.95**	**6.44**	**3.00**	**1.80**	**1.85**	**0.22**	**1.03**	**23.7**	**392**
WEEE + used EEE / EEE ratio	81%	76%	86%	99%	237%	106%	80%	71%	89%	89%
Export used EEE	**0.26**	**0.60**	**0.24**	**0.60**	**0.26**	**0.49**	**0.00**	**0.20**	**2.7**	**44**
Export used EEE HH whole appliances	0.23	0.54	0.22	0.22	0.04	0.49	0.00	0.00	1.7	29
Export used EEE B2B incl. refurbishing	0.03	0.06	0.02	0.38	0.23	0.00	0.00	0.20	0.9	15
WEEE Generated 2010 NL	**6.13**	**2.36**	**6.20**	**2.40**	**1.53**	**1.36**	**0.22**	**0.83**	**21.0**	**349**
WEEE / EEE ratio (excl. export)	78%	61%	83%	79%	202%	78%	80%	57%	79%	79%
Documented + export used EEE	**4.93**	**2.52**	**4.93**	**2.44**	**1.43**	**1.78**	**0.22**	**0.83**	**19.1**	**316**
Households										
Wecycle/ICT~Milieu	1.86	1.53	1.60	0.61	0.61	1.25	0.10	0.00	7.5	125
Complementary	2.29	0.00	1.22	0.29	0.12	0.00	0.00	0.00	3.9	65
Businesses										
Complementary	0.52	0.39	0.23	0.41	0.45	0.04	0.01	0.63	2.7	44
Compl. recycling B2B + HH	**2.81**	**0.39**	**1.45**	**0.70**	**0.56**	**0.05**	**0.01**	**0.63**	**6.6**	**110**
Waste/incineration	**0.00**	**0.00**	**1.64**	**0.54**	**0.00**	**0.00**	**0.11**	**0.00**	**2.3**	**38**
Not (yet) documented	**1.2 – 1.7**	**0.4 – 0.5**	**1.4-1.6**	**0.5 – 0.6**	**0.4 – 0.4**	**0.1 – 0.1**	**N/A**	**0.2 – 0.2**	**3.9 – 5.1**	**64 – 85**
Potentially identifiable min/max	0.7 – 1.0	0.2 – 0.4	0.6 – 1.0	0.1 – 0.2	0.1 – 0.1	0.0 – 0.0		0.1 – 0.1	1.8 - 2.8	31 – 46
Unidentifiable, min/max	0.5 – 0.6	0.1 – 0.2	0.6 – 0.8	0.4 – 0.5	0.2 – 0.3	0.0 – 0.1		0.1 – 0.1	2.0 – 2.4	34 – 40

Appendix F

Average in-stock product age in Dutch households in 2009 (Hendriksen, 2009)



Appendix G

Reported C&R weight recycled by WeCycle on behalf of Philips for WEEE category 2 (=SHA) in 2015

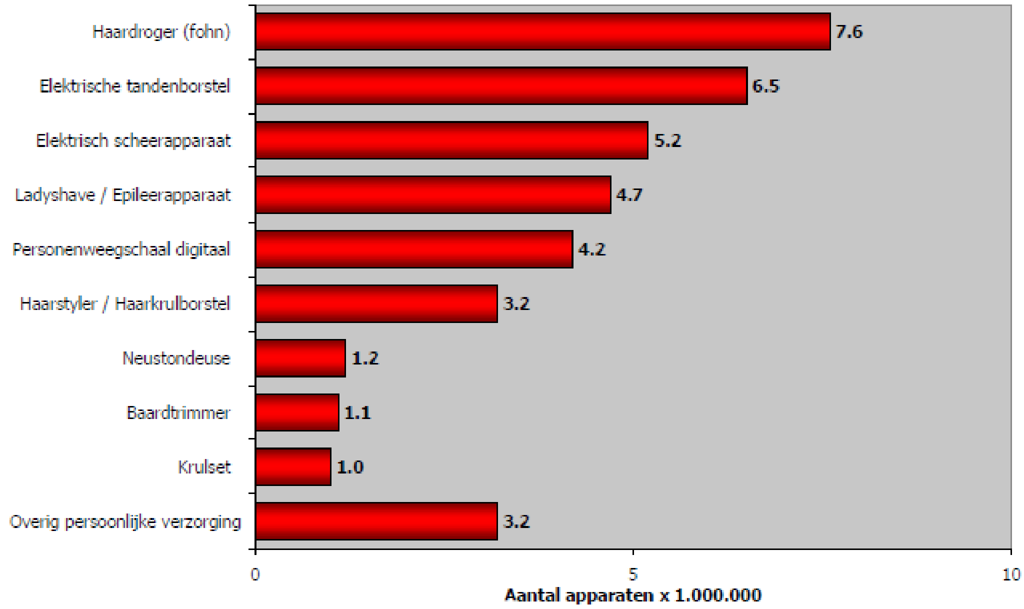
Naam: Philips Consumer lifestyle **Periode:** 1 januari - 31 december 2015

WEEE categorie	Naam categorie	PoM* producent	PoM* totaal	Aandeel producent	Ingezameld totaal	Ingezameld namens producent
2	Klein witgoed	6.045.723 kilo	33.236.000 kilo	18,2 %	6.839.000 kilo	1.244.000 kilo

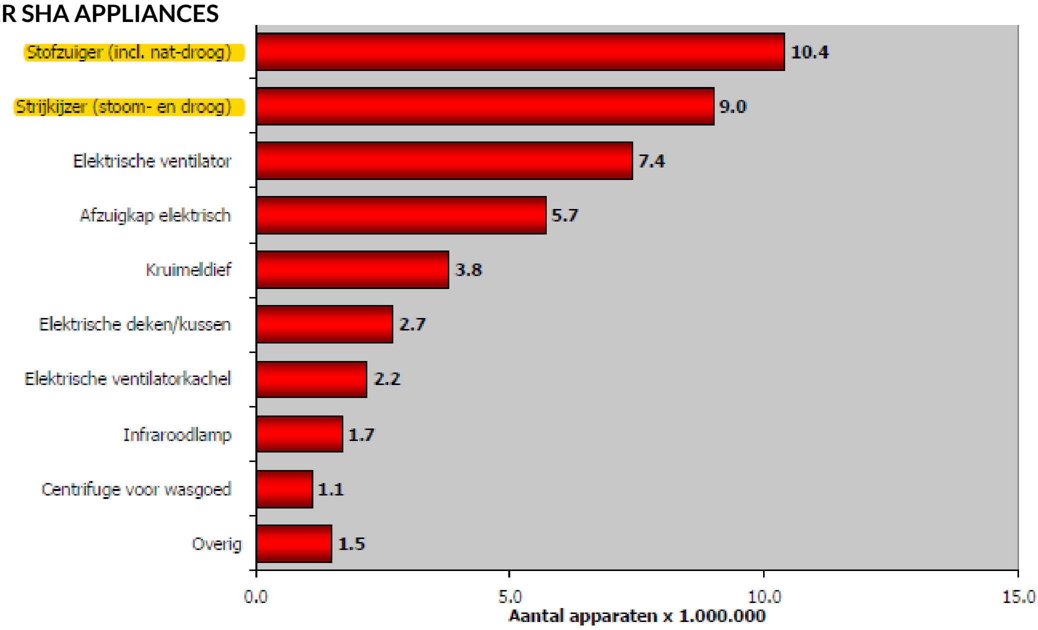
Appendix H

Number of SHA products found in Dutch households in 2006 (Hendriksen, 2009)

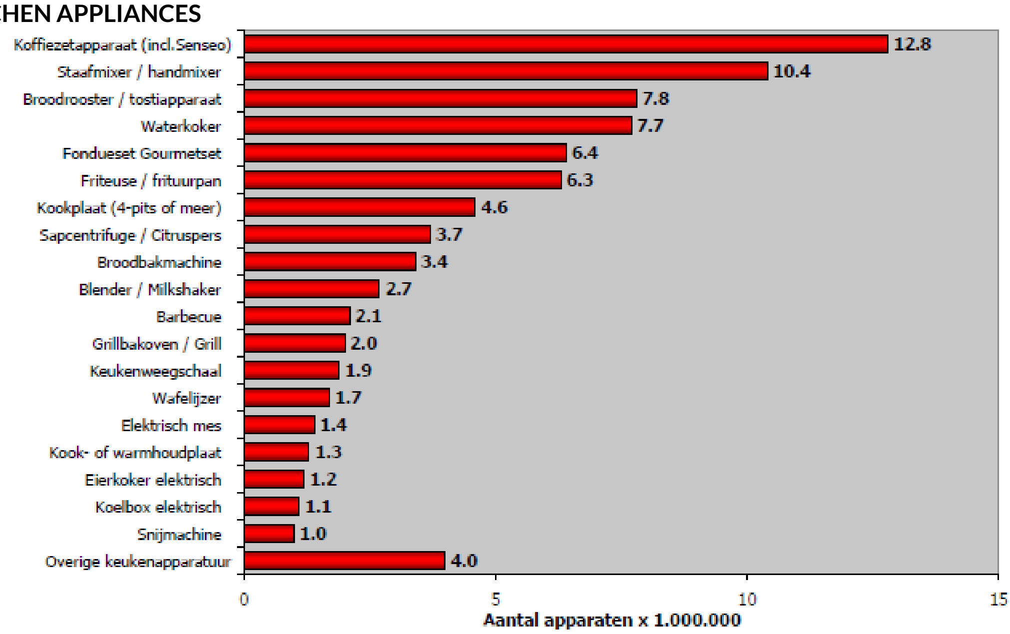
PERSONAL CARE APPLIANCES



OTHER SHA APPLIANCES



KITCHEN APPLIANCES



Appendix I

Number of Dutch households per year -CSB StatLine

Appendix I.1 - recorded households 2000-2016

Huishoudens; samenstelling, grootte, regio, 1 januari			
		Onderwerpen	Particuliere huishoudens: samenstelling
		Onderwerpen	Totaal particuliere huishoudens
		Onderwerpen	Totaal particuliere huishoudens
Leeftijd referentiepersoon	Regio's	Perioden	aantal
Totaal alle leeftijden	Nederland	2000	6801008
Totaal alle leeftijden	Nederland	2001	6866954
Totaal alle leeftijden	Nederland	2002	6934263
Totaal alle leeftijden	Nederland	2003	6995724
Totaal alle leeftijden	Nederland	2004	7049280
Totaal alle leeftijden	Nederland	2005	7090965
Totaal alle leeftijden	Nederland	2006	7146088
Totaal alle leeftijden	Nederland	2007	7190543
Totaal alle leeftijden	Nederland	2008	7242202
Totaal alle leeftijden	Nederland	2009	7312579
Totaal alle leeftijden	Nederland	2010	7386144
Totaal alle leeftijden	Nederland	2011	7443801
Totaal alle leeftijden	Nederland	2012	7512824
Totaal alle leeftijden	Nederland	2013	7569371
Totaal alle leeftijden	Nederland	2014	7590228
Totaal alle leeftijden	Nederland	2015	7665198
Totaal alle leeftijden	Nederland	2016	7720787

Appendix I.2 - projected households 2017 - 2040

Samenstelling van het huishouden	Perioden	Prognose(-interval)	Regio-indeling 2015	Nederland
Particulier huishouden	2017	Prognose	x 1 000	7812
Particulier huishouden	2018	Prognose	x 1 000	7883.9
Particulier huishouden	2019	Prognose	x 1 000	7938.6
Particulier huishouden	2020	Prognose	x 1 000	7983
Particulier huishouden	2021	Prognose	x 1 000	8027.5
Particulier huishouden	2022	Prognose	x 1 000	8072.1
Particulier huishouden	2023	Prognose	x 1 000	8115.1
Particulier huishouden	2024	Prognose	x 1 000	8156.3
Particulier huishouden	2025	Prognose	x 1 000	8195.6
Particulier huishouden	2026	Prognose	x 1 000	8232.9
Particulier huishouden	2027	Prognose	x 1 000	8268.4
Particulier huishouden	2028	Prognose	x 1 000	8301.9
Particulier huishouden	2029	Prognose	x 1 000	8333.4
Particulier huishouden	2030	Prognose	x 1 000	8362.5
Particulier huishouden	2031	Prognose	x 1 000	8389
Particulier huishouden	2032	Prognose	x 1 000	8412.8
Particulier huishouden	2033	Prognose	x 1 000	8434.4
Particulier huishouden	2034	Prognose	x 1 000	8453.6
Particulier huishouden	2035	Prognose	x 1 000	8470.8
Particulier huishouden	2036	Prognose	x 1 000	8486.1
Particulier huishouden	2037	Prognose	x 1 000	8499.5
Particulier huishouden	2038	Prognose	x 1 000	8511.4
Particulier huishouden	2039	Prognose	x 1 000	8521.8
Particulier huishouden	2040	Prognose	x 1 000	8531.2

Appendix J

Minimally expected covered warranty in years for consumer electronic retail prices in the NL (UNETO-VNI, 2014)

Televisies		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 299	3	36
€ 300 - 499	4	48
€ 500 - 999	5	60
≥ € 1000	6	72
Randapparatuur televisies		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
≥ € 200	3	36
Audio		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
€ 200 - 399	3	36
€ 400 - 999	4	48
≥ € 1000	5	60
Groot huishoudelijk (witgoed)		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
€ 200 - 299	3	36
€ 300 - 399	4	48
€ 400 - 499	5	60
€ 500 - 599	6	72
€ 600 - 699	7	84
≥ € 700	8	96
Klein huishoudelijk		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
≥ € 200	3	36
Koffiemachines (volautomatisch)		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
€ 200 - 499	3	36
≥ € 500	4	48
Computer (pc, notebooks, tablets, gameconsoles)		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 299	2	24
≥ € 300	3	36
Foto en video		
Aankoopprijs	**In jaren**	**In maanden**
€ 0 - 199	2	24
€ 200 - 399	3	36
≥ € 400	4	48
Portable (smartphones, smartwatches, audiospelers, navigatie)		
Aankoopprijs	**In jaren**	**In maanden**
≥ € 0	2	24
Accessoires		
Aankoopprijs	**In jaren**	**In maanden**
≥ € 0	2	24

Appendix K

MAG-level categorization of Philips Personal Health products within the organization and in relation to outside categorizations

BG name	BU name	MAG name	UNU-KEY	UNU Key Description	Hendriksen et al	UNETO-VNI cat
Coffee	FA&M Espresso	Full Autom. Espresso	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	Full Aut. Coffee
Coffee	FA&M Espresso	Manual Espresso	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	SHA
Coffee	Roast&Ground Coffee	Dripfilter	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	SHA
Coffee	Roast&Ground Coffee	Portioned Filter	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	SHA
Coffee	Roast&Ground Coffee	Senseo Sarista	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	Full Aut. Coffee
Domestic Appliances	Air	Air Cleaners	201	Other SHA (f.i. small ventilators, irons, clocks, adapters)	SHA Other	SHA
Domestic Appliances	Air	Air Humidifiers	201	Other SHA (f.i. small ventilators, irons, clocks, adapters)	SHA Other	SHA
Domestic Appliances	Floor Care	Bag	204	Vacuum Cleaners (excl. professional)	SHA Other	SHA
Domestic Appliances	Floor Care	Bagless	204	Vacuum Cleaners (excl. professional)	SHA Other	SHA
Domestic Appliances	Floor Care	Quick Cleaning	204	Vacuum Cleaners (excl. professional)	SHA Other	SHA
Domestic Appliances	Floor Care	Robotics	204	Vacuum Cleaners (excl. professional)	SHA Other	SHA
Domestic Appliances	Floor Care	Wet Cleaning	204	Vacuum Cleaners (excl. professional)	SHA Other	SHA
Domestic Appliances	Garment Care	Dry/Trav/Steam irons	201	Other SHA (f.i. small ventilators, irons, clocks, adapters)	SHA Other	SHA
Domestic Appliances	Garment Care	Garment Steamers	201	Other SHA (f.i. small ventilators, irons, clocks, adapters)	SHA Other	SHA
Domestic Appliances	Garment Care	Steam Generators	201	Other SHA (f.i. small ventilators, irons, clocks, adapters)	SHA Other	SHA
Domestic Appliances	Kitchen Appliances	China Led SubCat	202	Food (f.i. toaster, grills, food processing, frying pans)	SHA Kitchen	SHA
Domestic Appliances	Kitchen Appliances	Europe Led Subcat	202	Food (f.i. toaster, grills, food processing, frying pans)	SHA Kitchen	SHA
Domestic Appliances	Kitchen Appliances	HK Led Sub Cat	202	Food (f.i. toaster, grills, food processing, frying pans)	SHA Kitchen	SHA
Domestic Appliances	Kitchen Appliances	HK Led Sub Cat	203	Hot Water (f.i. coffee, tea, water cookers)	SHA Kitchen	SHA
Domestic Appliances	Kitchen Appliances	Remy	202	Food (f.i. toaster, grills, food processing, frying pans)	SHA Kitchen	SHA
Domestic Appliances	Povos	Philips Kitchen Appl	202	Food (f.i. toaster, grills, food processing, frying pans)	SHA Kitchen	SHA
Health&Wellness	Mother & Child Care	Breastfeeding Sol	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Mother & Child Care	Food Preparation	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Mother & Child Care	Secure Parenting-Mon	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Pain Relief	InfraCare	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Pain Relief	TENS	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Philips Oral Healthc	Basic Power Toothbr.	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Philips Oral Healthc	Inter dental	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Philips Oral Healthc	Oral Hygiene	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Philips Oral Healthc	Rech. Toothbrushes	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Health&Wellness	Philips Oral Healthc	Whitening	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Beauty	Female depilation	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Beauty	Hair Care	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Beauty	IPL Hair Removal	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Beauty	Skin Care	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Beauty	Vita-Light	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	2Header Shaver Range	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Grooming	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Hybrid	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Male Skincare	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Personal Care Acc.	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Recruit Male Gr	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA
Personal Care	Male Grooming	Shaving Core Range	205	Personal Care (f.i. tooth brushes, hair dryers, razors)	SHA Personal Care	SHA

Appendix L

Explanation of flowchart symbols (retrieved from: http://www.conceptdraw.com/How-To-Guide/flow-chart-symbols)

Terminator
Indicates the beginning or end of a program flow in your diagram.

Process
Indicates any processing function.

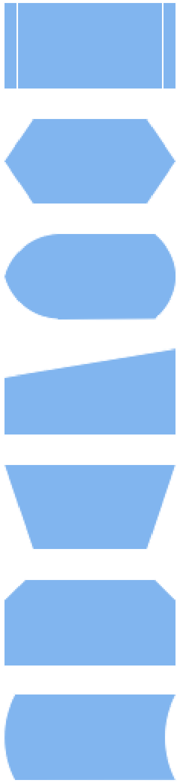
Decision
Indicates a decision point between two or more paths in a flowchart.

Delay
Indicates a delay in the process.

Data
Can represents any type of data in a flowchart.

Document
Indicates data that can be read by people, such as printed output.

Multiple documents
Indicates multiple documents.



Subroutine
Indicates a predefined (named) process, such as a subroutine or a module.

Preparation
Indicates a modification to a process, such as setting a switch or initializing a routine.

Display
Indicates data that is displayed for people to read, such as data on a monitor or projector screen.

Manual input
Indicates any operation that is performed manually (by a person).

Manual loop
Indicates a sequence of commands that will continue to repeat until stopped manually.

Loop limit
Indicates the start of a loop. Flip the shape vertically to indicate the end of a loop.

Stored data
Indicates any type of stored data.

Connector
Indicates an inspection point.

Off-page connector
Use this shape to create a cross-reference and hyperlink from a process on one page to a process on another page.

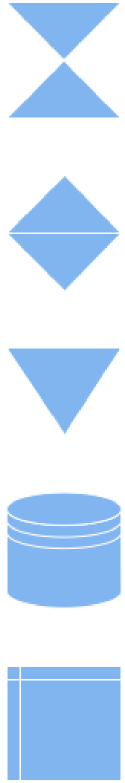
Off-page connector

Off-page connector

Off-page connector

Or
Logical OR

Summing junction
Logical AND



Collate
Indicates a step that organizes data into a standard format.

Sort
Indicates a step that organizes items list sequentially.

Merge
Indicates a step that combines multiple sets into one.

Database
Indicates a list of information with a standard structure that allows for searching and sorting.

Internal storage
Indicates an internal storage device.

Appendix M

Retrospective and prospective extrapolation of the 2005-2016 POM data

***M.1* -** Retrospective extrapolation of the 2005-2016 POM data

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***M.2* -** Historical extrapolation of the 2005-2016 POM data

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***M.3* -** Historical extrapolation of the 2005-2016 POM data

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***M.4* -** Prospective extrapolation of the 1995-2030 POM data for ‘2016-level‘

[redacted]

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***M.5* -** Prospective extrapolation of the 1995-2030 POM data for ‘trendline‘

[redacted]

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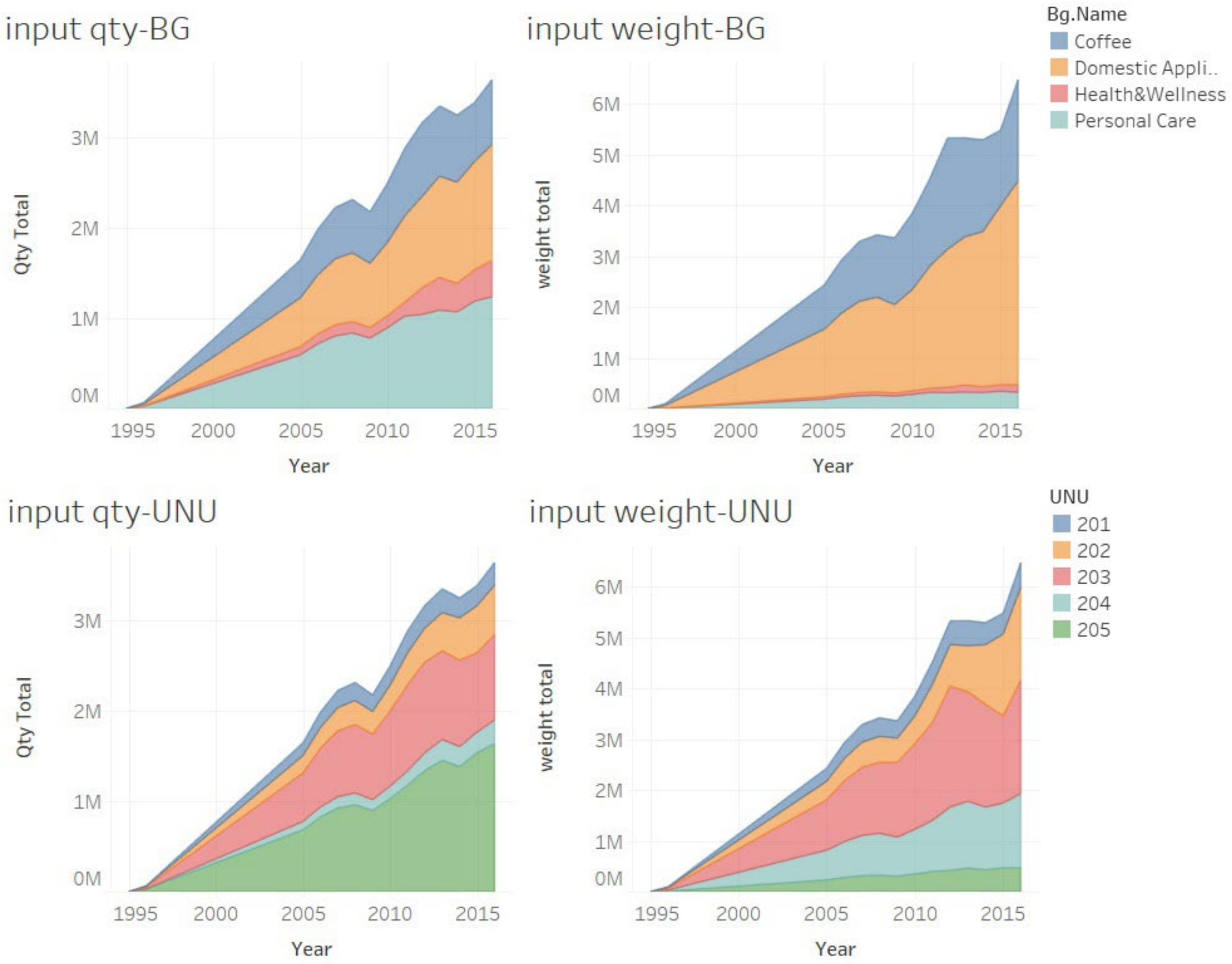
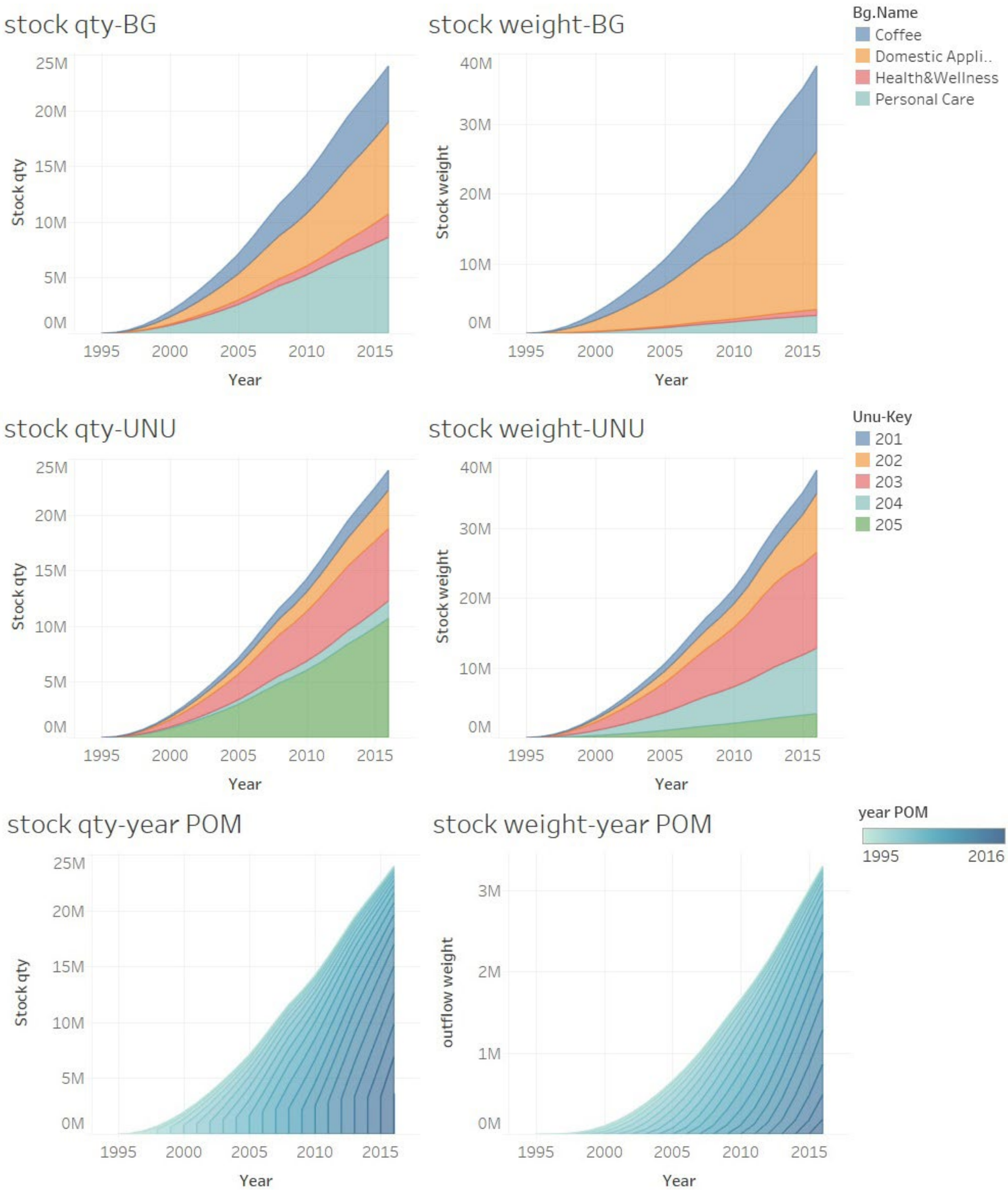
Appendix N

Breakdown of input, stock and outflow on different dimensions for 1995-2016 data

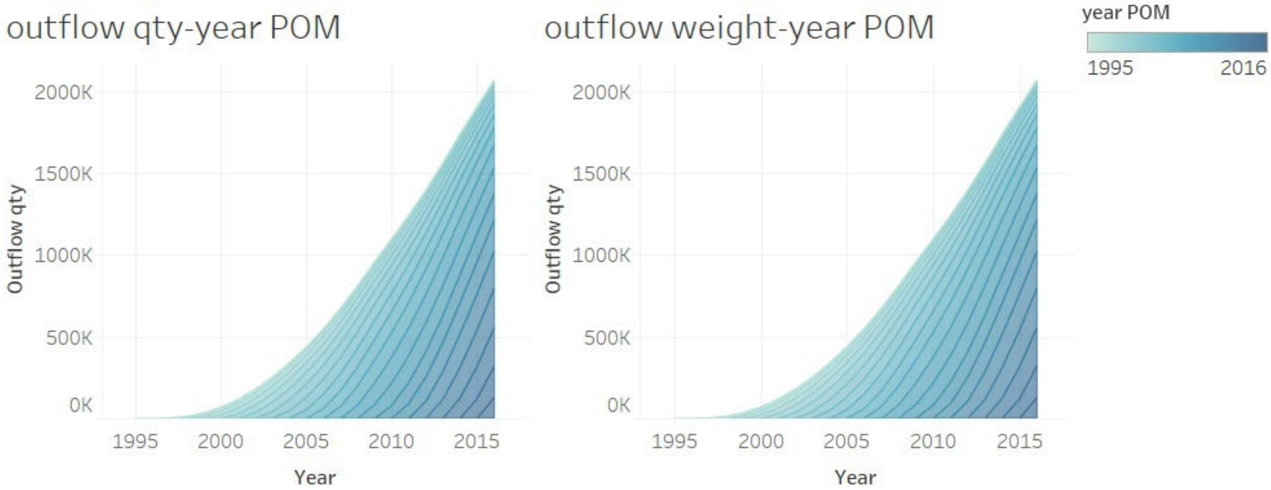
N.1 - breakdown of input on BG and UNU-key, shown in quantity (left) and weight (right)



N.2 - breakdown of stock size on BG, UNU-key and year POM, shown in quantity (left) and weight (right)



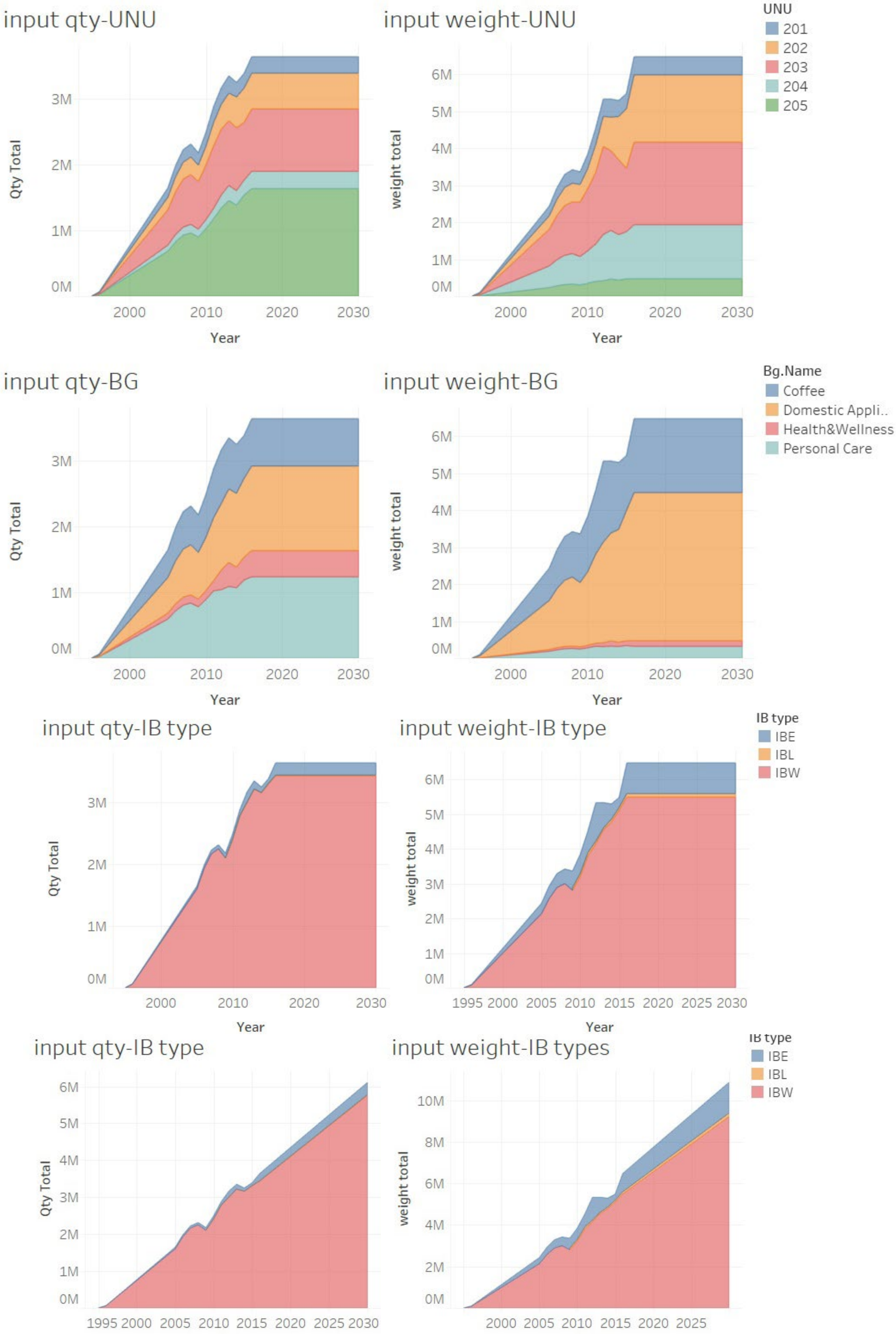
N.3 - breakdown ofoutflow on year POM, shown in quantity (left) and weight (right)



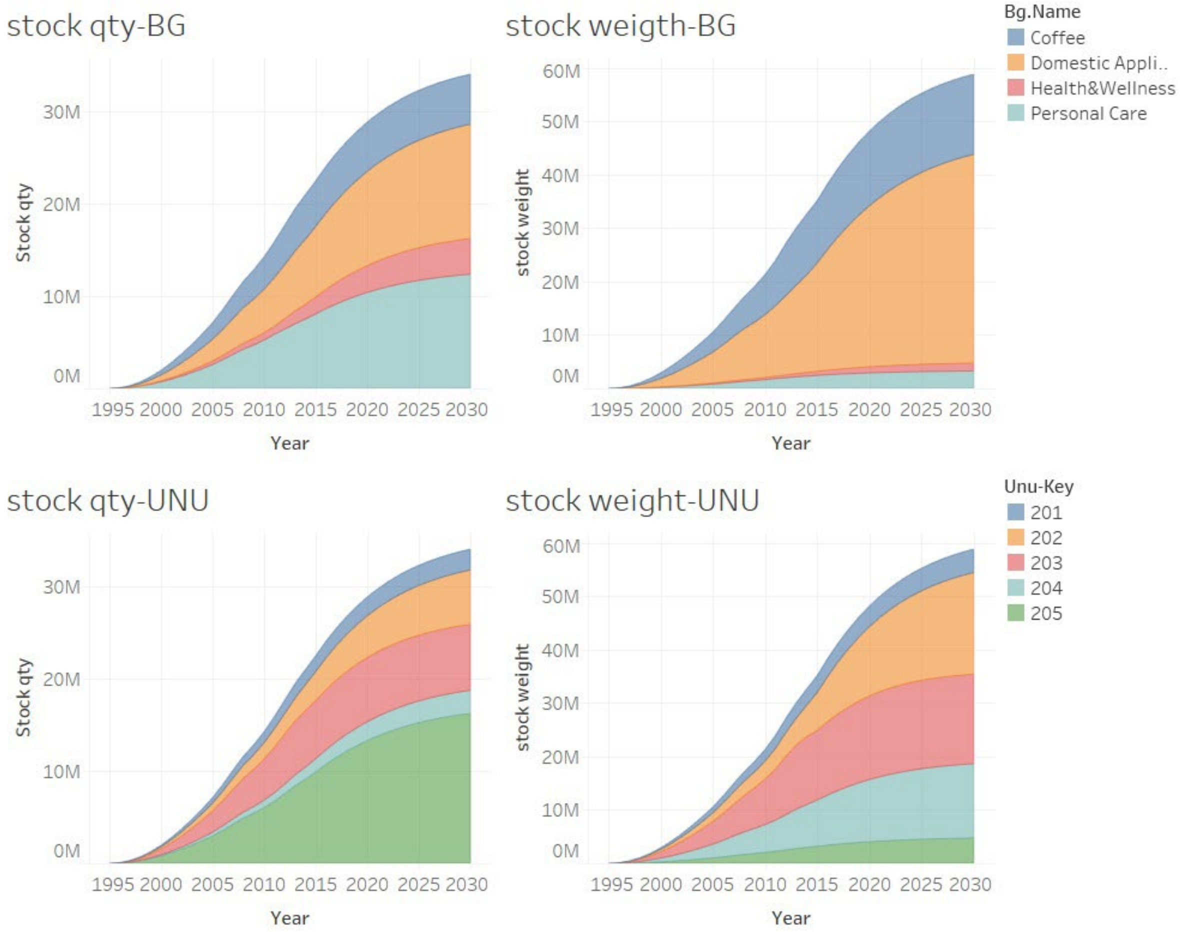
Appendix O

Breakdown of input, stock and outflow on different dimensions for 1995-2030 data for '2016-level' future sales

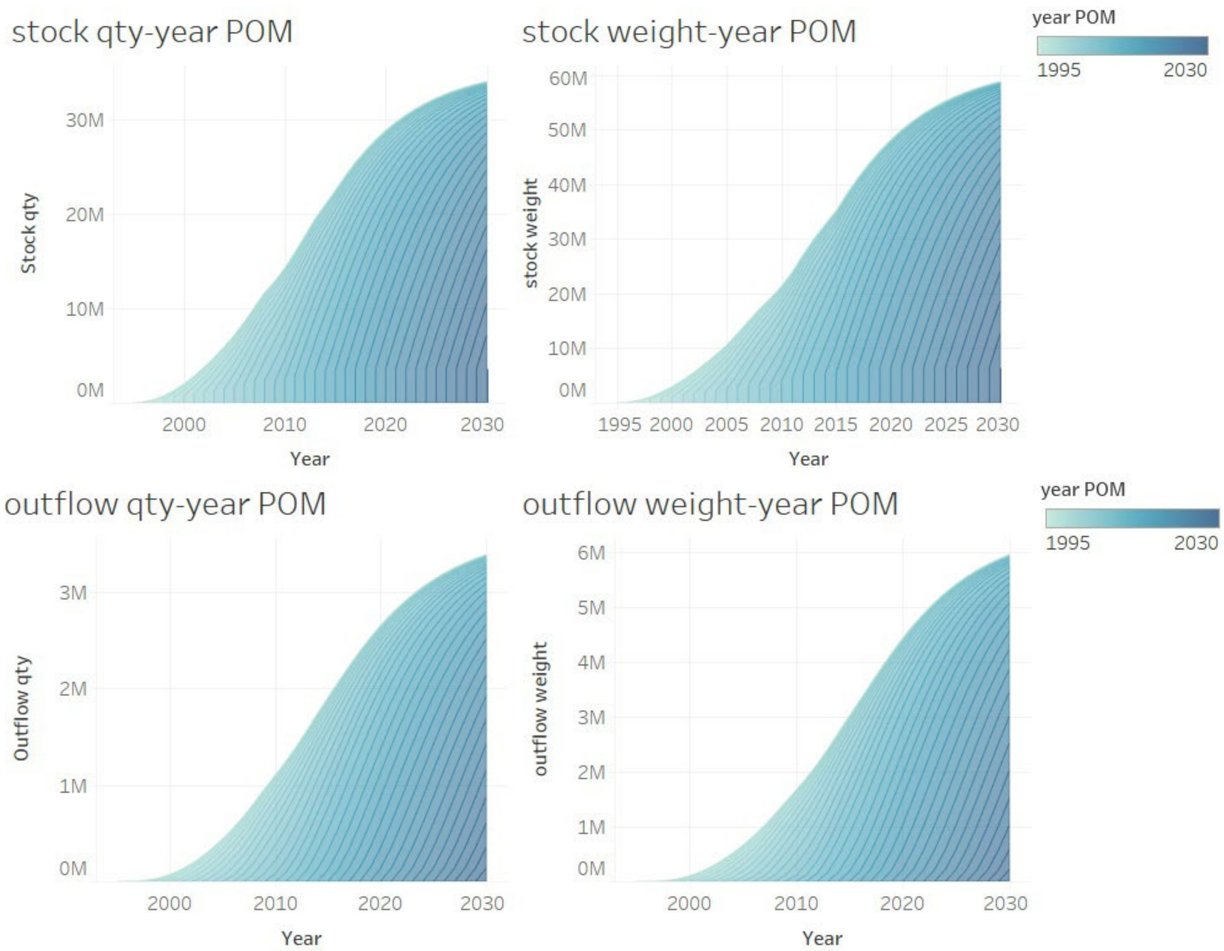
O.1 breakdown of input on BG, UNU-key and on high/low-end **(IBL+IBE= high-end, IBW=low-end)** shown in quantity (left) and weight (right)



O.2 **-** breakdown of stock size on BG and UNU-key, shown in quantity (left) and weight (right)



O.3 breakdown of stock size (top) and outflow (bottom) on year POM, shown in quantity (left) and weight (right)



Appendix P - CONFIDENTIAL(?)

Overview of all high-end to mid-end products ("IBL" and "IBE" respectively) according to the UNETO-VNI chart in appendix J.

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Appendix Q - Costs and revenue breakdown for the GranBaristo

Appendix W.1 - screenshot of a RSM student assignment deliverable on pricing for lease models for a product in the same price range as the GranBaristo

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Appendix Q.2 - cost and revenue entries for the GranBaristo used in model (not validated by expert), partially modeled after the values provided in Appendix W.1

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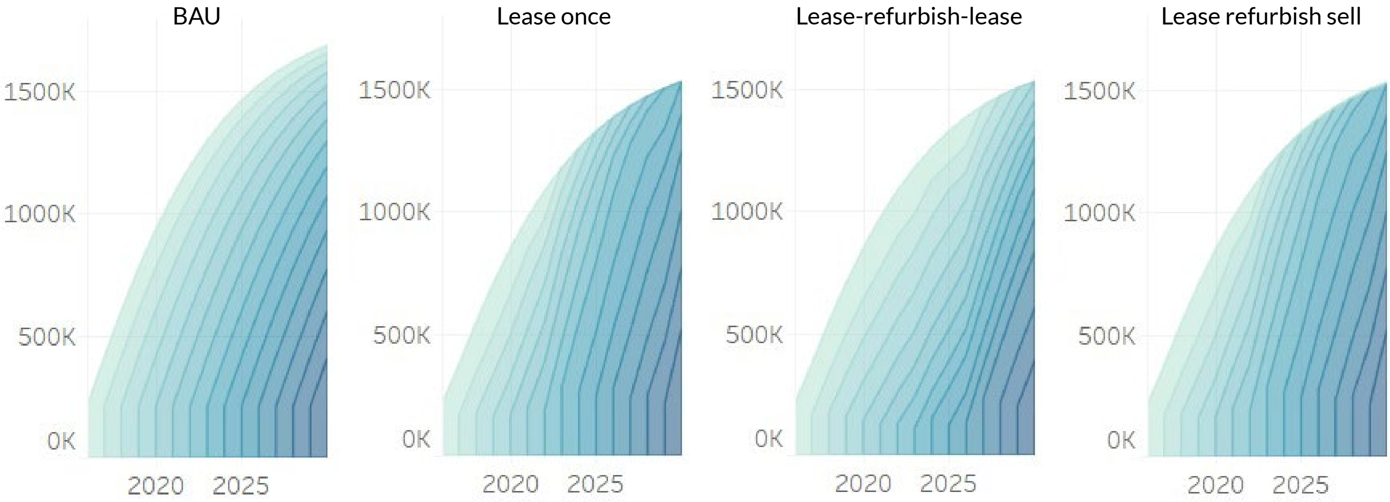
Appendix R

Input, stock and outflow results for high-end products for the four scenarios shown in quantity for a future '2016-level' sales projection for 2016-2030

Appendix R.1 - Results for Philips lifespan=100% of the original set lifespan

INPUT

STOCK

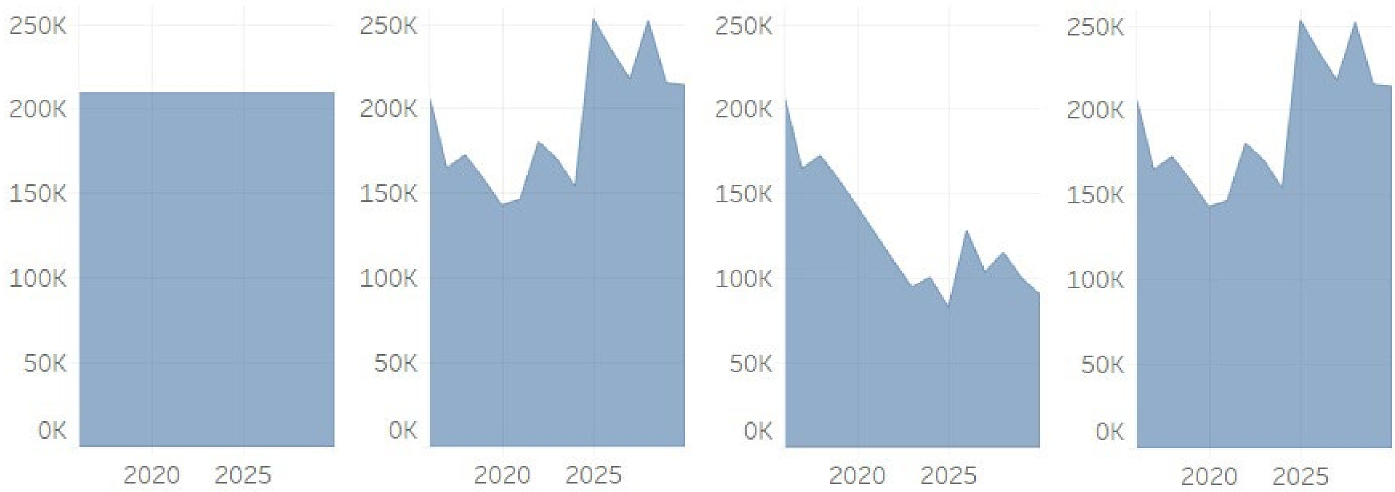


OUTFLOW

Appendix R.2 - Results for Philips lifespan=130% of the original set lifespan

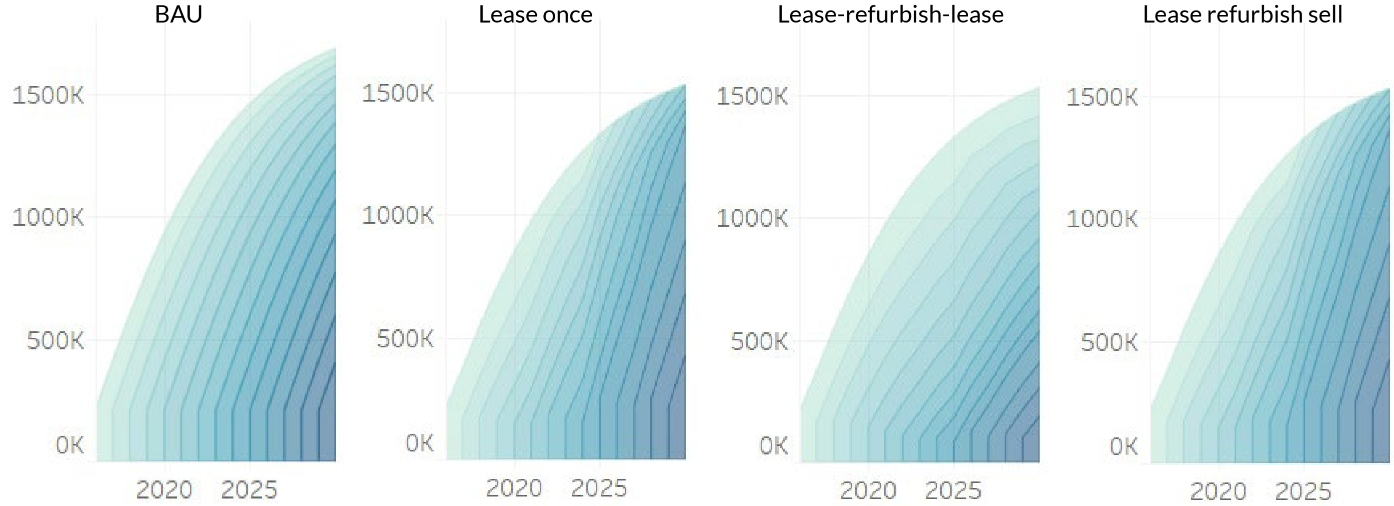
INPUT

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



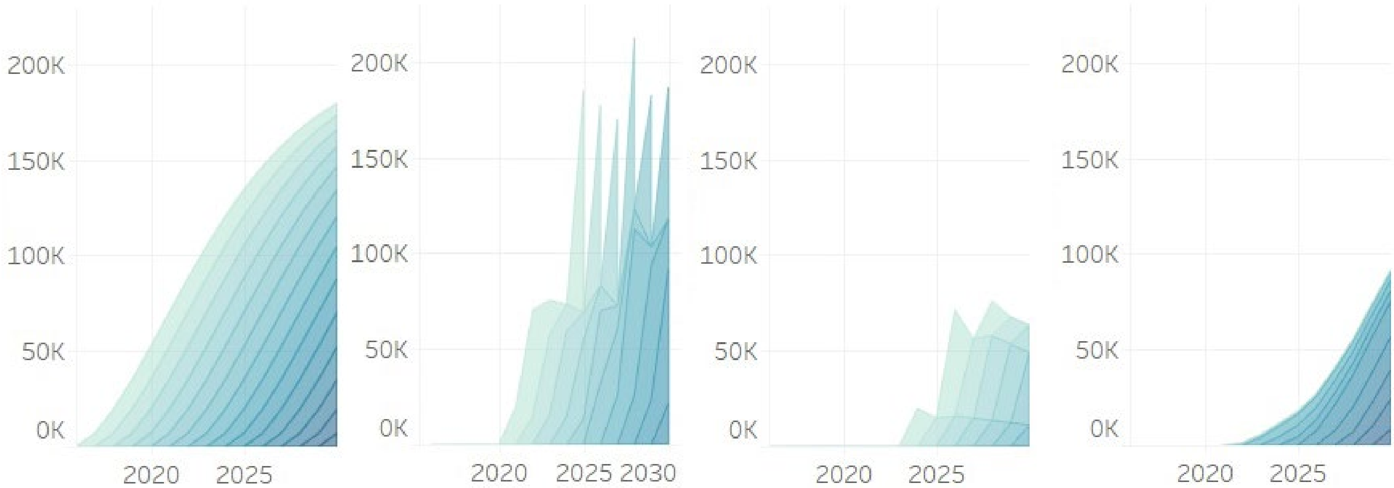
STOCK

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



OUTFLOW

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell

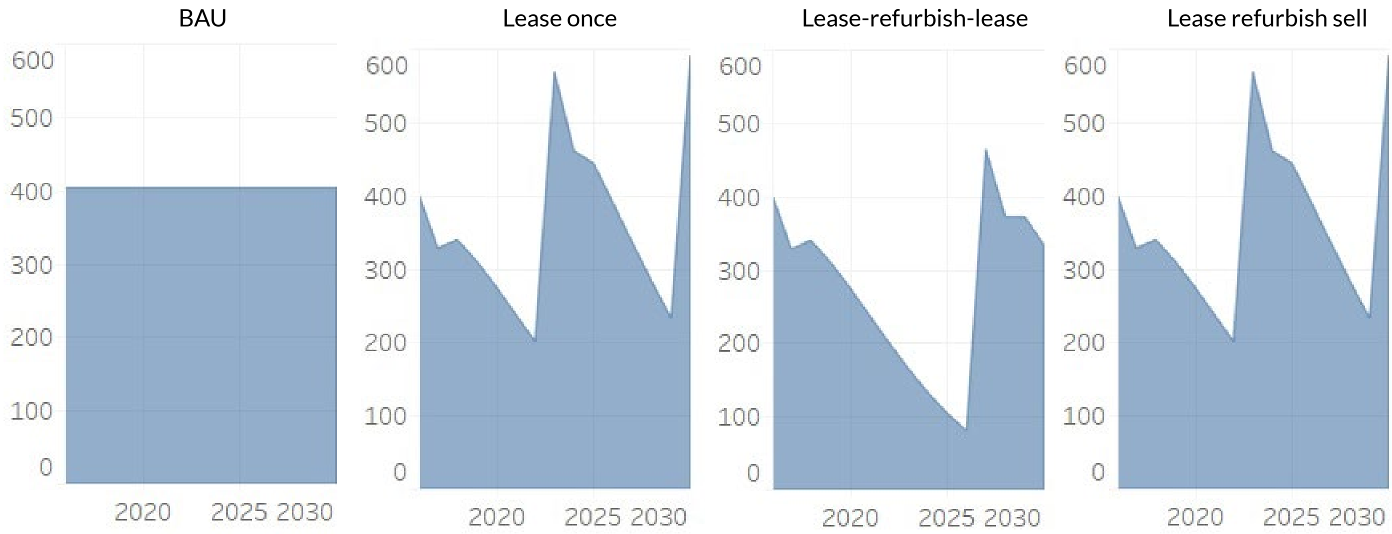


Appendix S

Input, stock and outflow results for the GranBaristo for the four scenarios shown in quantity for a future '2016-level' sales projection for 2016-2030

Appendix S.1 **-** Results for Philips lifespan=100% of the original set lifespan

INPUT



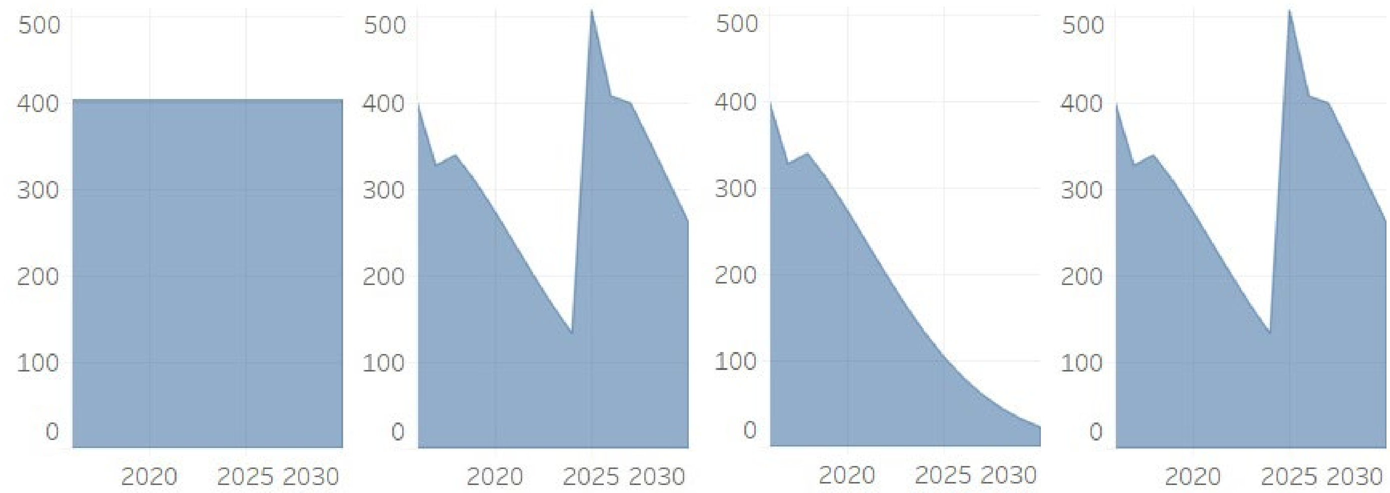
STOCK

OUTFLOW

Appendix S.2 - Results for Philips lifespan=130% of the original set lifespan

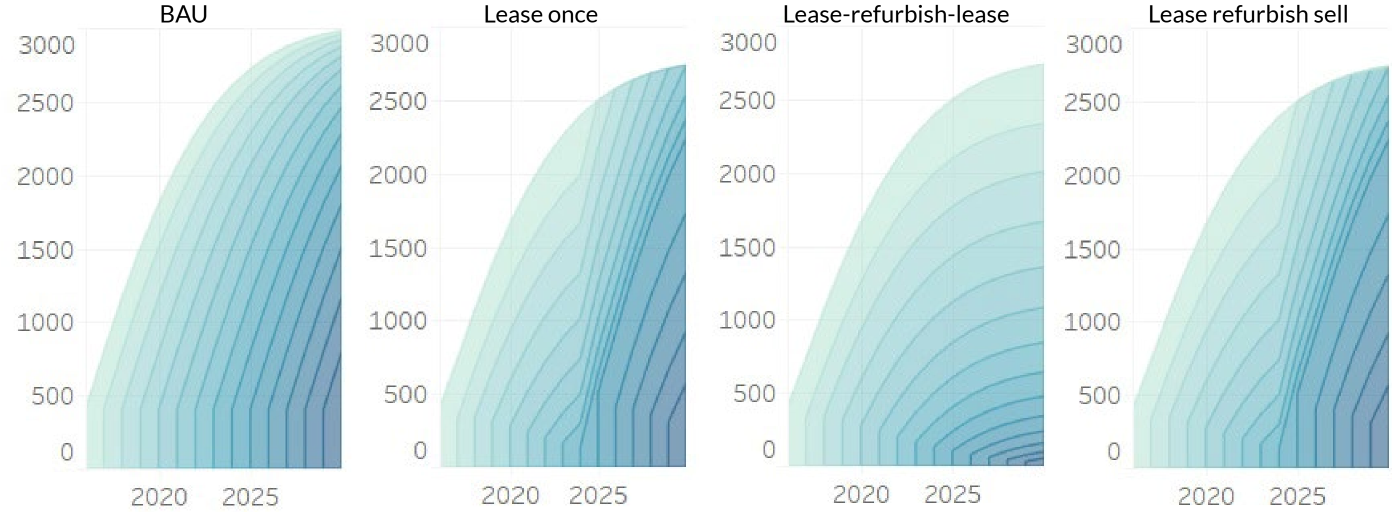
INPUT

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



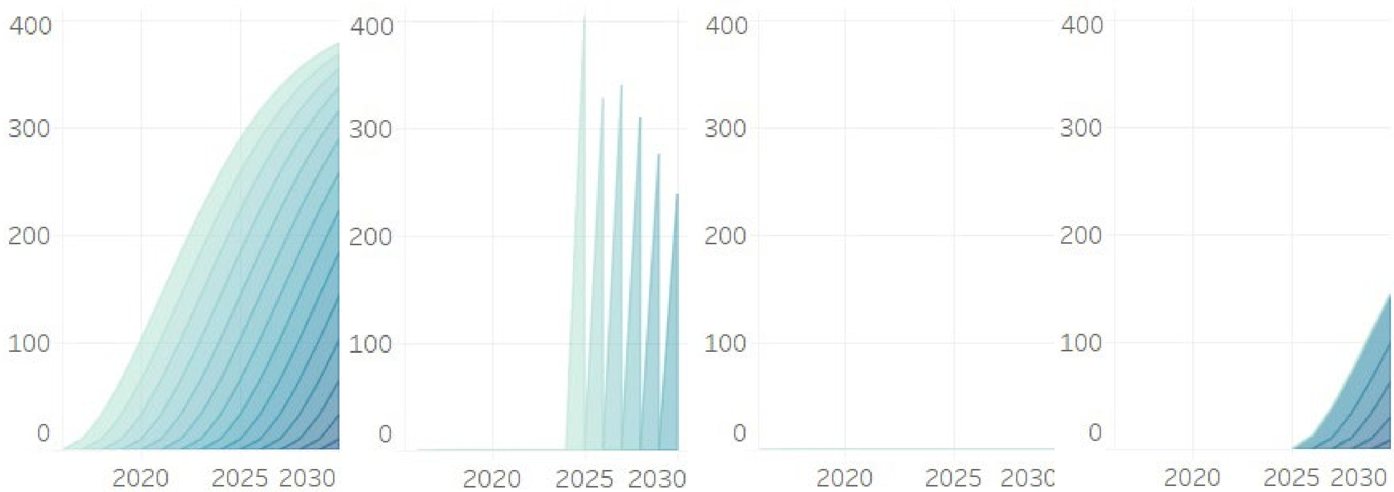
STOCK

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



OUTFLOW

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



Appendix T - CONFIDENTIAL (?)

Appendix T.1

The figures of Appendix H are processed into a spreadsheet and the quantities are divided by the number of households for 2006 to get the number of appliances per household. Furthermore, the Philips BU is added to each product type.

type	bu.name	qty *10E6	per hh
Koffiezetapparaat incl Senseo	Roast&Ground Coffee	12.8	1.81
Staafmixer/handmixer	Kitchen Appliances	10.4	1.47
Broodrooster/tostiapparaat	Kitchen Appliances	7.8	1.10
Waterkoker	Kitchen Appliances	7.7	1.09
Fondueset Gourmetset	Kitchen Appliances	6.4	0.90
Friteuse/Frituurpan	Kitchen Appliances	6.3	0.89
Kookplaat	Kitchen Appliances	4.6	0.65
Sapcentrifuge/citruspers	Kitchen Appliances	3.7	0.52
Broodbakmachine	Kitchen Appliances	3.4	0.48
Blender/Milkshaker	Kitchen Appliances	2.7	0.38
Barbecue	na	2.1	0.30
Grillbakoven/grill	Kitchen Appliances	2	0.28
Keukenweegschaal	Kitchen Appliances	1.9	0.27
Wafelijzer	Kitchen Appliances	1.7	0.24
Electrisch mes	na	1.4	0.20
Kook- of warmhoudplaat	Kitchen Appliances	1.3	0.18
Eierkoker electrisch	na	1.2	0.17
Koelbox electrisch	na	1.1	0.16
Snijmachine	na	1	0.14
Overige keukenapparatuur	na	4	0.56
Haardroger (fohn)	Beauty	7.6	1.07
Electrische tandenborstel	Philips Oral Healthc	6.5	0.92
Electrisch scheerapparaat	Male Grooming	5.2	0.73
Ladyshave/Epileerapparaat	Beauty	4.7	0.66
Personenweegschaal digitaal	na	4.2	0.59
Haarstyler	Beauty	3.2	0.45
Neustondeuse	Male Grooming	1.2	0.17
Baardtrimmer	Male Grooming	1.1	0.16
Krulset	Beauty	1	0.14
Overige persoonlijke verzorgin	na	3.2	0.45
Stofzuiger incl nat en droog	Floor Care	10.4	1.47
Strijkijzer (stoom en droog)	Garment Care	9	1.27
Electrische ventilator	na	7.4	1.04
Kruimeldief	Floor Care	5.7	0.80
Afzuigkap elektrisch	na	3.8	0.54
Elektrisch deken/kussen	na	2.7	0.38
Elektrische ventilatorkachel	na	2.2	0.31
Infraroodlamp	na	1.7	0.24
Centrifige voor wasgoed	na	1.1	0.16
Overig	na	1.5	0.21

Appendix - T.2 CONFIDENTIAL(?)

The outcome of the stock size consistency check by checking the realism of the marketshare for Philips categorized by BU. 'Per hh' is the amount of Philips products per household; 'per hh stock' is the total amounts of products found in households for whatever brand according to Hendriksen (2009).

```
In [99]: runfile('C:/Users/miche/Documents/model PH/stock sanitycheck.py', wdir='C:/Users/miche/Documents/model PH')
```

	bu.name	per hh	per hh stock	marketshare Philips
0	Male Grooming	[redacted]	1.057684	[redacted]
1	Kitchen Appliances		8.447369	
2	Roast&Ground Coffee		1.805114	
3	Beauty		2.326905	
4	Garment Care	CON-	1.269221	CON-
5	Philips Oral Healthc	FIDEN-	0.916659	FIDEN-
6	Floor Care	TIAL	2.270495	TIAL
7	Mother & Child Care		NaN	
8	FA&M Espresso		NaN	
9	Air		NaN	
10	Pain Relief		NaN	
11	Povos		NaN	

Appendix U

Appendix U.1

The upper two tables show the results for the 2016-level input (left) and the trendline input (right) for the highend products. The lower table show the percentage point differences for the results between the trendline input and 2016-level input.

	Lease duration = 100% LS					
	2016			trendline		
	L	LRL	LRS	L	LRL	LRS
new input qty [high-end]	5.9%	-21.7%	5.9%	3.3%	-22.4%	3.3%
new input qty [all]	0.3%	-1.2%	-0.3%	0.2%	-1.3%	0.1%
WG [high-end]	-4.5%	-51.3%	-100.0%	-7.3%	-56.1%	-100.0%
WG [all]	-0.8%	-8.9%	-10.6%	-1.3%	-9.7%	-10.3%
C&R [high-end]	100.0%	100.0%	-	100.0%	100.0%	-
C&R [all]	66.9%	65.7%	64.3%	67.1%	65.7%	64.3%

	Lease duration = 130% LS					
	2016			trendline		
	L	LRL	LRS	L	LRL	LRS
new input qty [high-end]	-8.2%	-39.5%	-8.2%	-9.9%	-37.4%	-9.9%
new input qty [all]	-0.5%	-2.3%	-1.0%	-0.6%	-2.1%	-0.5%
WG [high-end]	-30.6%	-93.4%	-100.0%	-34.4%	-94.1%	-100.0%
WG [all]	-5.3%	-16.2%	-13.8%	-5.9%	-16.3%	-13.6%
C&R [high-end]	100.0%	100.0%	-	100.0%	100.0%	-
C&R [all]	66.2%	64.4%	64.3%	66.3%	64.4%	64.3%

	100% LS			130% LS		
	L	LRL	LRS	L	LRL	LRS
new input qty [high-end]	-2.6%	-0.7%	-2.6%	-1.7%	2.1%	-1.7%
new input qty [all]	-0.1%	0.0%	0.5%	-0.1%	0.1%	0.4%
WG [high-end]	-2.8%	-4.8%	0.0%	-3.7%	-0.7%	0.0%
WG [all]	-0.5%	-0.8%	0.3%	-0.6%	-0.1%	0.2%
C&R [high-end]	0.0%	0.0%	-	0.0%	0.0%	-
C&R [all]	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%

Appendix - U.2

The upper two tables show the results for the 2016-level input (left) and the trendline input (right) for the GranBaristo. The lower table show the percentage point differences for the results between the trendline input and 2016-level input.

	Lease duration = 100% LS					
	2016			trendline		
	L	LRL	LRS	L	LRL	LRS
new input qty	-10.6%	-31.9%	-10.6%	-11.6%	-31.7%	-11.6%
WG	-13.0%	-54.9%	-75.5%	-15.6%	-59.7%	-77.9%
C&R	100.0%	100.0%	63.9%	100.0%	100.0%	63.9%
profit	26.4%	-1.7%	43.9%	12.2%	-10.3%	26.6%

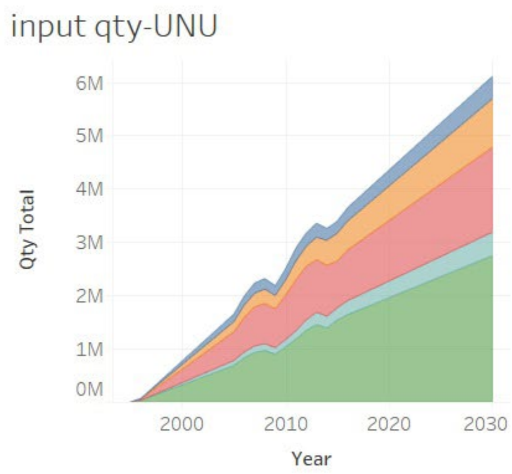
	Lease duration = 130% LS					
	2016			trendline		
	L	LRL	LRS	L	LRL	LRS
new input qty	-23.4%	-54.7%	-23.4%	-23.5%	-50.1%	-23.5%
WG	-38.1%	-100.0%	-87.7%	-41.8%	-100.0%	-89.3%
C&R	100.0%	100.0%	63.9%	100.0%	100.0%	63.9%
profit	48.9%	44.9%	58.0%	33.3%	30.1%	39.9%

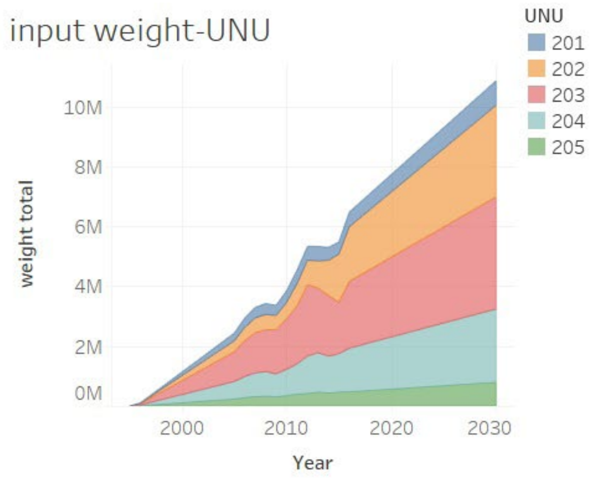
	100% LS			130% LS		
	L	LRL	LRS	L	LRL	LRS
new input qty	-1.0%	0.2%	-1.0%	-0.1%	4.7%	-0.1%
WG	-2.7%	-4.8%	-2.4%	-3.7%	0.0%	-1.5%
C&R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
profit	-14.2%	-8.6%	-17.2%	-15.6%	-14.8%	-18.1%

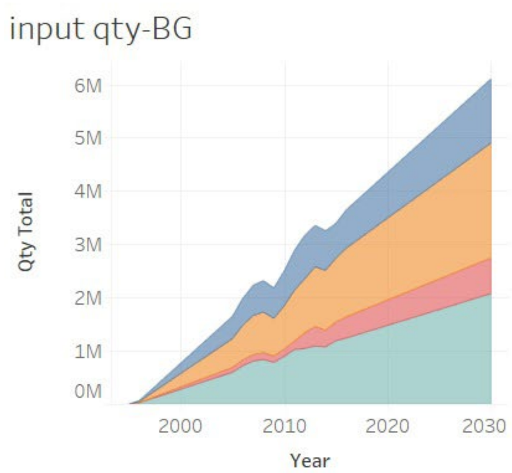
Appendix V

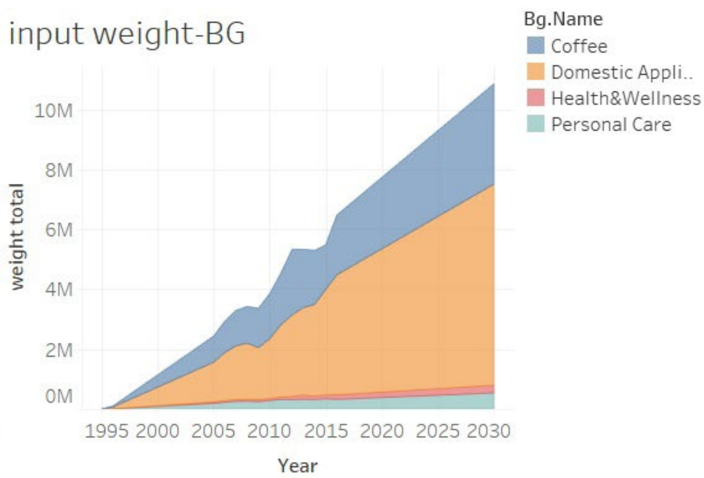
Breakdown of input, stock and outflow on different dimensions for 1995-2030 data for 'trendline future sales

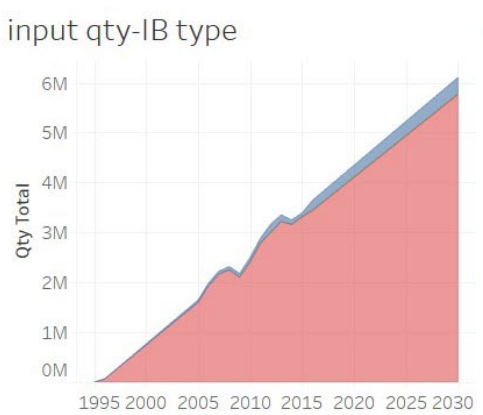
V.1 breakdown of input on BG and UNU-key and high/low end, shown in quantity (left) and weight (right)

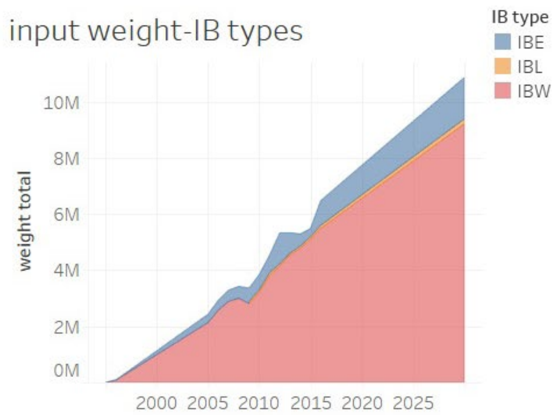




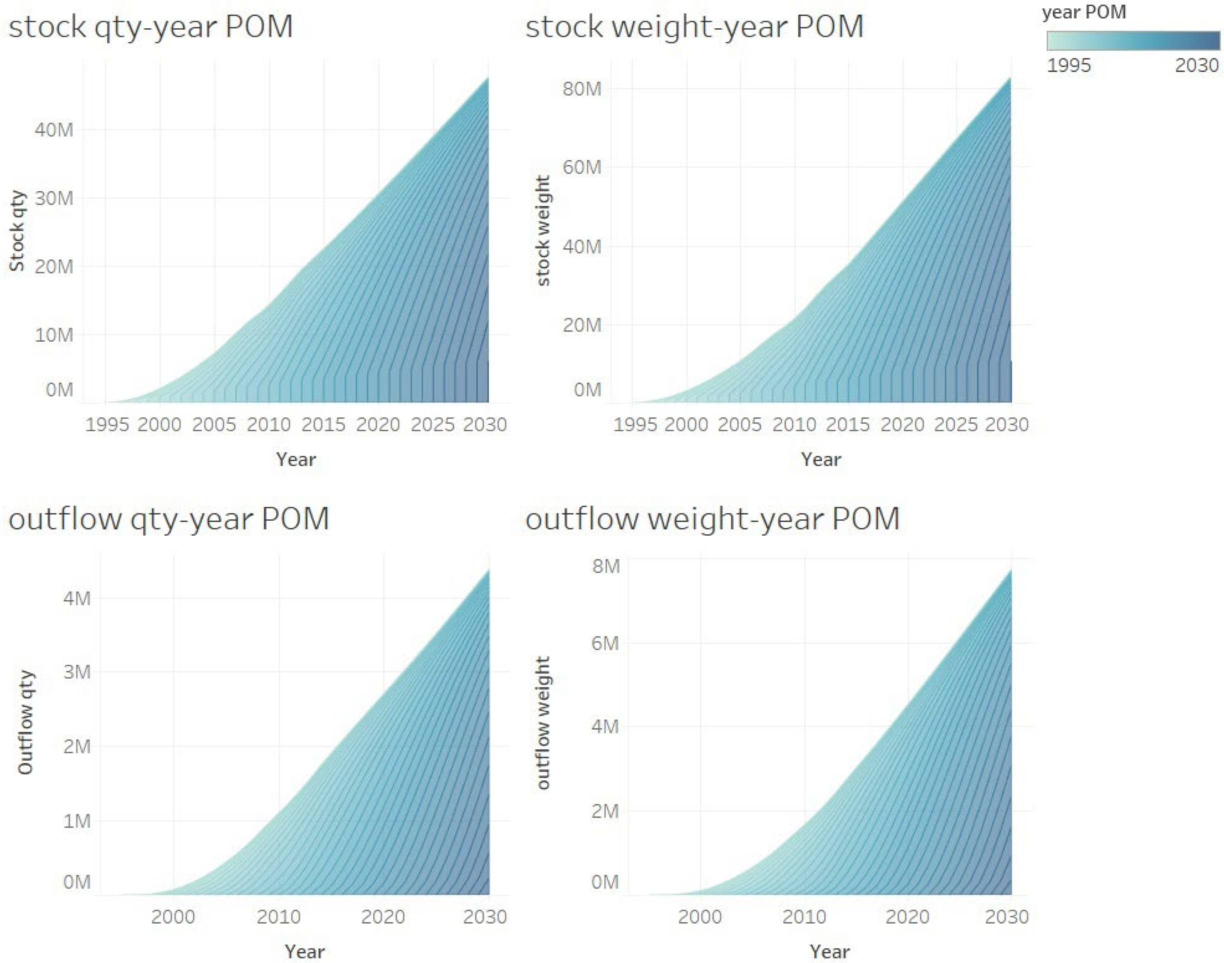




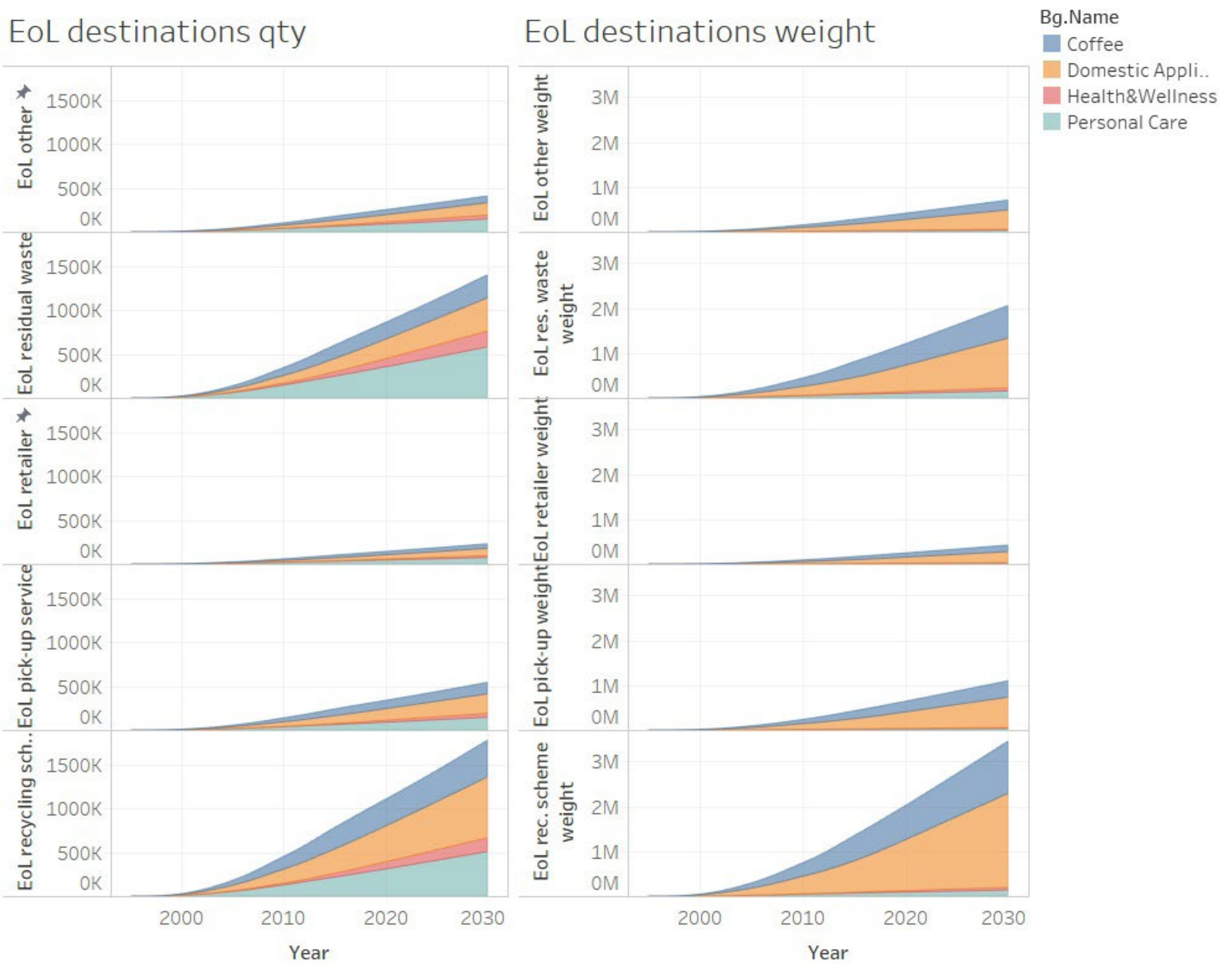




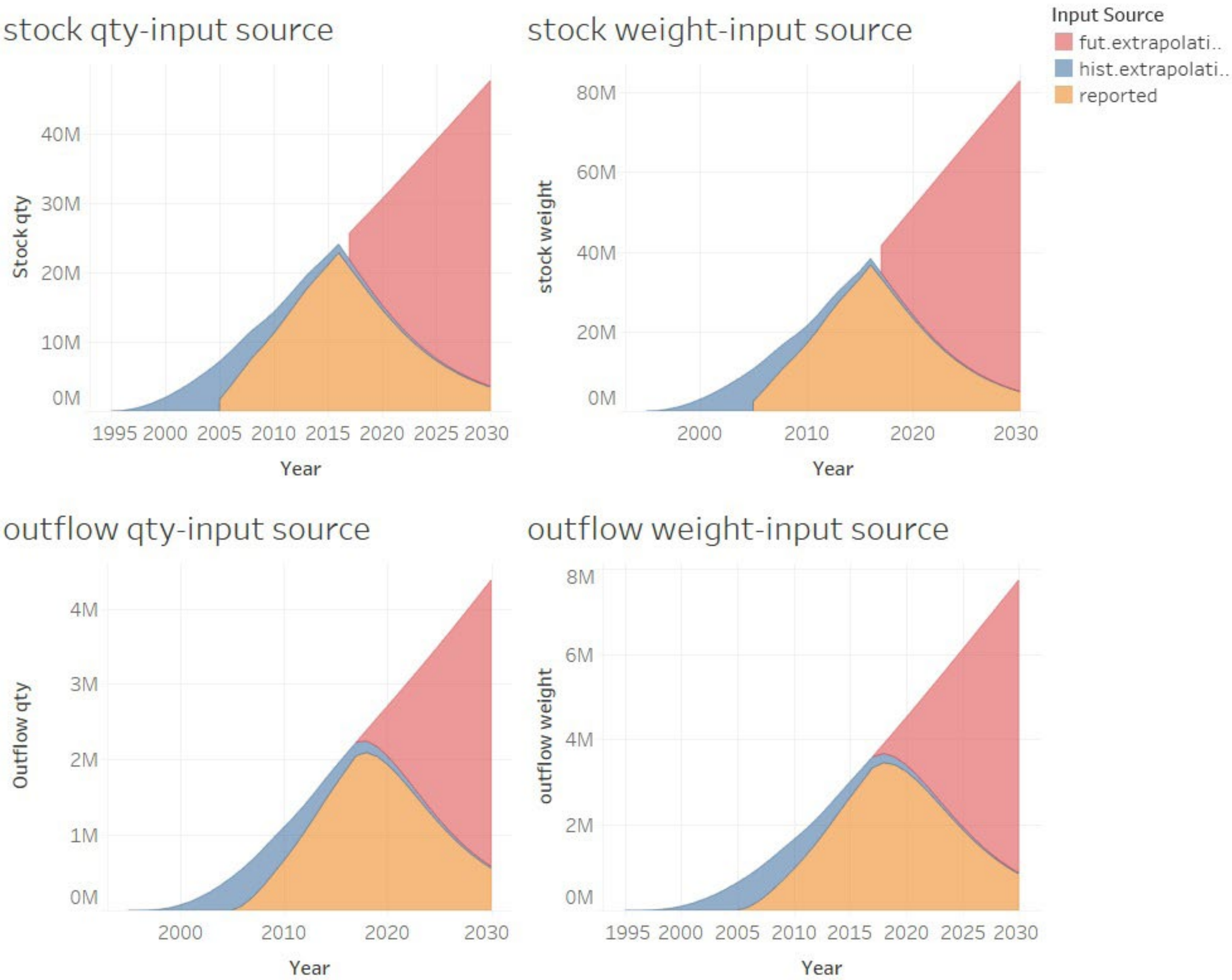
V.2 **-** breakdown of stock size (top) and outflow (bottom) on year POM, shown in quantity (left) and weight (right)



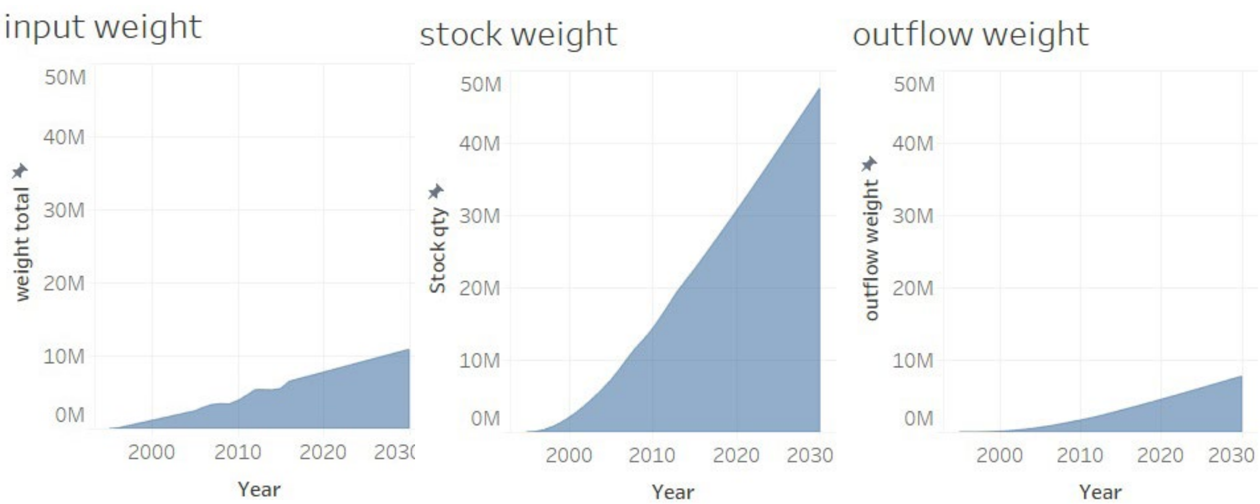
V.3 **-** Breakdown of outflow based on the EoL desinations, shown in quantity (left) and weight (right)



V.4 -Graphs of the stock (top) and outflow (bottom) in unit quantity (left) and weight (right), broken down on the sales data source; retrospective extrapolated (blue), reported (orange) and prospective extrapolation (red)



V.5 -Overview of the input weight per year, accumulated stock weight and outflow weight per year for 1995-2030



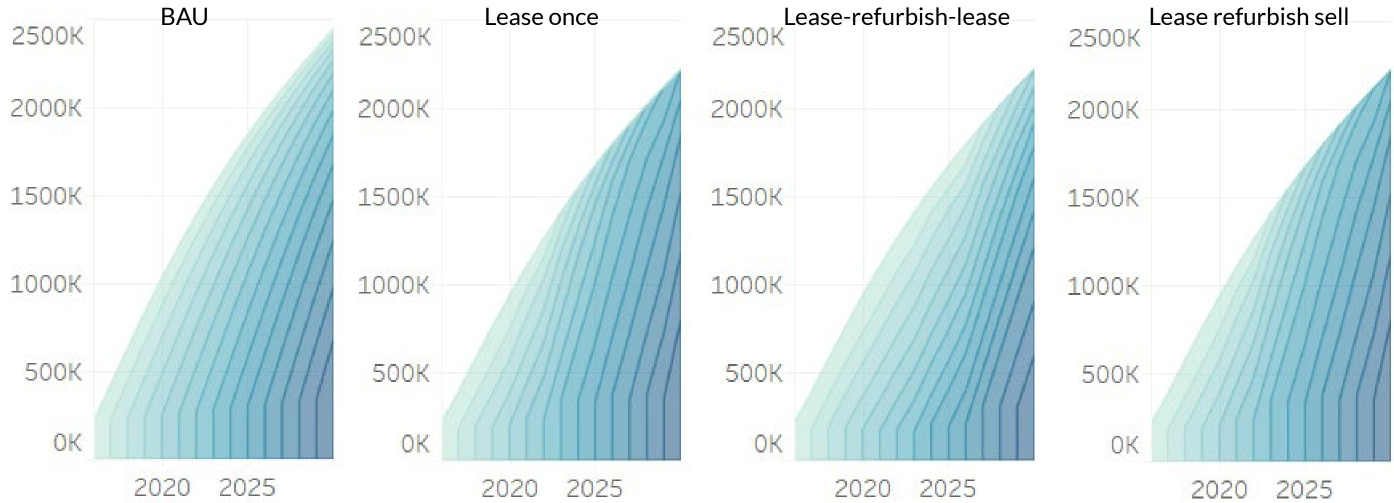
Appendix W

Input, stock and outflow results for high-end products for the four scenarios shown in quantity for a future trendline sales projection for 2016-2030

Appendix W.1 - Results for Philips lifespan=100% of the original set lifespan

INPUT

STOCK

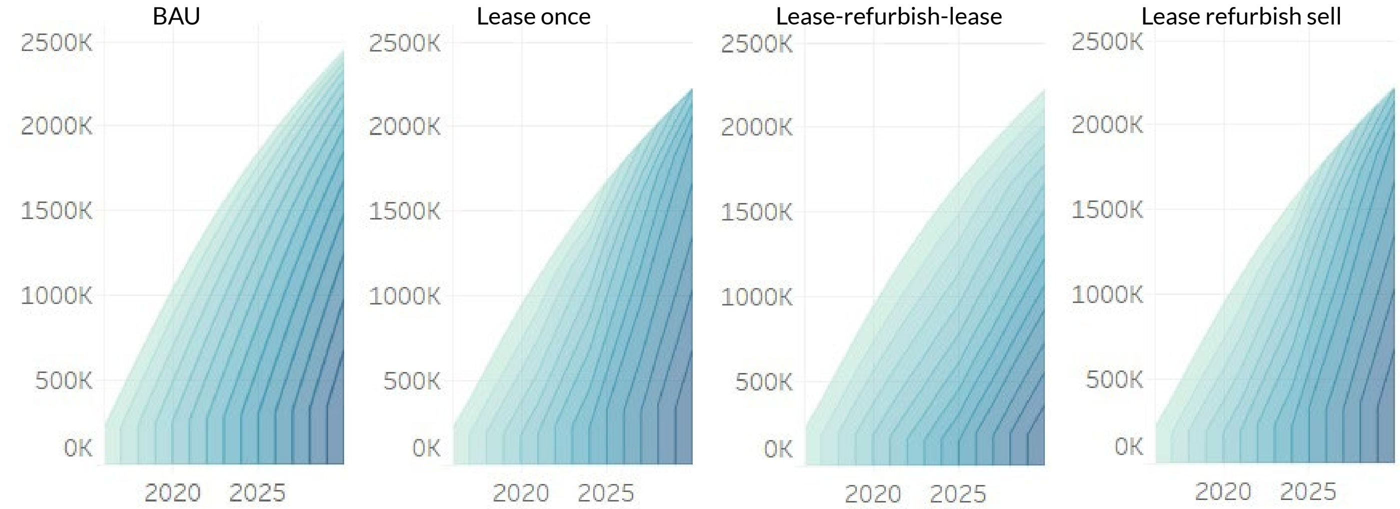


OUTFLOW

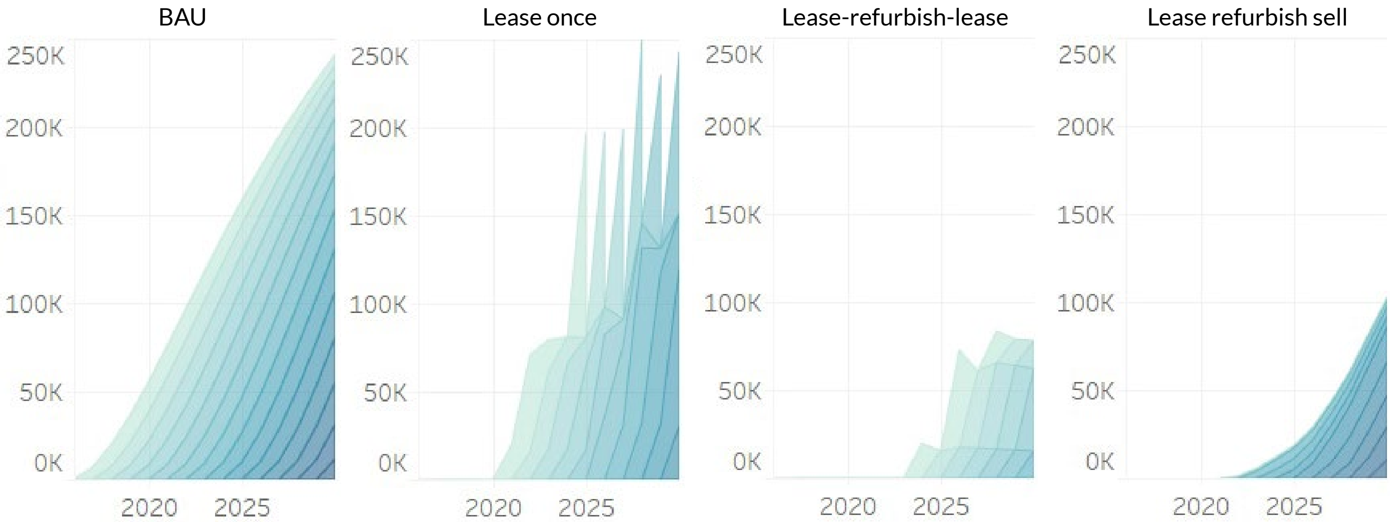
Appendix W.2 **-** Results for Philips lifespan=130% of the original set lifespan

INPUT

STOCK



OUTFLOW



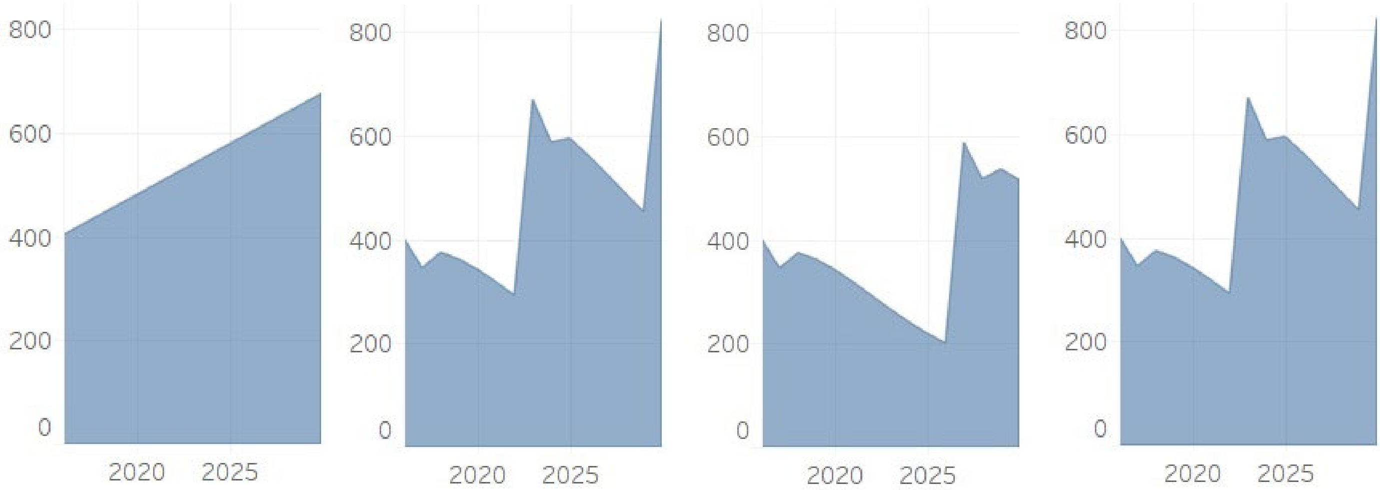
Appendix X

Input, stock and outflow results for the GranBaristo for the four scenarios shown in quantity for a future trendline sales projection for 2016-2030

Appendix X.1 **-** Results for Philips lifespan=100% of the original set lifespan

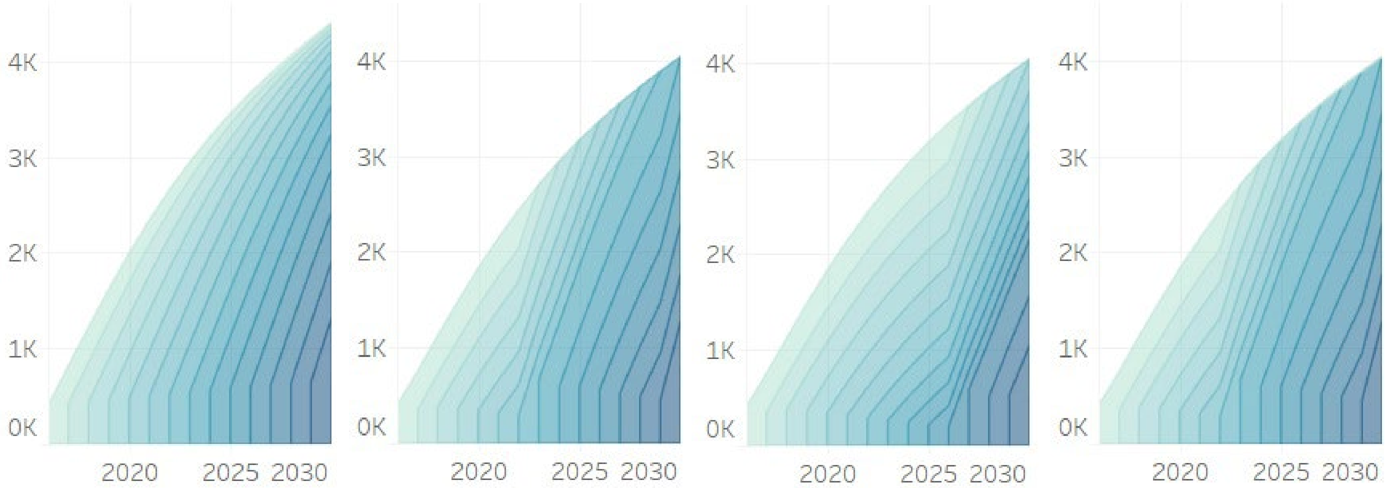
INPUT

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



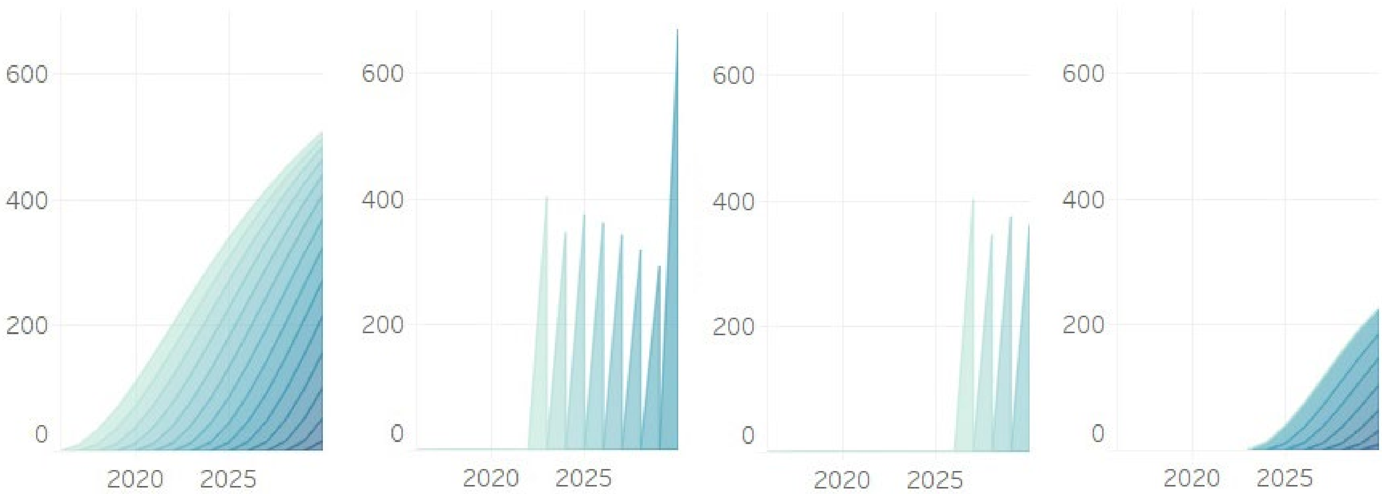
STOCK

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



OUTFLOW

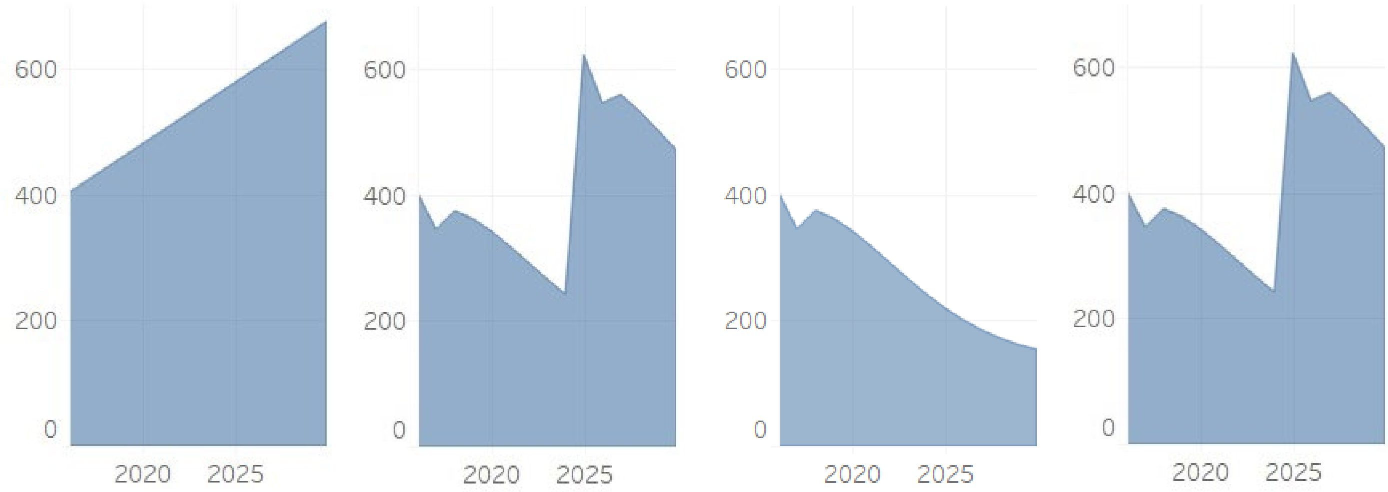
BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



Appendix X.2 - Results for Philips lifespan=130% of the original set lifespan

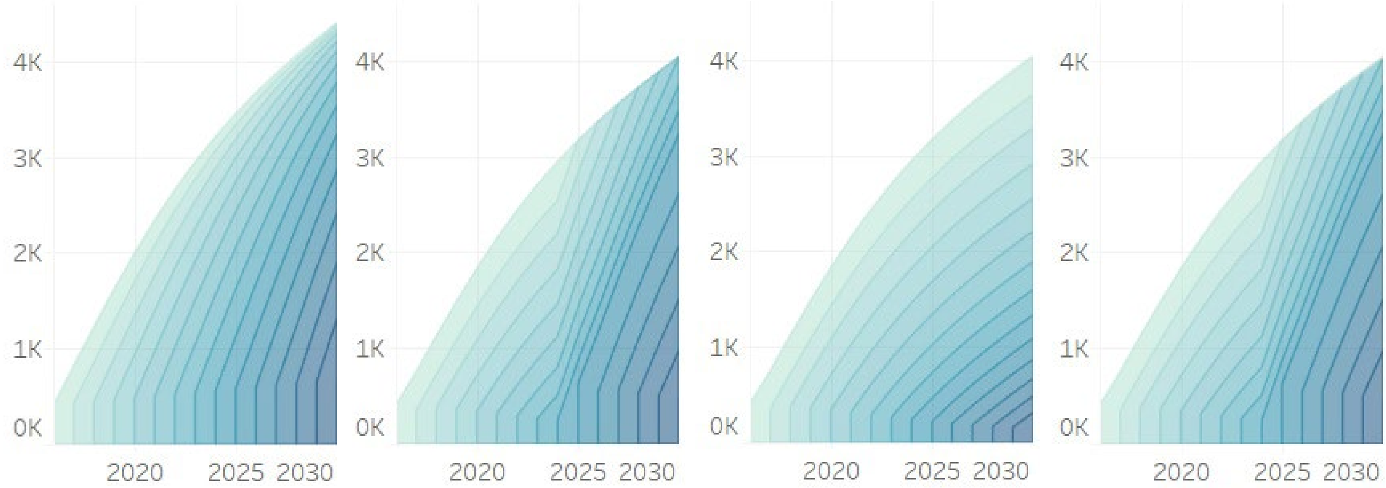
INPUT

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



STOCK

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell



OUTFLOW

BAU | Lease once | Lease-refurbish-lease | Lease refurbish sell