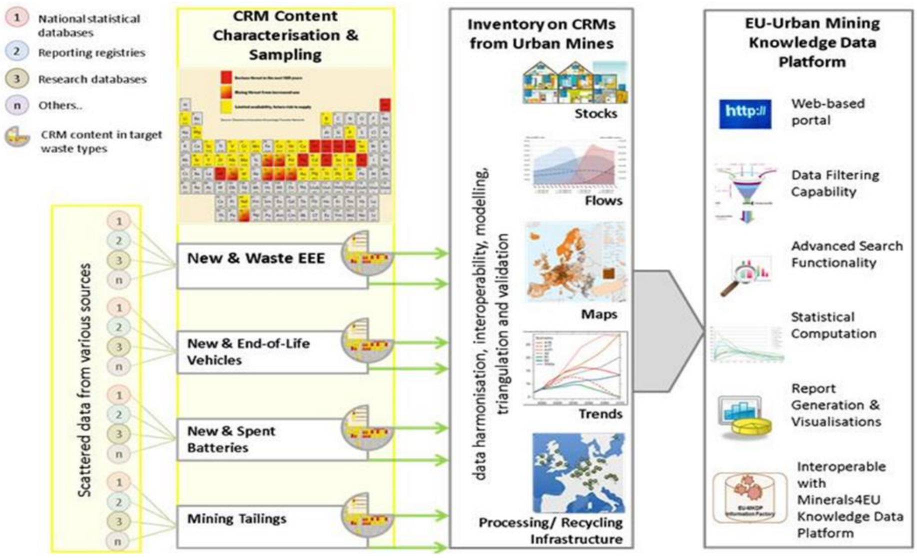
Product Stocks and Flows
Deliverable 3.3



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Notice

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PURPOSE

The objective of this report is to describe the steps taken to deliver (an) innovative, robust and dynamic model(s) assessing the historic and current stocks and flows of in-use and end-of-life batteries (BATT), vehicles (ELV), and electric and electronic equipment (EEE) in EU28+2. Deliverable 3.3 ''Product stocks and flows'' is an extension and further iteration of Deliverable 3.1 ''Historic and Current flows'' which takes an inventory of the data sources, and provides an approach to assess the product market inputs and stocks of selected waste streams leading to the waste generation.

The *Multivariate Sales-Stock-Lifespan method* is used to determine stock and flows of EEE. From this model, applied in several EU member states, the required modelling parameters are extracted. This is used in a common methodology for which the market input component is determined by the apparent consumption method and subsequently the WEEE generated volumes are calculated by using the lifespan parameters in a *sales-lifespan approach*. The WEEE data model is written in R (a programming language and environment for statistical computing and producing of graphics).

A similar *sales-lifespan approach* is also applied to determine battery stocks and flows, similar to the WEEE approach, where for the sales component the data is provided by the industry partners Eucobat and Recharge. Here, the data model is constructed in Excel. For vehicles, a *stock-lifespan approach* is used and the model is constructed in Python. In this case, the main data sources for vehicle fleets is derived from Eurostat.

This deliverable consists of:

- This report which is describing the attributes, architecture and limitations of the developed product group specific data models and the highlights from the results.
- Three attachments in Excel with the current BATT, ELV and WEEE datasets according to the ProSUM harmonized format. The attached datasets include data uncertainty and data quality for each data point. This is also including any comments related to the data quality assessment, the description of data consolidation steps where applicable, and the type of estimation in cases where a measured data and/or coherent estimate was included e.g. from extrapolation, interpolation, etc. Also included are all sources used and their (temporary) meta-data ID's as they will be used in the knowledge base. The datasets are also provided internally in the ProSUM project for use within WP5 to populate the unified ProSUM data model and to further develop the necessary programming.

EXECUTIVE SUMMARY

This Deliverable describes the individual stocks and flow models for BATT, ELV and WEEE, the outcomes of the modelling work and the resulting datasets. For each of the product groups the relative availability of data limits the extent to which stocks and flows can be modelled. Furthermore, the techniques used for modelling are based on the expertise of the relevant ProSUM partners and, as a result, differ for each of the product groups. For BATT MS Excel is used, for ELV it is Python and for WEEE it is R (a language and environment for statistical computing and graphics) and MS Excel. However, the unified data model previously developed within ProSUM allows the results of stock and flow modelling for each product group to be harmonised.

Two versions of Input Output Analysis (IOA) have been used for determining stocks and flows of products. The vehicles stocks and flows data model is based on *stock-lifespan approach,* and the batteries and WEEE stock and flow analysis is based on *multivariate sales-stock-lifespan* analysis. Both models are structured in a similar way but the calculation sequence is different. The stock and flow modelling is in place and is functioning but does need further reconciliation linked to WP2 and WP4 and for D3.4 and D3.5 work.

The WP3 work was conducted by executing the following steps:

1. Model selection (completed in D3.1)
2. Arranging data accordingly (partly completed in D3.1)
3. Harvesting of data (completed in D3.2)
4. Processing and consolidating the data, (partly covered in D3.1 and D3.2 and completed here in D3.3 for EEE and ELV and partly for BATT with an overview of results provided in Chapter 3, below).
5. Describing the consolidation procedure including specification of data quality, uncertainty and metadata for all sources used. (Finalised as a first complete dataset for this D3.3).

Battery results

Preliminary research in D3.1 and D3.2 concluded that it is necessary to conduct the stocks and flows modelling, not only according to the BATT sub-keys, but also differentiating between the different applications in which batteries are embedded such as EEE and vehicles. A list of 50 combinations of keys, sub-keys and applications for the stocks and flows modelling was developed. Compared to the status quo presented in Deliverable 3.1, the coverage of the collected data has been considerably expanded, and the modelling approach has been tested. Preliminary results for laptops and tablets for the European Union as well as Switzerland and Norway are presented as the proof of principle of the 'ProSUM harmonised approach'. Further data will become available in early 2017 and this will enable stocks and flows modelling to be finalised for BATT.

Key limitations and uncertainties are related to parameters used in the modelling. They are subject to a range of uncertainties regarding the use of average weights per battery, the lifetime distribution, the POM volumes, and the national data.

Vehicles results

Following on from the work undertaken in D3.1, the vehicle stock-flow model has been implemented and preliminary results are available. The focus in this Deliverable is on testing, verification and integration of all available data. The preliminary outputs are now available and can be tested. In terms of the project requirements, the model is capable of expressing stocks and flows of vehicles inside the EU28 + European Free Trade Association (ETFA), to a granular level of detail (vehicle keys) which is both novel and a prerequisite for linking the vehicle flows to the product (WP2) and waste stream composition (WP4).

WEEE results

Similar to ELV, the WEEE stock and flow modelling is implemented with essentially completed data specifications. In addition, the stock and flow analysis adopts previous published research for the

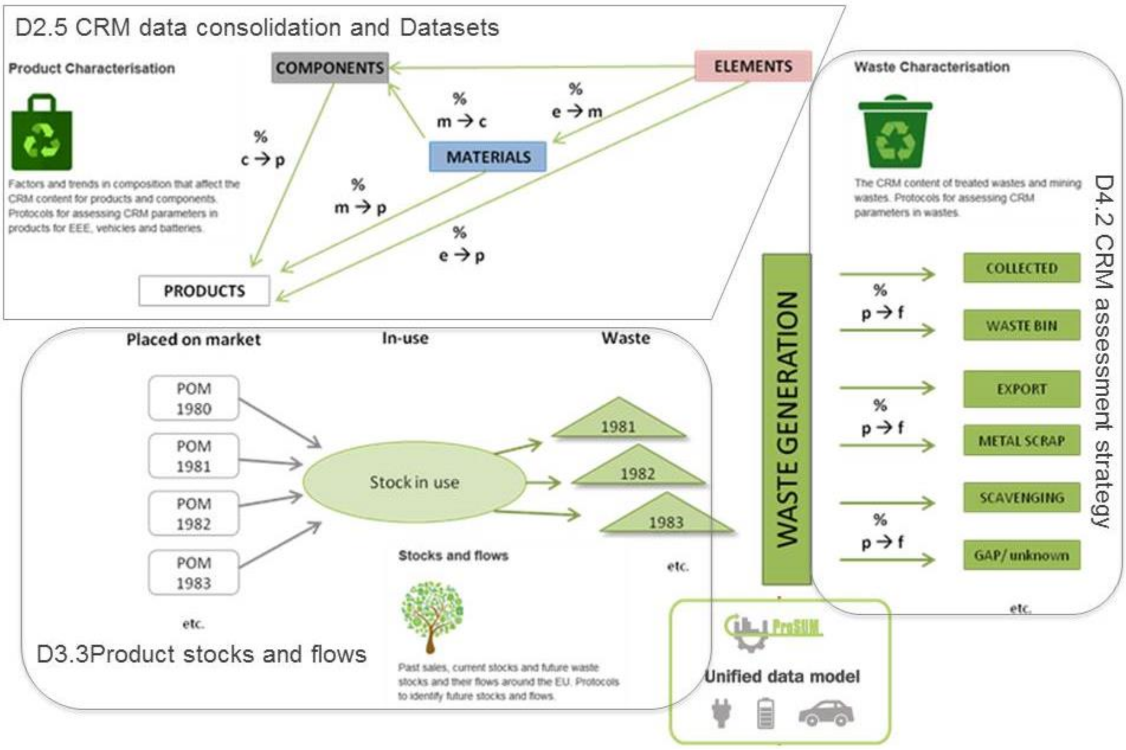
WEEE Article 7 common methodology report. A dedicated script is written in R by Statistics Netherlands enabling the public release of the stocks and flows model including the amounts placed on the market. A detailed instruction to construct and to download the source data files is given at https://github.com/Statistics-Netherlands/ewaste.

The open stocks and flows model also provides users the option to export data in XLS format. The stock and flows model is specifically categorised according to the 'ProSUM harmonised approach' (in both UNU Keys and recast WEEE directive categories in Annex III) and allows for filtering and updating for new electronic products. It is important to note that this work is ongoing due to the huge amount of measured raw data available. This work is ongoing, for example, to update data for PV panels (UNU key 0002), correction of odd average weights and product count combinations in cases where the multiplication is plausible, but the underlying parameters are not realistic.

Next steps for BATT, ELV and WEEE

The stocks and flows are quantified and available for further reconciliation and programming in WP5 and allows the continuation of WP3 as planned for the upcoming Deliverables 3.4 and 3.5 aiming to link the product stocks and flows with the compositional work from WP2 on product composition and from WP4 for waste stream compositions.

Using the principles for the EU-UMKDP architecture, the outcomes and detailed calculation sequences of the individual stock and flow models for BATT, EEE and ELV are now structured according to the **ProSUM single unified data model** shown in the figure below. The unified data model will link product composition (WP2) and waste stream composition (WP4) with stocks and flows. It is important that data consolidation is harmonised according to the ProSUM data quality parameters explained in D2.5, D3.2 and D4.2. This will allow for error propagation analysis and full assessment of the results over the entire calculation schema from elements to materials to component and products and flows as well as a uniform way of describing all sources used.



The ProSUM unified data model

1. Introduction

1.1. Aim of the deliverable

According to the Description of Action, this Deliverable 3.3 addresses and analyses different models for characterising stocks and flows, in order to determine the required sophistication level needed for WEEE, BATT and ELV, given the data quality, uncertainty, and availability of different data. Since key modelling decisions for the respective product groups are taken in D3.1 and in the stock and flow modelling discussions in WP3, the aim of this deliverable goes beyond selection of the desired stock and flow quantification method. For WEEE the aim is to consolidate and finalise available data. For the BATT and ELV, the aim is to continue the data gathering in D3.1 and D3.2 to select the stocks and flows model, and to consolidate all findings.

From section 1.3 of Deliverable 3.1, a set of basic quantification methods in D3.1 including the a) Time Step approach, b) Market Supply or sales- lifespan approach, c) Stock-lifespan approach, d) Leaching Model; the most appropriate model has been selected for ELV and BATT. For EEE, UNU developed, and has applied here, the e) Multivariate Sales – Stock- Lifespan approach from which specific lifespan parameters are extracted for use in a more direct version of the sales lifespan approach (b). Based on previous analysis, a sales – lifespan model (b) is also being applied for BATT. For ELV, due to the highest quality of data being available for vehicle fleet sizes, a stock – lifespan model (c) is being used.

The second aim of this deliverable is to provide a complete, harmonised approach according to the classifications developed in Deliverable 5.3. This is aligned with work undertaken in:

- Deliverable 2.5 on the product composition: Here the focus is on the composition of individual products, components and materials to determine composition(s) (trends).
- Deliverable 3.3 on the product stocks and flows: Here the focus is on product characteristics such as average weight and lifespan resulting from the model in order to compare against the respective information in the collected and other streams (the 'p' value in Figure 1).
- Deliverable 4.2 on the waste flows. The WEEE generated amounts are compared to the actual measured product counts in the various flows (the 'p-f' values) in Figure 1. In addition, from the composition and stocks and flows, the available e-f (and c-f plus m-f) steps are included. These will be further elaborated and consolidated by June 2017 when the scheduled data reconciliation process is finalised.

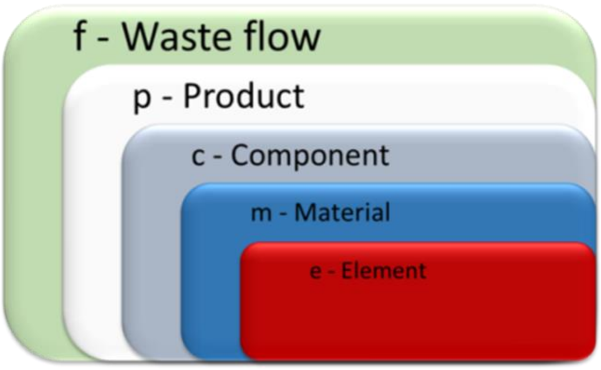


Figure 1. Simplified ProSUM calculation sequence

Utilising data from WP2 and WP4, a single inventory has been developed in order to describe all sales, stock and waste (flow) information in a consistent manner and to allow WP5 to further develop the programming for data presentation in the EU-UMKDP. This includes recent updates to the code lists derived from additional analysis and description of the meta-data for both individual sources, and the entire stocks and flows datasets for BATT, ELV and WEEE.

Figure 2 shows the position of this deliverable in relation to other deliverables in ProSUM. Deliverables 3.3–3.5 cover the stocks and flows model development for end of life products together with an inventory of CRM's (D2.5 CRM data consolidation and datasets), and report on the methodology used for CRM stocks and flows model. In D3.3 data models are processed and prepared for the database developed within WP5 (EU-UMKDP).

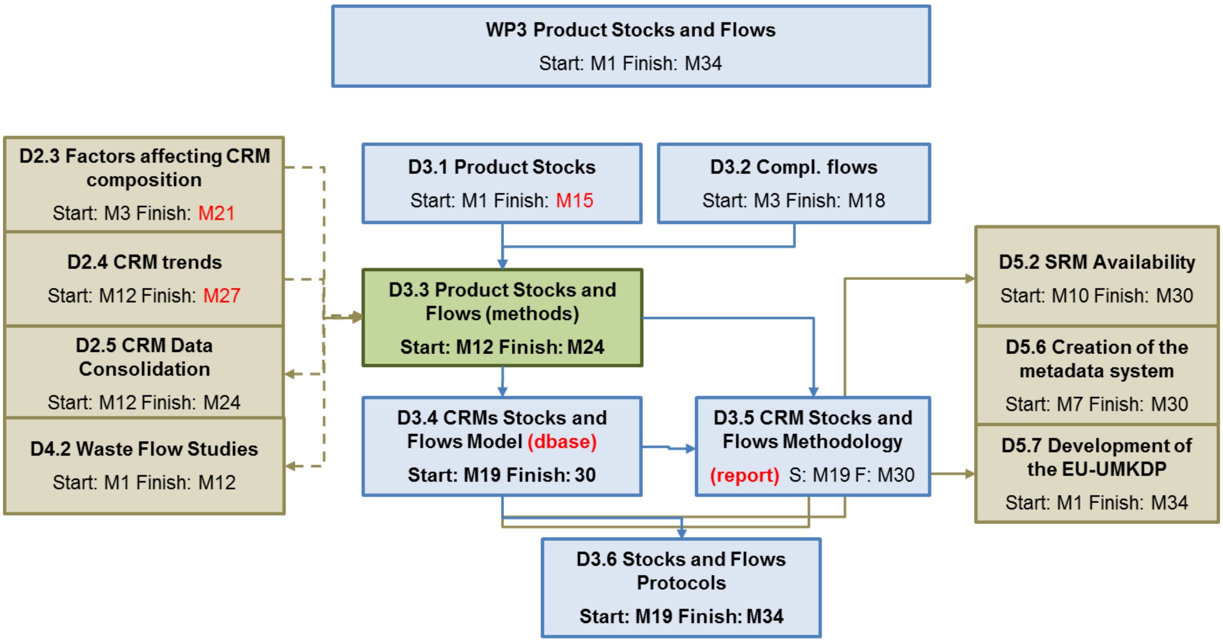


Figure 2. Pert chart positioning D3.3 in WP3 and other work packages

1.2. Overview of methodologies

The following are available methodologies described in the literature (Wang et al., 2013) which have been considered for stocks and flows characterisation:

- *Disposal related analysis* uses WEEE data obtained from collection channels, treatment facilities and disposal sites. It usually requires empirical data from parallel disposal streams to estimate the overall generation (Walk, 2004).
- *Group/comparative analysis* of qualitative and quantitative variables gathered from the different strategies within the scope of the study i.e. compare with different regions, countries and appliances. This approach is not used for the three waste groups, rather the reverse: after waste generation determination, these amounts become the starting point for the further waste flows (see also deliverable D4.1 and deliverable D3.2).
- *Time series analysis (projections model)* forecast the trend for WEEE generation by extrapolating historical data into the future. It can be also applied to fill in the gaps for past unknown years from available datasets. This approach has not been applied. However, after determining waste generation numbers, interpolation for countries, or UNU or BATT keys, the approach may be used on cases with relatively complete data to cover instances of no or incomplete data.
- *Factor/correlation models* are based on hypothesised causal relationships between exogenous factors like population size and income level versus WEEE generation (Huisman et al., 2008; Huisman, 2010). With developing more advanced Input Output Analysis (IOA), mass balance based approaches are preferred.
- Material Flow Analysis (MFA), quantitatively evaluates the sources, pathways and final sinks of material flows. Often input output tables are used to feed the analysis. MFA, also referred to as Substance Flow Analysis, is the analysis of a set of material flows, stocks, and processes within a defined boundary (e.g. a region, country, a private household, etc.) (Brunner and Rechberger, 2004). The system boundary is defined in space and time. It can consist of geographical borders (region) or virtual limits (e.g., private households, including processes serving the private household such as product residence time, waste collection, etc.). For the

purpose of this project, the default geographical boundaries are the national territories of the EU member states (Brunner and Rechberger, 2004).

- Different versions of MFA models include:
    - Time step model: the approach is based on measuring detailed changes in the stock within a period in a system which equals the difference between the total inflows and outflows (Araújo et al., 2012).
    - Market supply models estimate waste generation from product sales in all historical years with their respective obsolescence rates in evaluation year (Streicher-Porte et al., 2005; Jain and Sameer, 2006; Oguchi et al., 2008; Dwivedy and Mittal, 2010).
    - Stock and lifespan model, which combines time-series stock data with lifespan distributions of products can also estimate WEEE generation (Binder et al., 2001; Müller et al., 2009; Walk, 2009).
    - The leaching model calculates the WEEE generation as a fixed percentage of the total stock divided by the average product lifespan (van der Voet et al., 2002; Robinson, 2009; Chung et al., 2011; Araújo et al., 2012).
    - Multivariate Sales-Stock-Lifespan model is an advanced and flexible method, which can be used when multiple datasets are available. It was developed for the Dutch Future Flows study (Huisman, 2012) and it links product sales, stock and lifespan data to construct mathematical relationships between various data points, based on best available data to calculate WEEE generated. See Section 2.3 for more details. By applying this method, the data consolidation steps facilitate the production of more comprehensive time series datasets from the available datasets, which increases the reliability of WEEE estimates (Wang et al., 2013; Magalini et al., 2016).

Data sources in literature and various options for stock and flow estimation methods, in particular IOA methods (also called mass flow analysis methods), have been reviewed. For these IOA methods, in simple terms, at least two parameters must be known, estimated, or otherwise defined to determine the waste generation: that means two data points from sales, stocks and lifespan as the three main parameters (Wang et al., 2013). A summary list is available in Table 1. A more detailed data inventory is available in Deliverable 3.1, Annex 2.

Table 1. Literature overview of main IOA models (Wang et al., 2013)

Estimation Model	Variables and data requirements						Key references
	Sales Cont.*	Dis.*	Stock cont.	Dis.	Lifespan age distribution	Average lifespan	
A. Time Step Model		✓	✓				Oguchi et al., 2008; Yu et al., 2010, Araújo et al., 2012
B1. Market Supply Model (Distribution Delay)	✓				✓		Melo, 1999, Yang et al., 2008, NemaNord, 2009
B2. Market Supply Model (Simple Delay)		✓				✓	van der Voet et al., 2002
B3. Market Supply Model (Carneige Mellon method)	✓					✓	Kang and Schoenung, 2006; Peralta and Fontanos, 2006; Dwivedy and Mittal, 2010; Steubing et al., 2010
C. Stock and Lifespan model			✓		✓		Müller et al., 2009; Walk, 2009; Zhang et al., 2011
D. Leaching model			✓			✓	van der Voet et al., 2002; Robinson, 2009; Chung et al., 2011; Araújo et al., 2012
E. Multivarate Sales-Stock-Lifespan model	✓		✓		✓	✓	Wang et al., 2013

Note: ''Cont.'' means that continuous datasets in the current and all historical years are required for calculation; ''Dis'' means that discrete data (mainly in the current evaluation year) are sufficient for calculation.

The different methods for characterising stocks and flows above have been analysed in order to determine the appropriate choice for the model type and sophistication level in relation to the data availability and quality for ProSUM. From past experience, UNU developed the advanced specific method (E) that can handle different data sources when multiple sources for all three key parameters are available. By combining and judging the plausibility of multiple data sets that have their confidence levels specified, advanced solving is used to evaluate the most plausible solutions when considering different data sources with different data qualities. For EEE, in the detailed country studies in the Netherlands (Huisman et al., 2012), Italy (Magalini et al., 2012), Belgium (Wielenga and Huisman, 2013), France (Monier et al., 2013), Romania (Magalini et al., 2015b) and Latin America (Magalini at al., 2015a), the Multivariate Sales-Stock-Lifespan method (E) is used. This detailed analysis method, which only functions for multiple and high quality data available in some countries, enables the derivation of key parameters like lifespans, split factors, estimates and correlations. These in turn are used for EEE with the more simplified methods B to analyse future data in a more streamlined manner for future years and for all EU28+2 countries. In section 1.2, these parameters are used in the method B1 in the table above. The stocks and flows model has been built using a unified and robust mathematical approach following a common modelling methodology for all product groups. The same approach is used for BATT stock and flow modelling. In the case of ELV, the stock-lifespan approach (method C) is more suitable since relatively reliable data is available on the vehicle fleet size in Europe.

2. Model for stocks and flows of end of life products

This chapter provides the model characteristics for BATT, ELV and WEEE using the methodologies described in section 1.2. This chapter also highlights the model's limitations. The WEEE data model written in R has been advanced and an ELV model developed in Python. The BATT data model is in preliminary stages and will be completed in March 2017.

2.1. Model for BATT (extended from D3.1)

2.1.1. Model attributes

As explained in Section 1.2 and in Deliverable 3.1, the BATT stock–lifespan based model requires three types of data:

1. Volumes of batteries placed on the market (POM) in weight and/or units for all years and countries;
2. Average weight of the batteries (which can be calculated when the POM volumes are available both in weight and units); and
3. Data on the lifespan distribution, gathered experimentally by checking the age of collected waste batteries, and modelled, using a Weibull function (see Deliverable 3.1).

According to the ProSUM classification, batteries are categorised into 6 keys and 17 sub-keys. Most batteries (except the single cells sold separately) are placed on the market embedded in products like EEE and vehicles.

Although some data are valid for a BATT key without regard to the product they are embedded in e.g. most data on CRM mass fractions, some data also depend on the product in which they are embedded. This is usually the case for the average battery weight and for the lifespan distribution, which may be product and battery type specific. For example, lead-based batteries in vehicles have different lifespans to industrial lead-based batteries and also a different lifespan than the vehicles they are embedded in. This results in the necessity to conduct the stocks and flows modelling not only according to the BATT sub-keys but also differentiating for product type. Based on the available data and the relevance in terms of CRM content, a list of combination of keys, sub-keys and applications for which the stocks and flows modelling is conducted separately has been developed, shown in Table 2.

Table 2. Combinations of keys, sub-keys and applications for which the stocks and flows modelling is conducted separately

Key	Sub-key	Application	UNU Key or Sub-key	Comment
battLiRechargeable	battLiCoO2	Portable PC	030301	
		cell phones	0306	
		cameras/games	0406	
		ebikes	0703	
		Medical	0801	
	battLiMn	cameras/games	0406	
		others portable		UNU keys 02xx, 03xx, 04xx, 06xx
		ebikes	0703	
		PHEV		
		BEV		
		forklift, handling equipment		
		Others industrial		
	battLiNMC	Portable PC	030301	
		tablets	030302	
		cell phones	0306	
		cameras/games	0406, 0702	
		cordless tools	0601	
		others portable		UNU keys 02xx, 03xx, 04xx, 06xx
		ebikes	0703	
		HEV		
		PHEV		
		BEV		
		Telecom	0301, 0305	
battLiPrimary	battLiMnO2			No differentiation of the sub-keys in the available data
	battLiCFx			
	battLiFePO4			
	battLiSO2			
	battLiSOCl2			
battNiCd	battNiCdSealed	cordless tools	0601	
		others portable		UNU keys 02xx, 03xx, 04xx, 06xx
	battNiCdVented	security lighting	0901	
		UPS		
		Military/space		
		Others industrial		
battNiMH	battNiMHSealed	Portable PC	030301	
		cordless tools	0601	
		others portable		UNU keys 02xx, 03xx, 04xx, 06xx
		HEV		
	battNiMHVented			No data available, very low volumes expected
battPb	battPbSealed	cordless tools	0601	
		SLI		
		ebikes	0703	
	battPbVented	forklift, handling equipment		
		Telecom	0301, 0305	
		UPS		

		grids		
		Military/space		
		Medical	0801	
		Others industrial		
battZn	battZn			No further differentiation
battOther	battOther	others portable	02xx, 03xx, 04xx, 06xx?	
		ebikes	0703	
		UPS		
		grids		
		Others industrial		

Abbreviations: PHEV: Plug-in hybrid electric vehicle, BEV: Battery electric vehicle, HEV: Hybrid electric vehicle, UPS: Uninterruptible power supply, SLI: Starting lighting ignition

The stocks and flows modelling differentiates 23 types of lithium-based rechargeable batteries, groups all lithium-based primary batteries together (due to missing data), and further groups 6 types of NiCd batteries, 4 types of sealed NiMH batteries (vented NiMH batteries are neglected), 10 types of lead based batteries, all zinc-based batteries together, and 5 other battery types. In total, 50 different stocks and flows models will be compiled to cover the different types of batteries.

2.1.2. Model architecture

The modelling is conducted using the Microsoft Excel spreadsheets. The parameters to be entered into Excel are:

1. POM for each year of a defined geographical area;
2. Weibull parameters of the lifespan distribution; and
3. Average weight of the battery to allow for data on POM volumes, stocks and generated waste both in weight and in number of units.

Based on the data, the file calculates the stocks and the modelled generation of waste batteries in the year t_1 by multiplying the POM volume at year t_0 by the probability that a battery that entered the use phase at t_0 exits use as a waste battery at time t_1. The total modelled generation of waste batteries for the year X is the sum of the generation in year X of batteries put on the market in all years before X. The stocks are the sum of the batteries already put on the market but not yet generated as waste:

$$Stock\ in\ year\ X = \sum_{i=0}^{X} \left(POM\ in\ year\ i - \sum_{j=0}^{i} BATT\ POM\ in\ year\ i\ generated\ as\ waste\ in\ year\ j\right)$$

Several data sources were combined to get data on the flow (f) and the flow composition (p-f) related to POM batteries:

1. (Avicenne, 2016) provides data on the volumes of rechargeable portable, industrial and automotive batteries put on the European market.
2. (EPBA, 2015) provides national data on the volumes of portable batteries put on the market, and therefore the percentage representing the share of the national battery markets compared to the European market. These data are consistent with the Eurostat data on portable batteries POM, but they are more comprehensive, because they cover more countries.
3. (Eucobat, 2016) provides data on the shares of the different types of batteries POM. The overall Eucobat average was considered to be the European average. For some countries, national data are available.

4. National authorities like the ADEME (SYDEREP, 2015) in France and the UK Environment (Agency, 2016) provide detailed data on the types of batteries POM on their national market.
5. (Eurobat, 2013, 2016) provides data on industrial batteries complementing the Avicenne data.

Table 3 provides a comprehensive overview of the data sources combined. All data sources offer useful data and have limitations. The metadata of each dataset document the origin of the data through a reference to a publication or a description of the decisions taken to select or calculate the most accurate data.

Table 3. Opportunities and limitations of the different data sources on POM batteries

Data source	Geographical coverage		Application			Recharge-ability		Data on electrochemical systems		
	European data	National data	Portable	Automotive	Industrial	Rechargeable	Primary	Very detailed	Some differentiation	No or very limited
Avicenne	X		X	X	X	X		X		
EPBA	X	X	X			X	X			X
Eucobat	Eucobat members		X	X	X	X	X		X	
National authorities		X (some countries)	X	X	X	X	X		X	
Eurobat	X	Some		X	X	X			X	

Data on the average weight of batteries to convert data in weight (mostly tonnes) to units are mostly provided by (Avicenne, 2016) (Table 4) and (Eucobat, 2016). For some battery types and applications, the available data reflect these variations of the average weight in time and location. For the battery types for which the available data is not reflecting these variations, the data quality is estimated to be lower.

Table 4. Average weight of batteries depending on the BATT sub-keys and the applications (in kilograms) (Avicenne, 2016)

BATT Sub-key	Application	Link to UNU Keys	2011	2012	2013	2014
battLiCoO2 and battLiNMC	Portable PC	030301	0.30	0.30	0.33	0.29
battNiMHSealed			0.62	0.62	0.62	n/a
battLiCoO2	cell phones	0306	0.02	0.03	0.03	0.03
battLiNMC			0.03	0.03	0.03	0.03
battLiCoO2 and battLiNMC	cameras/games	0406	0.18	0.17	0.17	0.17
battLiCoO2, LiMn and battLiNMC	ebikes	0703	2.28	2.22	2.22	2.22
battPbSealed			7.58	7.50	7.50	7.50
battLiNMC	Tablets	030302	0.16	0.14	0.12	0.13
battLiNMC	cordless tools	0601	0.35	0.32	0.36	0.37
battNiMHSealed			0.69	0.69	0.69	0.69

BATT Sub-key	Application	Link to UNU Keys	2011	2012	2013	2014
battNiCdSealed			0.88	0.85	0.90	0.92
battPbSealed			1.41	1.40	1.40	1.40
battPbSealed	SLI		18.94	18.75	18.75	18.75
battLiNMC	HEV		5.66	5.44	5.44	5.44
battNiMHSealed			15.40	15.40	16.90	16.90
battLiMn and battLiNMC	PHEV		58.50	55.60	55.60	55.60
battLiMn and battLiNMC	BEV		160.80	155.60	155.60	155.60

n/a: not available

Data on the lifespan distribution of portable batteries were collected in 2012 by Bebat and presented at the International Congress for Battery Recycling 2014 (Bebat, 2014). These data were used for testing the stocks and flows modelling. These data are currently being refined by Eucobat with a more comprehensive study in six European countries. The data will be available for the modelling in February 2017. The stock and flow analysis will then be updated and consolidated.

The data from the different sources have been compared and combined. Each dataset on batteries POM, lifespan and average weight displays the data source, which can be either a reference to a publication or a metadata, in which the decisions taken to select or calculate the most accurate data were documented.

2.1.3. Model limitations

All the parameters used in the modelling are subject to a range of uncertainties:

Use of average weights per unit

The diversity on the battery markets in terms of technical requirements for the batteries, the product in which the batteries are embedded, economic constraints etc. lead to the fact that the characteristics of the batteries, including their weight, can vary considerably. Even though this range is intended to be reduced by differentiating some main products (see Table 4), the uncertainties on the average weights are high. For some battery types, the average weight of a battery may depend on time (e.g. batteries in laptops got lighter over time) and location. For some battery types, the available data reflect these variations for the average weight in time and location. For the battery types for which the available data does not reflect these variations, the data quality is estimated to be lower.

Lifespan distribution

There are a high number of variables affecting lifespan, e.g. disposal of the product in which the battery is embedded, the representativeness of the waste battery collection channels against battery waste generation, and the representativeness of the sorting and sampling procedure. Consequently, the Weibull modelling, even where the correlation coefficients are high, may not exactly depict the reality of the lifespan distribution. Geographical effects on the lifespan parameters are described in a limited measure at present, because data will soon be available for six countries from the current Eucobat study.

European data on batteries placed on the market

The available data do not present a comprehensive view of the batteries POM with the level of detail required for the modelling, so that different sources of data were combined as described in section 2.1.2 and in the metadata of the datasets. Each data source brings uncertainties, and the combination of several data sources leads to higher uncertainties due to the error propagation.

National data on batteries placed on the market
For each category of battery as defined in Table 2, the European data on the weight of batteries POM were multiplied by a percentage representing the share of the national battery markets compared to the European market to calculate the weight of batteries POM in each country. Due to limited data, in most cases the same percentage was used for all types of batteries, even though some countries may have a larger market for some types of batteries than for others. For example, it may be expected that highly industrialised countries like Germany or Belgium are, proportionally, bigger markets for industrial batteries than less industrialised countries. This is not reflected by the available data due to limited sources of national data. Also regional effects on the average weights cannot be described quantitatively at present.

The combination of all uncertainty factors leads to uncertainties in the modelling results. The results indicate trends and give orders of magnitude of the expected generation of waste batteries and of the stocks. They should be used with caution bearing in mind the uncertainties and error propagation related to the uncertainty in a range of parameters used to make the calculations.

2.2. Model for ELV (extended from D3.1)

2.2.1. Model Attributes

The stock-lifespan model for tracking the vehicle fleet is written in Python with the overall aim of keeping stock-flow consistent over all subsets (based on the vehicle keys described below) of the fleet in the EU. Achieving this requires the following:

- Separate tracking of every subset of the fleet (i.e. vehicle keys);
- Maintaining stock-flow consistency for the whole lifecycle of each vehicle key, inclusive of trade between regions;
- Consistent tracking of the age of every subunit between time periods; and
- Support for inference and interpolation.

2.2.2. Model Architecture

Data representation
The fundamental unit of the model is a vehicle (piece), and the corresponding atomic data unit, 'a group', is a quantity of vehicles with the same vehicle key, which specifies the various properties of the vehicle (engine type, etc.). The reason for this basic unit is that the other properties, e.g. age, location, can vary with time or trade but one vehicle key can't change into another. The overall model thus tracks vehicles through their lifecycle from POM to end-of-life and is analogous in architecture to a mass-flow model (MFA), with the base unit of pieces rather than mass, and with vehicle keys instead of different substances. It is possible to view the model output using mass as an alternative unit, but the conversion is inferred from unit mass averages in the primary data sources and the internal basic unit is always in vehicle pieces. The inference method incurs a substantial penalty in estimated error when considering the results based on mass.

Within each stock and flow within the model, the data is subdivided into both countries and years. Any quantity of vehicles (pieces) is represented internally as an age distribution, i.e. the individual ages of all vehicles in a vehicle group are maintained as a vector, with the quantity being the sum. The model logic assures stock-flow consistency by enforcing rules for allowable data manipulations. As an example, comparing two stocks from different years, the model will enforce that the age distributions are updated to the same base year. Finally, each group can be tagged with arbitrary data, such as average mass, and the model allows rules to be set for how to preserve or update this supplementary data. The addition of supplementary data is both useful and necessary as it allows both richer visualisations, and better linking with other work packages and thus full compliance with the PROSUM data model specification.

Vehicle Keys

The specification for the different vehicle groups that the model tracks and the derivation of their unique reference (the vehicle key) is shown in the following table. In addition to the keys that the model tracks, several primary data sources use a different keying convention. These keys are converted when the data is imported and are not tracked past that point, although the EUROSTAT representation of age is trivial to regenerate given an age vector.

One group exists within the model for every combination of vehicle key, model stock or flow, country, and year of the model. The distinction between vehicle keys is necessary to couple vehicle flows with their components and mass content. It is necessary to distinguish between countries and time periods to link national scrappage data to the flows and because the CRM content of vehicles and, therefore, that of ELV flows may change with time.

Table 5. Vehicle keys, sub-keys based on type, drivetrain, engine displacement, and weight

VEHICLE KEYS *e.g. V01010203 = car, petrol, <1400cm³ cylinder, 1250-1499kg*									
0a	*Type*	*0b*	*Drivetrain type*	*0c*	*Engine Displacement*	*0d*	*Weight*		*(Age)*
00	Unknown	00	Unknown	00	Unknown	00	Unknown		*Preserved as*
01	Car	01	Petrol	01	< 1400 cm3	01	< 1000 kg		*vector with*
02	Light Utility Vehicle	02	Diesel	02	1400-1999 cm3	02	1000-1249 kg		*individual years*
		03	Liquified Petroleum Gas (LPG)	03	> 2000 cm3	03	1250-1499 kg		
		04	Natural Gas (CNG)	04	no cylinder (only for drivetrain keys 0,6,7,8)	04	> 1500 kg		
		05	Hybrid						
		06	Plug-in hybrids (PHEV)						
		07	Battery or fuel-cell vehicles (BEV/FCV)						
		08	Other (flexifuel)						
Additional keys in primary sources, converted during data import									
SOURCE:			*ICCT drivetrain*		*COMEXT cylinder*				*EUROSTAT age*
		11	PHEV+BEV	11	< 1000 cm3			00	Unknown
		12	LPG+CNG	12	1000-1499 cm3			01	0-2 years
				13	1500-2999 cm3			02	2-5 years
				14	>3000 cm3			03	5-10 years
				15	<1500 cm3			04	10+ years
				16	1500-2499 cm3				
				17	>2500 cm3				

Model Structure
The model includes the following stocks and flows:

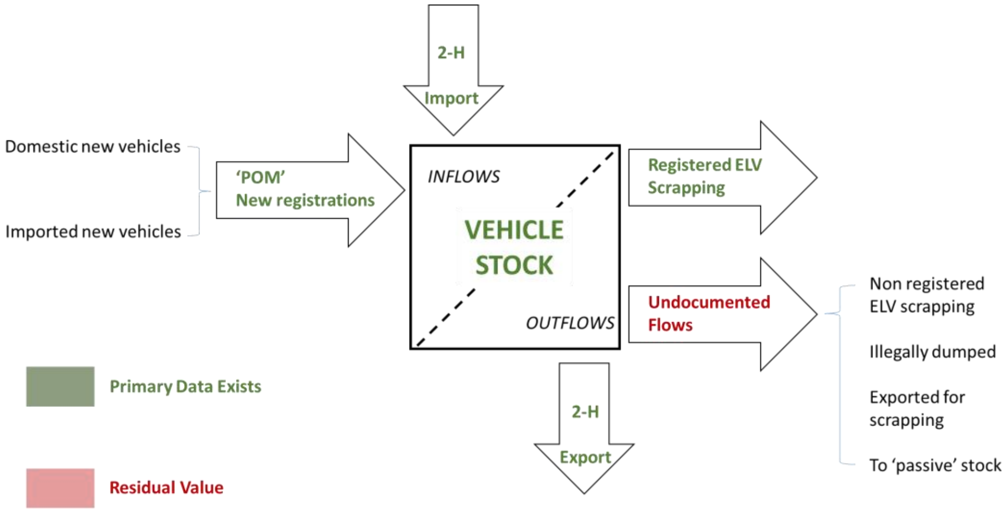


Figure 3. Vehicle stock flow model - elements and primary data sources

The stock at time (t) is calculated as:

Stock(t-1) + net trade flows(t) + POM (t) – end of life flows (t).

This formulation of the calculation is consistent with how the EUROSTAT (see Table 6) align dates, e.g. the stock is reported as it was at the end of the calendar year, and with the methodology in other available literature, e.g. (Öko institute, 2010).

2.2.3. Execution

The model has four stages:

1. *Intake of external data*: data from the primary sources is read and converted into a unified format including checking units and assigning vehicle key fragments where possible.
2. *Data validation*: the data is checked for consistency, the full vehicle key specification is enforced (vehicle key fragments are combined), and additional data such as mass is attributed to the fully specified vehicle keys.
3. *Internal inference*: the remaining aspects of the model that are not directly supplied by primary data sources are inferred through various algorithms.
4. *Final calculation and output:* The stock-flow model is run through all time steps and the complete data set is output into the common harvesting format.

Intake of external data
The primary data sources for the intake are as follows:

Table 6. Data sources for model input, by model component

Model Component	Keys / Data Items	Source
POM	All	EUROSTAT, 2016
	PHEV, EV, Hybrid additional detail	ICCT 2016, proprietary data
Vehicle Stock	All	EUROSTAT, 2016
	Certain years additional data:	ACEA 2010, ACEA 2014
Internal (between included countries") Trade, second hand	All	COMEXT, 2016
External (outside included countries*) Trade, second hand	All	COMEXT, 2016
ELV	Vehicle Number, Total Mass	EUROSTAT, 2016
	Switzerland additional detail	EMPA
Deregistrations	*All*	*Calculated, can be compared with aggregate figures from EUROSTAT, 2016 and ACEA 2010,2014*
Undocumented Flow and Stock	*All*	*Calculated*
** Included countries are the EU28 + ETFA (Norway, Switzerland, Iceland)*		

The data is compiled into a single input spreadsheet for faster loading and reconciliation, but individual data points can also be added separately. Uncertainty is calculated for each country.

Data Validation

In this step, the input data is checked for consistency and prepared into a fully harmonised data set with every entry assigned to a fully formed vehicle key.

The data is first checked for consistency as follows:

- Ensure that all units are harmonised e.g. many Eurostat tables are reported in 'thousands' rather than vehicles.
- Check that subdivisions of a given key fit into the parent key, e.g. check that the sum of all engine size subdivisions of a drivetrain type is less than the data for the drivetrain total.
- The remainder (the total minus the sum of the subdivisions) is assigned to the unknown key; to continue the example, the difference between the value for petrol and the sum of all petrol cylinder size data points is keyed as unknown engine size.
- Check that the sum across various model attributes is equal to aggregates that exist in primary data e.g. that the sum of a group in all countries in the EU is equal to that reported for the EU as a whole.

The next step is to combine vehicle key fragments. This is necessary because there is no unified primary data covering all vehicle keys. Figure 4 below shows how data is structured in the input datasets referenced in Table 6. One can see for instance that EUROSTAT reports the full distribution of drivetrain and cylinder capacity keys for each country, but the mass and age keys are reported in different tables that can't be combined from the primary source.

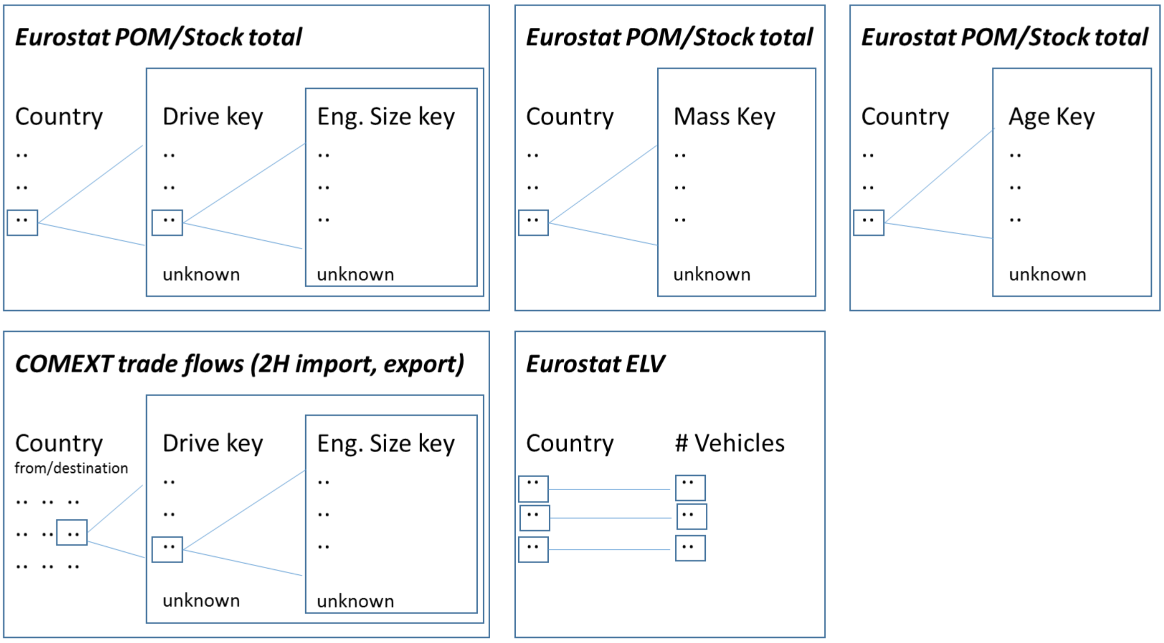


Figure 4. Data Structure of the main tables in the primary data sources

To unify the input data into the full vehicle key specification, it is therefore necessary to attribute the age and mass vehicle key data into the drive-capacity set of vehicle key fragments. At present this is done by assuming that each country/drive/size combination has the same mass and age distribution as the corresponding country/mass or country/age distribution for that year. Each drive-capacity data point thus becomes four drive-capacity-mass data points with relative weight from the country/mass distribution and ensuring that the total number of vehicles is the same before and after. This approach is not ideal. However, the potential error introduced by this step is very low for the vast majority of the data set, is included in the reported errors, and is mitigated by the age reconciliation process described later.

Following this step, other data sources, such as POM data for PHEVs, BEVs, and hybrids from the ICCT (ICCT, 2016), are patched into the model, updating or replacing the EUROSTAT keys where necessary. As an example, the hybrid vehicle (HEV) totals are included in EUROSTAT as part of the gasoline drive total, but can be found as a separate data point in the ICCT data. To use the ICCT data, a group of hybrid vehicles is created, but the creation of the new HEV vehicle group also removes the corresponding quantity of vehicles from the gasoline group in the same country/year. The model allows for subdivision of existing groups, e.g. gasoline to gasoline and hybrid, and enforces numerical consistency for the operation.

Internal inference

In this model stage, relevant parameters that are not in the primary data sources are derived through various algorithmic operations. The most important are deriving the average mass for the vehicle keys, transforming the EUROSTAT-format age keys into a full age distribution, and estimating the loss functions that are used for model projections into the future.

The ICCT data gives an average mass for the POM vehicles for a given year in each country. Given that value, and the number of vehicles in each mass key, it is possible to guess the average mass of a vehicle in each mass group with a reasonable degree of accuracy. These figures are calculated and attributed to the vehicle keys in each country, for each year of the model. Future values can be either extrapolated from trend, or assumed to remain constant.

At the beginning of this step, the complete vehicle keys are implemented, but the age distribution for each key is still in the EUROSTAT database format which groups the vehicles into four age ranges (0-2 years, 2-5 years, 5-10 years, 10 or more years). It is however possible to further refine these estimates to individual age buckets (0-1 years, 1-2 years, ... , n years +). The upper limit is set arbitrarily in the model; in this project an upper limit of 30 is used. This step is not strictly necessary for the historical database, because the calculated components of the model (ELV and complementary unknown flows) can be derived as all the other stocks and flows in the model are available from the input data. It is however a desirable step, as calculation of the full age distribution as well as modelling the loss functions (the probability that a vehicle of a certain age in each vehicle group reaches end of life each year) is important for improving the accuracy of future projections.

Deriving the full age distributions is accomplished by a recursive algorithm that begins by comparing the POM figure for the previous year with the 0-2 year age bucket. This splits 0-2 years into 0-1, and 1-2 year age buckets. The 1-2 year age bucket can then be compared with the POM figures for 2 years previous. The algorithm progressively widens in scope until a guess for all age distributions is formed, that is consistent with all observed EUROSTAT data points.

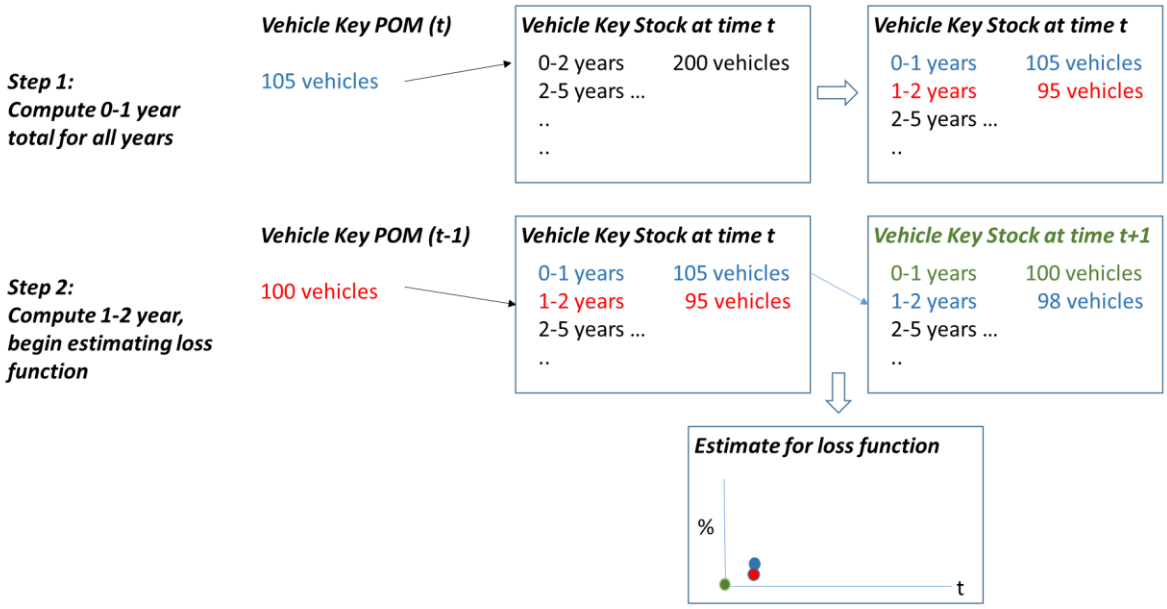


Figure 5. Illustration of the first steps of the algorithm to infer the full age distribution and associated loss function

This process allows for deriving estimates for both the full age distribution as well as the loss function of each national vehicle fleet at a vehicle key level of granularity. The loss function is modelled after a Weibull distribution, which is a continuous probability distribution that, when used for stock and flow models, can be described as modelling the population given a variable and time-dependent failure rate. The model derives this distribution for each vehicle key and country, as well as for any arbitrary aggregate (EU level, all petrol vehicles, etc.).

Calculation is considerably enhanced as the full age distribution for various national fleets is available from ACEA for 2014 and 2010.

Final calculation and output.
With the vehicle key data now fully separated into an age distribution from 0-30+ years, the stock flow model can subsequently calculate the deregistered flows by calculating the projected stock at t+1, and comparing it to the data for that stock.

$$\text{Projected stock (t+1)} = \text{stock (t)} + \text{net trade flows (t+1)} + \text{POM (t+1)}$$

The difference between the projected stock and the recorded one is thus the number of deregistered vehicles. Our model can supplement this identity with the full vehicle key and an estimate for age distribution. Deregistered vehicles can either be assigned to ELV flows, or the remainder is by definition a complementary undocumented flow. Given that ELV flows in crude units of number of vehicles (or mass) is recorded data (EUROSTAT, 2016), the model estimates their composition in terms of vehicle keys and age, with the difference in quantity being assigned to undocumented flows. The overall approach is for most intent and purposes identical to that taken by the (Öko institut, 2016) in their investigation of 'missing flows' in ELV vehicles in Europe. For future projection, instead of using ELV data, the total deregistration can be estimated from the inferred loss functions.

2.2.4. Model Limitations

The primary limitations of the model are uncertainty. Uncertainty is very low (typically 1-5%) in years and model stocks and flows for which primary data exists, since the data coverage is excellent. Uncertainty is, however, comparatively high for the distribution of ELV flows. The reason is that undocumented flows are a significant fraction of the deregistered flows for all nations and all years under study. This significantly affects the uncertainty of the vehicle key distribution of ELV flows; because the only available heuristic for calculating them is to assume that the distribution of ELV flows equals the distribution of de-registrations equals the distribution of undocumented flows. We currently possess some data for individual nations and years, and the model is capable of integrating this data to improve the historical allocation of deregistered vehicles to ELV and dark flows. Uncertainty is even higher when projecting future ELV flows. All of the uncertainty from the distribution mentioned above is present, but additionally, uncertainty from the Weibull fit of the loss function as well as the unknown impact of future events such as economic conditions or policy drives, e.g. "cash incentives to scrap cars'', compounds the uncertainty that already exists.

Another limitation of the model is that vehicles are treated as a monolithic unit, unchanging from assembly to end-of-life. This is certainly not the case; maintenance, spare parts, and upgrades over the vehicle life are significant. This is more of a limitation for using mass as the functional unit, rather than vehicles. It does however mean that significant material flows, and changes in CRM composition do occur that are completely invisible to this approach. Several cases of this (e.g. batteries) are handled separately in other areas of the project, but others (e.g. spare parts) will lead to additional flows that are not captured. Only passenger cars and light commercial vehicles (less than 3.5t) are modelled. Buses, heavy commercial vehicles, and other modes of transit are excluded.

2.3. Model for WEEE (extended from D3.1)

2.3.1. Model attributes

The *apparent consumption method* is used for the sales component of the Multivariate Input Output Model as described in Section 1.2. The script has been written by Statistics Netherlands. It uses European production and trade statistics to estimate sales in weight of products. The script also comes with data on life times of EEE, and allows for calculation of the urban mine and to forecast waste generated. More details of the script and source code of data model can be found here https://github.com/Statistics-Netherlands/ewaste.

2.3.2. Model architecture

Illustrated in Figure 6, the structure begins with the sale of a product, followed by the *residence time,* the time a product stays with the consumer either in households or in businesses. This includes the exchange of second hand equipment between households and businesses. This period does not distinguish between product in-use or dormant time. Depending on the sales and lifetime profile, the product is disposed of. This is termed as *WEEE generated.*

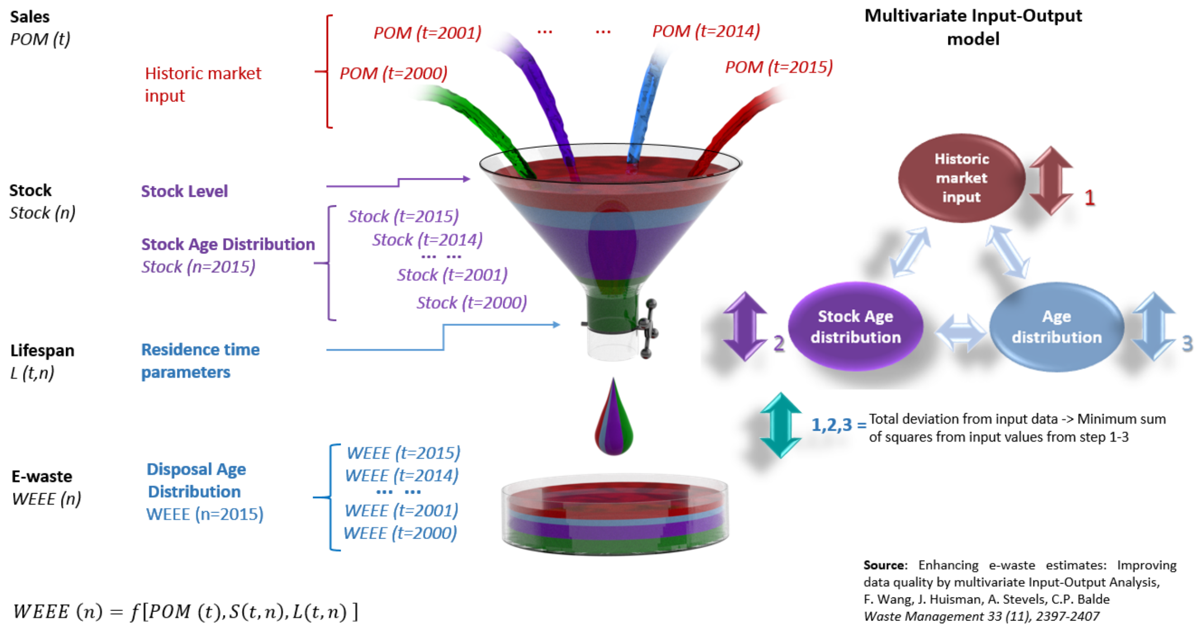


Figure 6. Illustration of Multi-variant Input Output Model

Preparing source data sets of ProdCom and international trade

This series of scripts uses ProdCom and international trade data. It calculates the apparent consumption and then estimates missing values and corrects outliers. The script uses two main input data files for the calculations:

- *ProdCom data*, within EU, the figures for domestic production can be taken from the ProdCom statistics.
- *International trade data*, EEE products produced domestically can also be sold abroad, thus need to be corrected for by subtracting exports. Imports of EEE, on the other hand, can also be consumed in the country of import, thus need to be added to the total.

Each ProdCom code has one or more corresponding trade codes. With these codes, the EEE POM for a certain type of equipment in a territory can be calculated with the following equation:

Apparent consumption = Domestic Production + Import – Export

For some ProdCom and trade codes, the data is available in weight; in other cases, pieces are used as the primary unit. In such cases, a conversion to weight is needed. In the context of this study, the average weight detailed in Table 7 has been retrieved from a detailed analysis carried out by previous country studies in the Netherlands (Huisman et al., 2012), Italy (Magalini et al., 2012), Belgium (Wielenga and Huisman, 2013), France (Monier et al., 2013), Romania (Magalini et al., 2015b) and Latin America (Magalini at al., 2015a).

Table 7. Product average weight per UNU key (in kg/pc)

UNU Keys	Average Weight			UNU Keys	Average Weight		
	2005	2010	2015		2005	2010	2015
0001	30.85	30.85	30.33	0309	5.32	5.49	5.5
0002	12	20	20	0401	0.39	0.39	0.38
0101	67.12	59.73	13.23	0402	0.3	0.23	0.22
0102	45.46	43.31	40.76	0403	2.59	3.41	3.67
0103	45.44	47.65	42.56	0404	3.91	2.79	2.17
0104	71.38	72.36	57.59	0405	2.45	2.14	2.06
0105	43.23	45.91	26.36	0406	0.54	0.29	0.29
0106	6.53	6.24	3.9	0407	28.6	n/a	n/a
0108	50.63	53.07	49.78	0408	11.97	14.7	14.7
0109	43.91	44.07	37.86	0501	0.09	0.09	0.08
0111	26.66	26.66	17.5	0502	0.11	0.11	0.11
0112	41.29	41.18	23.42	0503	0.11	0.12	0.11
0113	107.81	94.14	56.23	0504	0.08	0.11	0.11
0114	20.59	22.88	16.63	0505	n/a	n/a	0.11
0201	0.83	0.84	0.82	0506	0.47	0.47	0.41
0202	4.22	3.03	2.14	0507	2.67	2.67	2.48
0203	1.36	2.67	1.94	0601	2.92	3.32	5.89
0204	5.52	5.88	4.56	0602	16.79	16.79	11.21
0205	0.49	0.51	0.43	0701	0.45	0.45	0.42
0301	0.84	0.32	0.43	0702	1.7	1.7	1.97
0302	9.23	8.78	8.04	0703	7.37	7.37	7.37
0303	3.68	3.23	3.17	0801	0.18	0.18	0.17
0304	9.14	10.32	10.23	0802	67.06	14.02	1.06
0305	0.55	0.49	0.45	0901	0.3	0.37	0.57
0306	0.1	0.09	0.09	0902	5.51	5.51	4.71
0307	50.78	15.67	7.83	1001	44	44	12.01
0308	19.36	22	5.93	1002	92.22	92.22	29.42

n/a: not available

A detailed instruction to construct and to download these source data files is given at https://github.com/Statistics-Netherlands/ewaste. The script also estimates confidential ProdCom codes, statistical and manual corrections and also contains an update of the keys data for UNU key 0002 (PV panels), data corrections and how to back cast and forecast placed on the market data. With the above mentioned link, the basic source code in particular for the market input data is available online.

Calculation of WEEE generation and cumulative stocks

The WEEE generated is calculated by using the apparent consumption and lifecycle profiles of each of the product groups (UNU Keys). According to Model E explained in section 1.2, the quantity of WEEE generated in a specific year is calculated by a collective sum of discarded products that were placed on the market in all historical years multiplied by the appropriate lifespan distribution. The lifespan distribution reflects the probability of a product batch being discarded over time, thus matching the definition of waste according to article 3 of the Waste Framework Directive.

The change of stocks within a period of time equals the difference between the total inflows of sales and outflows of WEEE in a system, and this follows the methodology in Model A (Time Step model).

$$W(n) = POM(n) - [S(n) - S(n-1)]$$

where *W(n)* is the WEEE generation in evaluation year *n*, *POM(n)* is the quantity of product sales in year *n*, while *S(n)* and *S(n - 1)* are the quantities of appliances in stock for sequential years *n* and *n - 1* respectively (Araújo et al., 2012). The method entails two types of data input: sales in the evaluation year and stock data for two consecutive years.

The disposal age of e-waste in evaluation year$_n$ can be calculated from historical sales and lifespan profiles:

$$\mathrm{W(t,n)} = POM(t).L^{(p)}(t,n)$$

where *S(t, n)* is the number of appliances in stock in evaluation year *n*, which was originally sold in year *t*; *L(c)(t, n)* is the cumulative lifespan distribution from year *t* to *n*, which reflects the total obsolescence rates of products (sold in year t) during this period.

Total product stock size in the evaluation year$_n$ can be calculated by:

$$\mathrm{S(n)} = \sum_{t=t_0}^{n} POM(t).L^{(p)}(t,n)$$

where *POM (t)* is the product sales in the historical year *t*= *t₀* is the initial year that product has ever been put on the market; *L(p)(t, n)* is the discard-based lifespan profile for the batch of products sold in historical year *t*, which reflects its probabilistic obsolescence rate in evaluation year *n* (discarded equipment in percentage to total sales in year *t*) (Melo, 1999; Murakami et al., 2010; Oguchi et al., 2010).

Stock age composition in the evaluation year$_n$ can be calculated from historical sales and lifespan profiles:

$$\mathrm{S(t,n)} = POM(t).[1 - L^{(c)}(t,n)]$$

Where *S(t,n)* is the number of appliances measured in stock in evaluation year$_n$, originally sold in year *t*, or has the stock age of (*n*—*t*) years; $L^{(c)}(t,n)$ is the cumulative lifespan distribution for products sold in historical year *t*, which reflects the total number of products that become obsolete from year *t* to *n* (Wang et al., 2014).

The lifespan of a product differs between individual owners (Murakami et al., 2010) and due to social and technical developments, the lifespan of a product is time-dependent, so lifespan distributions have to be modelled for each historical sales year. The Weibull distribution function is applied to model the lifespan profile, defined by a time-varying shape parameter *α (t)* and a scale parameter *β(t)* (van Schaik and Reuter, 2004; Polak and Drapalova, 2012):

$$\mathrm{L}^{(\mathrm{p})}(\mathrm{t,n}) = \frac{\alpha(\mathrm{t})}{\beta(\mathrm{t})^{\alpha(\mathrm{t})}} (\mathrm{n\text{-}t})^{\alpha(\mathrm{t})\text{-}1} \mathrm{e}^{-\left[\frac{\mathrm{n\text{-}t}}{\beta(\mathrm{t})}\right]^{\alpha(t)}}$$

Table 8 provides α (shape) and β (scale) parameters of Weibull distribution. In the ProSUM project, static lifespan per UNU keys have been used regardless of put on the market year.

Table 8. Weibull distribution per UNU key

WEEE recast Directive per UNU key	Lifespan distribution (Weibull curve)		WEEE recast Directive per UNU key	Lifespan distribution (Weibull curve)	
	α (Shape)	β (Scale)		α (Shape)	β (Scale)
1. Temperature exchange equipment			0802	2	14
0108	2	17	0902	2	12
0109	1	19	1001	2	10
0111	2	21	5. Small equipment (no external dimension more than 50 cm)		
0112	2	13	0114	2	18
0113	2	15	0201	1	8
1002	2	15	0202	2	11
2. Screens, monitors, and equipment containing screens having a surface greater than 100 cm2			0203	1	8
0303	2	9	0204	1	11
0308	1	16	0205	1	8
0309	2	12	0401	1	10
0407	2	12	0402	2	10
0408	2	11	0403	2	10
3. Lamps			0404	1	8
0502	2	8	0405	1	13
0503	2	6	0406	1	7
0504	2	7	0501	1	9
0505	1	11	0506	2	17
4. Large equipment (any external dimension more than 50 cm)			0507	2	13
0001	2	14	0601	2	15
0002	3	25	0701	1	5
0101	2	16	0801	2	13
0102	2	17	0901	2	6
0103	2	19	6. Small IT and telecommunication equipment (no external dimension more than 50 cm)		
0104	2	13	0301	1	6
0105	3	18	0302	2	10
0106	2	13	0304	2	9
0307	1	8	0305	1	8
0602	3	16	0306	2	6
0703	2	12	0702	1	5

2.3.3. Model limitations

The primary limitations of the WEEE stock and flow model is uncertainty related to the use of average weights per product type, the lifetime distribution, the POM volumes and availability of detailed national data. Detailed comparison of market input data between WEEE Forum and Eurostat carried out in D3.2 concludes an overall ±15% uncertainty level, with a confident data quality level for POM, waste generated and stock amounts for 1995-2014. From 2015 onwards data is extrapolated. Here uncertainty is much higher. For certain UNU keys, uncertainty is comparatively high for product average weights over time. For other UNU keys, for instance for relatively stable products in the market like washing machines, due to detailed country studies and stock data available. Uncertainty is relatively low for lifespan parameters resulting in a confident data quality level.

Several other data limitations and uncertainties are part of data model:

ProdCom and International trade codes
For the apparent consumption method the International trade codes and ProdCom codes are aggregated to UNU keys. However, due to similar code properties and product specifications, sometimes it causes confusion while linking them to UNU Keys. The commonly occurring problem is UNU Keys 0601 Household Tools ,e.g. drills, saws, high-pressure cleaners, lawn mowers, and 0602 Professional Tools e.g. for welding, soldering, milling.

Use of average weights per unit
The diversity of EEE products grouped together based on similar product properties can lead to uncertainty in product average weight for a particular key. Using the previous example of 0601 and 0602, trade codes linked to alternate keys result in Household tools weight between 11.21-15 kg and Professional tools between 2-5.89 kg. For some product types, the available weight reflects the variations in time and geography of the average weight of a product. For product types where available data is not sufficiently precise to reflect possible variations in time and per specific country, the data quality is estimated to be lower.

Lifespan distribution
Given the poor availability of user behaviour data per UNU Key, per year and per country, Weibull distribution leads to data uncertainties. In the ProSUM project Weibull parameters are being calculated from the country studies mentioned above. Static Weibull parameters are used instead of dynamic, which leads to possible uncertainties in Waste generation and stocks.

European placed on the market and waste generated data
Eurostat data is available for the old WEEE directive in 10 categories, by using split factors to divide such amounts per UNU Key leads to data uncertainties and to generalisations for some products and country strata.

Product disposal age and stock age
As described in section 2.3.2, currently the R-based data model does not calculate product disposal age and stock age (distributions). However, for the further evaluation of the datasets, these are calculated by processing all of the data for all POM, Stock and WEEE years. The result is further scrutinised and compared against available stock data sources or indicators like saturation levels in households and consumer possession studies. From this analysis, both missing and over-estimated POM data points are identified and corrected where they can possibly be substantiated. The return stream data collected from WEEE Forum third parties, i.e Wecycle and Recupel provides also relevant clues of the product disposal age for a limited number of products, and will be included in WEEE data model. Here it is important to note that the official collection stream usually is not representative for all waste flows due to trading, scavenging and reuse of the youngest appliances. Dependent on the UNU key, the disposal age information is used as the maximum expected limit.

Split factors to convert Eurostat database
The data provided in the Eurostat database covers old WEEE directive 10 collection categories. However, to convert them into recast WEEE directive 6 collection categories (Annex III) and in UNU

Keys, split factors have been used. Due to the uncertainty in split factors, it leads to the uncertainty in modelling results. Internally collected WEEE collection data per country from the WEEE Forum will strengthen the substantiation of the split factors applied. Where applied, the resulting uncertainty is described and included for future overall error propagation analysis.

3. Results
3.1. Results BATT

As explained in the previous sections, data sources from Avicenne, EPBA, Eucobat, national authorities and Eurobat were combined to consolidate the POM data. Data on the average weight of batteries are mostly provided by Avicenne and Eucobat. Experimental data on the lifespan distribution of portable batteries were collected in 2012 and presented by Bebat at the International Congress for Battery Recycling 2014 (Bebat, 2014). These data were used for testing the stocks and flows modelling. These data are currently being refined by Eucobat with a more comprehensive study in six European countries. The data will be available to ProSUM in February 2017. The stock and flow analysis will then be updated and again consolidated.

Preliminary results were obtained for the example of laptops and tablets for the European Union and for selected member states. The results were presented at the Electronics Goes Green conference in September 2016 in Berlin.

Figure 7 shows the estimated amounts of LiCoO2, Li-NMC and Ni-MH batteries POM in laptops and tablets in million units per year in the European Union.

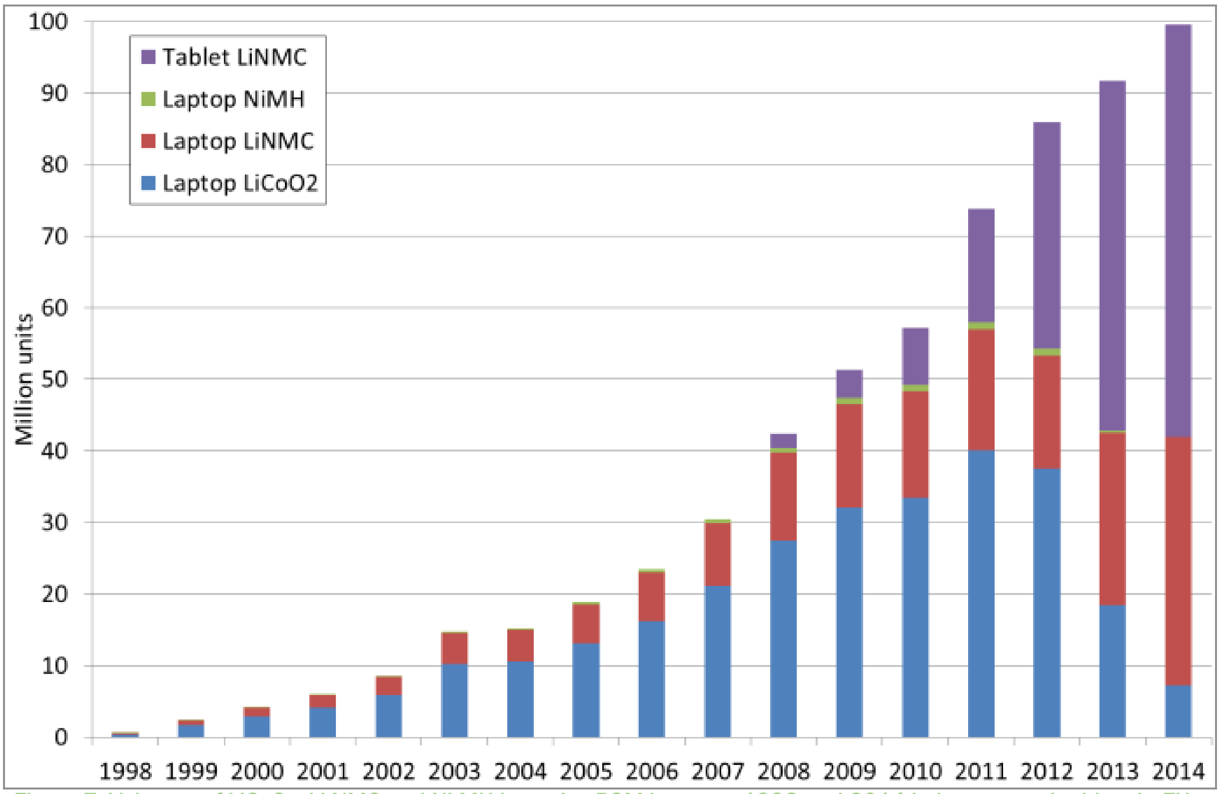


Figure 7. Volumes of $LiCoO_2$, Li-NMC and Ni-MH batteries POM between 1998 and 2014 in laptops and tablets in EU-28. (Data source: Avicenne, extracted by RECHARGE)

Data on the lifespan distribution presented by (BEBAT, 2014) were used preliminarily, since the final data for ProSUM are not available yet. BEBAT determined the lifespan of a large sample of 17,000 waste batteries with a known production date collected in Belgium in 2012. For lithium rechargeable batteries, contained in 4 products types, the probability density function determined using a Weibull distribution had a median lifespan for 102 sampled waste batteries from laptops of 9.8 years. For tablets, a median lifespan of 6.1 years as measured for mobile phones batteries was assumed. The median age of collected waste batteries is expected to decrease.

For the years after 2014, the preliminary assumption, which will be improved in the future research, was that the market stays stable, i.e. the POM volumes of 2014 were used for the years

2014-2020. Modelling based on the POM and the lifespan distribution provided estimates of the volumes of waste batteries generated until 2020 (Figure 8) and of the stocks in million units per year (Figure 9, example of Germany).

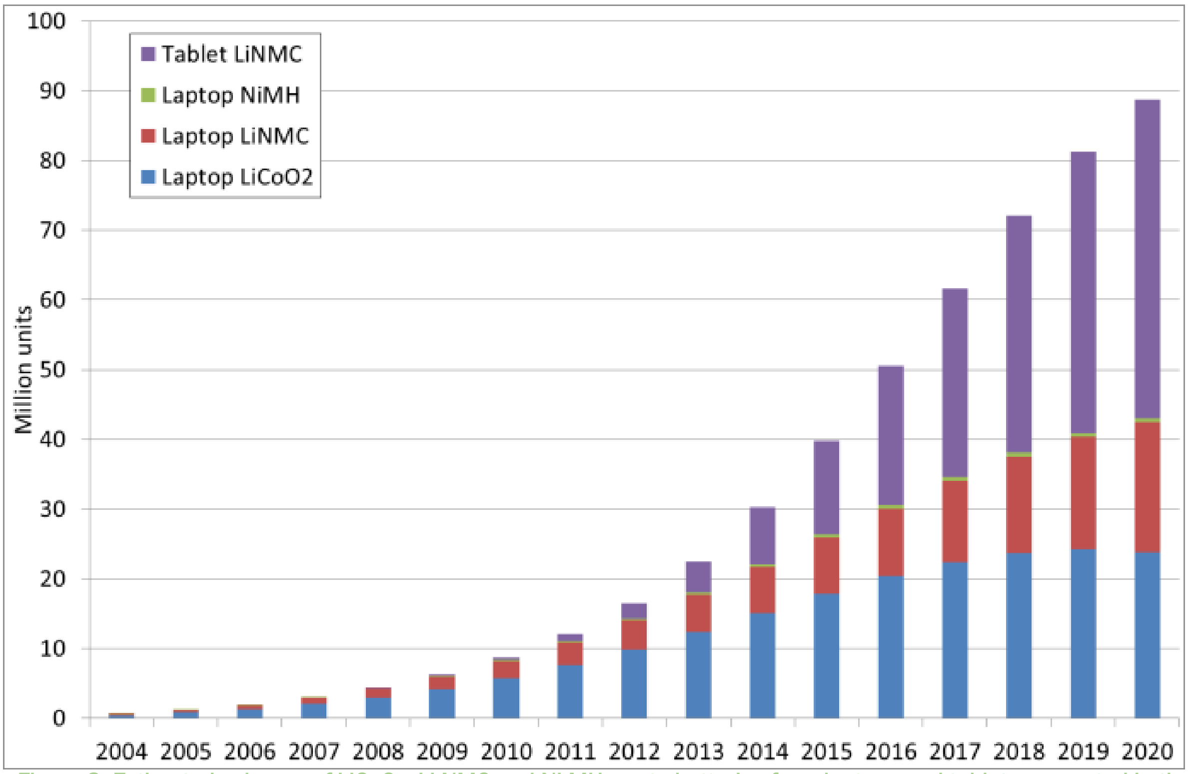


Figure 8. Estimated volumes of $LiCoO_2$, Li-NMC and Ni-MH waste batteries from laptops and tablets generated in the EU between 2004 and 2020. (Data sources for the stocks and flows modelling: POM: Avicenne, extracted by RECHARGE; residence times: Bebat)

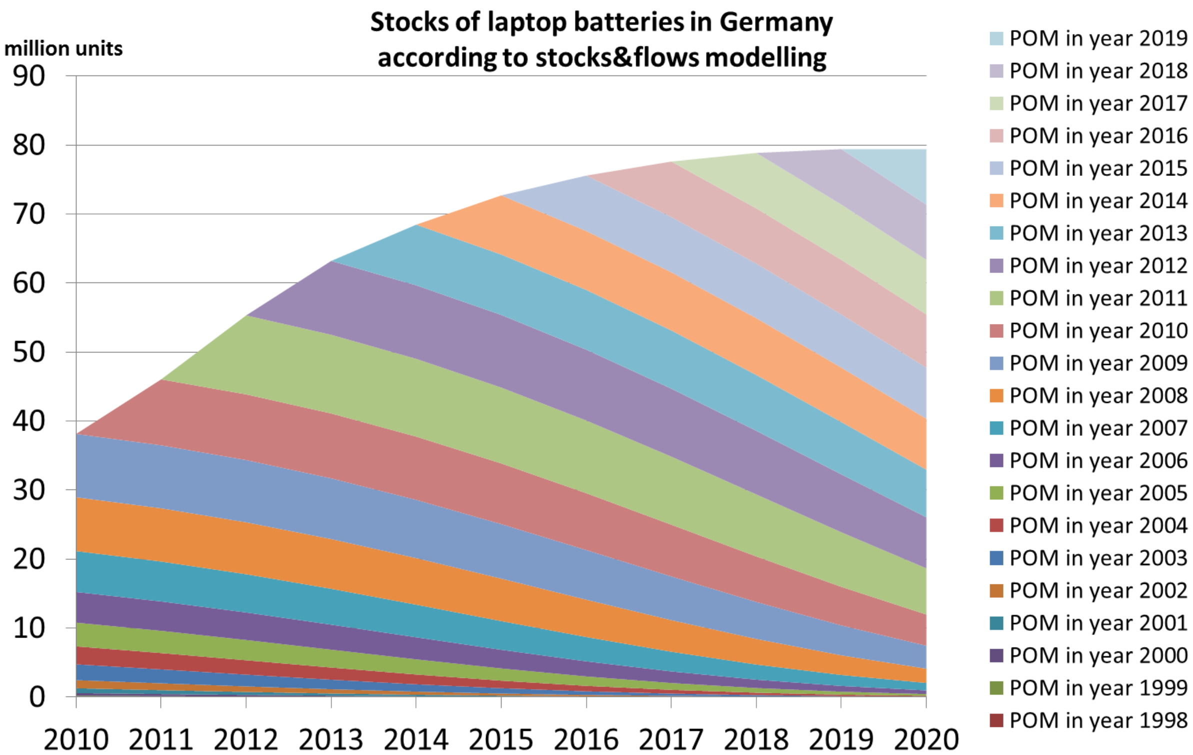
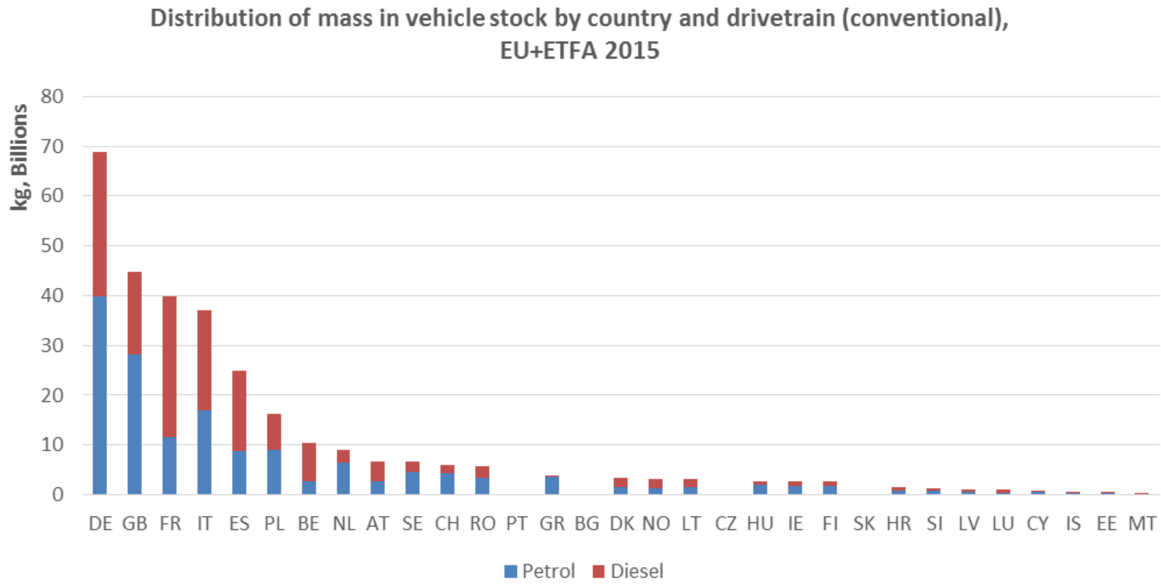


Figure 9. Evolution of the stocks of batteries of laptops and tablets in Germany. (Data sources for the stocks and flows modelling: POM: Avicenne, extracted by RECHARGE; residence times: Bebat)

3.2. Results ELV

The following are preliminary results demonstrating the use of the model for several key statistical groups. Several of the following figures can only be obtained by running a similar model as no such data exists in primary sources.

Figure 10 shows the calculated distribution of vehicle mass per drivetrain and country in the EU+ETFA fleet:



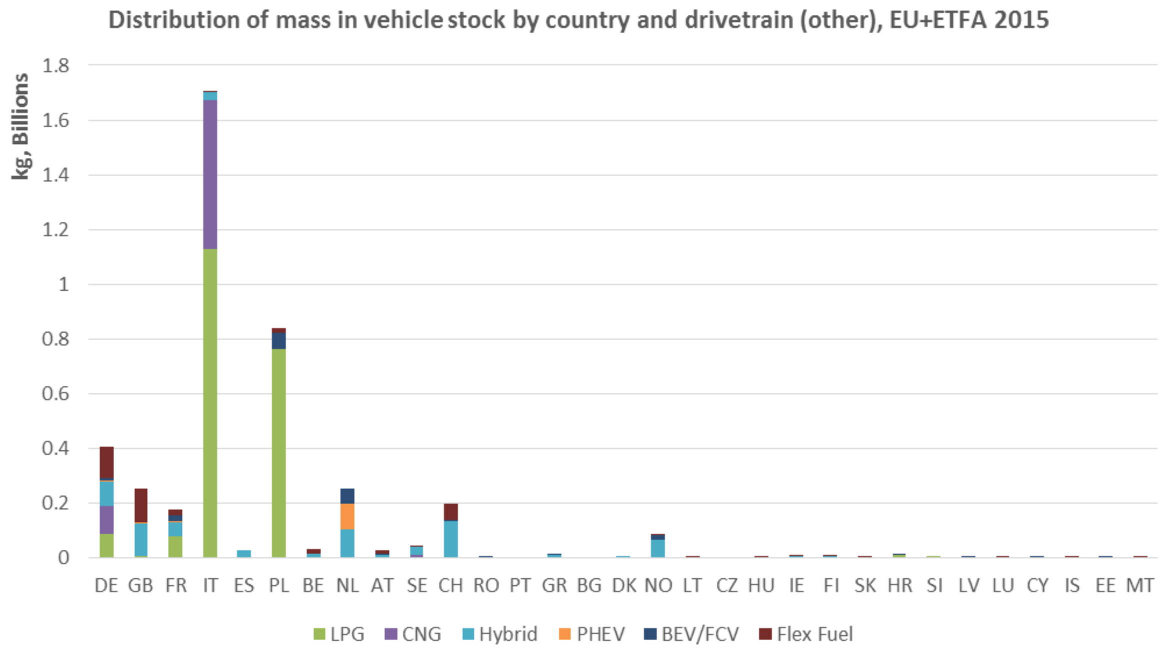


Figure 10. Distribution of total mass of vehicles in the fleet by drivetrain type and country, EU+ETFA 2015. Note the very different scales for the two graphs. Data sources for the stocks and flows modelling: POM and Stock: EUROSTAT, Trade Flows: COMEXT, Average Mass per POM year: ICCT

It is clear that although the sale of alternative vehicles has been on the rise (e.g. 2% of vehicles POM in the EU in 2015 were hybrids), the percentage in the stock is still ~0.1% due to very long residence times. The vast majority of the stock mass is petrol+diesel vehicles, with much of the remainder being natural gas vehicles of very similar composition.

The data underlying Figure 10 can be produced at any level of detail, down to estimates of mass for a given vehicle key in a country for a year, for any of the model stocks or flows. An example is shown in the following table:

Table 9. Estimated average mass per vehicle key, EU+ETFA in use stock, 2015

Vehicle Key	Avg Mass [kg/vehicle]	Vehicle Key	Avg Mass [kg/vehicle]	Vehicle Key	Avg Mass [kg/vehicle]
V01000000	1389	V01010302	1103	V01020304	1843
V01000001	819	V01010303	1330	V01030000	1373
V01000002	1098	V01010304	1843	V01030001	838
V01000003	1325	V01020000	1357	V01030002	1132
V01000004	1841	V01020001	805	V01030003	1358
V01010000	1356	V01020002	1172	V01030004	1867
V01010001	803	V01020003	1291	V01040000	1434
V01010002	1067	V01020004	1804	V01040001	810
V01010003	1288	V01020100	1405	V01040002	1100
V01010004	1803	V01020101	829	V01040003	1321
V01010100	1400	V01020102	1108	V01040004	1834
V01010101	826	V01020103	1330	V01050003	1272
V01010102	1104	V01020104	1844	V01050103	1321
V01010103	1331	V01020200	1400	V01050203	1321
V01010104	1844	V01020201	826	V01050303	1322
V01010200	1402	V01020202	1105	V01060403	1325
V01010201	825	V01020203	1332	V01070403	1314
V01010202	1104	V01020204	1844	V01080000	1393
V01010203	1331	V01020300	1402	V01080001	820
V01010204	1844	V01020301	825	V01080002	1188
V01010300	1402	V01020302	1104	V01080003	1311
V01010301	825	V01020303	1331	V01080004	1813

A final point of note is that the vast majority of historical ELV flows, and roughly half of ELV flows in the last decade have been undocumented. There is therefore a very large pool of material that is of unknown whereabouts. We are awaiting the completion of a report by the Öko Institut, slated for early 2017 that will shed light on this. Their results will be able to be integrated into the model.

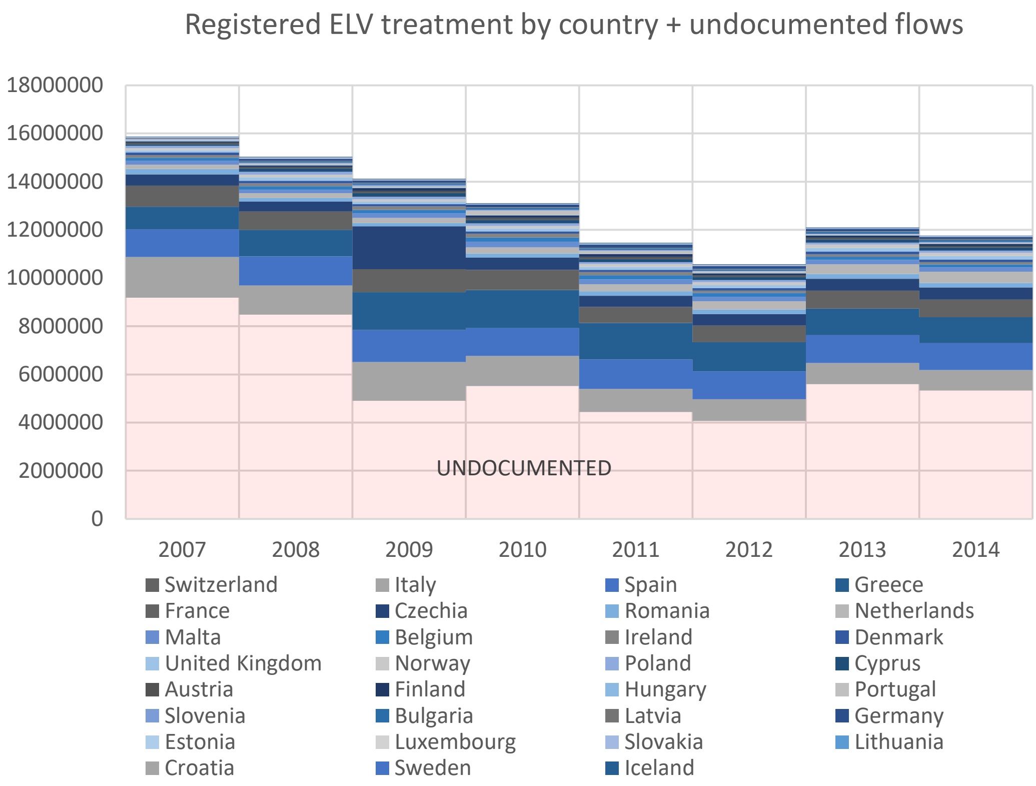


Figure 11. Registered ELV treatment and undocumented end of life flows. Source: adapted from EUROSTAT and model results for deregistered vehicles

3.3. Results WEEE

Following the methodology of Chapter 2, EEE POM is presented per collection categories according to the WEEE recast directive Annex III (see Figure 12). In 2015, small appliances provide the largest share of 3641 kt, followed by large equipment (3274 kt). The smallest share is provided by lamps (140 kt). The observed peak around 2010 – 2012 is entirely due to high sales of PV panels as part of the large equipment collection category. The PV panels (UNU key 0002), peaked in 2011 with 1,927 kt of POM due to the ending of various subsidy programs in various EU Member States.

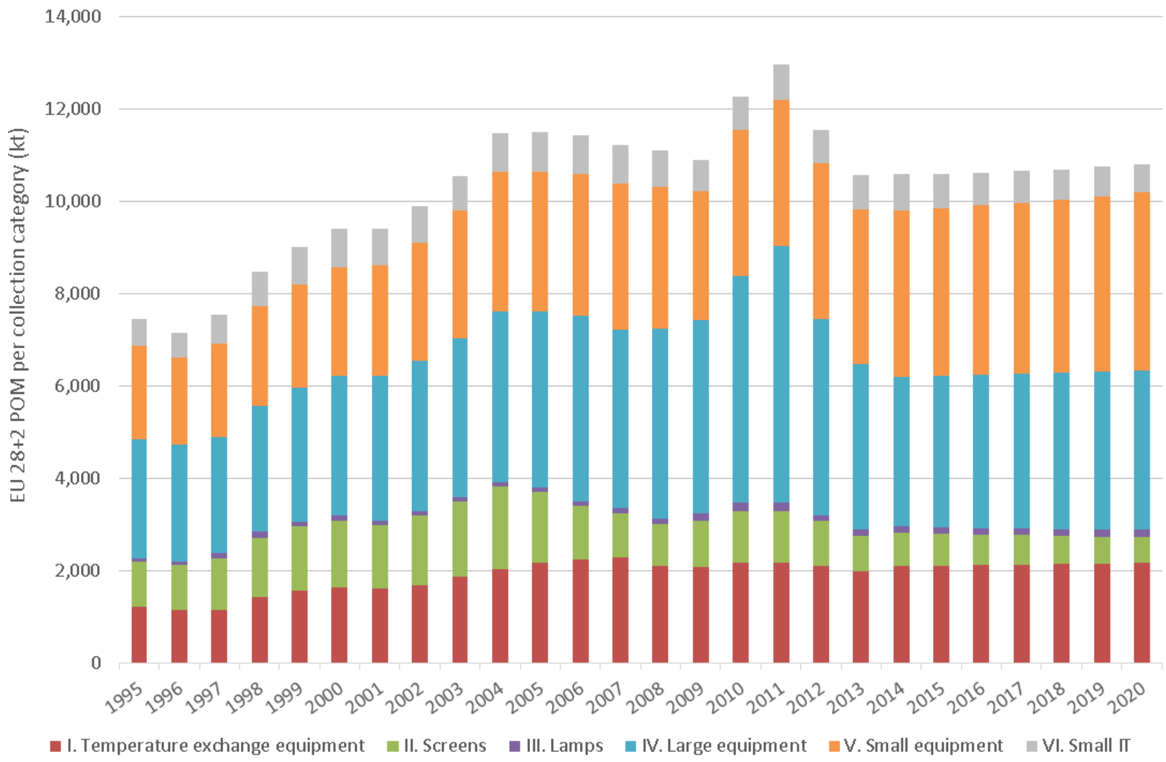


Figure 12. POM per Member State in kg/inh, 2015

The total stocks and WEEE generation is determined per collection category, per country for 2015. The resulting stock per country is presented in Figure 14 for 2015 in kg per inhabitant (inh.). The values range here from around 300 kg/inh. for the richest countries being Norway and Switzerland to around 125 kg/ inh. for the lower income countries Romania and Latvia.

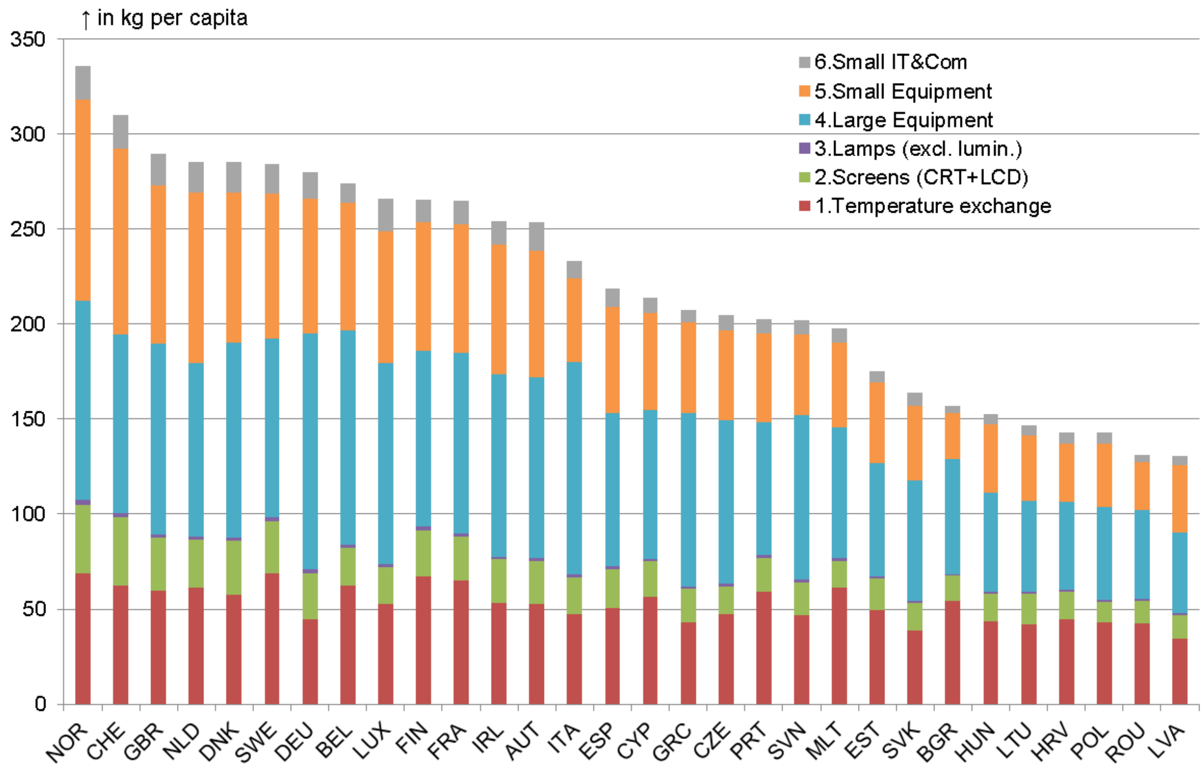


Figure 13. Stock in kg/ inh per Member State for year 2015

The WEEE generation for the EU market, resulting from the sales lifespan approach is displayed in Figure 15 in kg/inh.. The WEEE Generation ranges from around 25 kg/inh. for Norway and Switzerland to around 10 kg/inh. for Bulgaria, Poland and Romania.

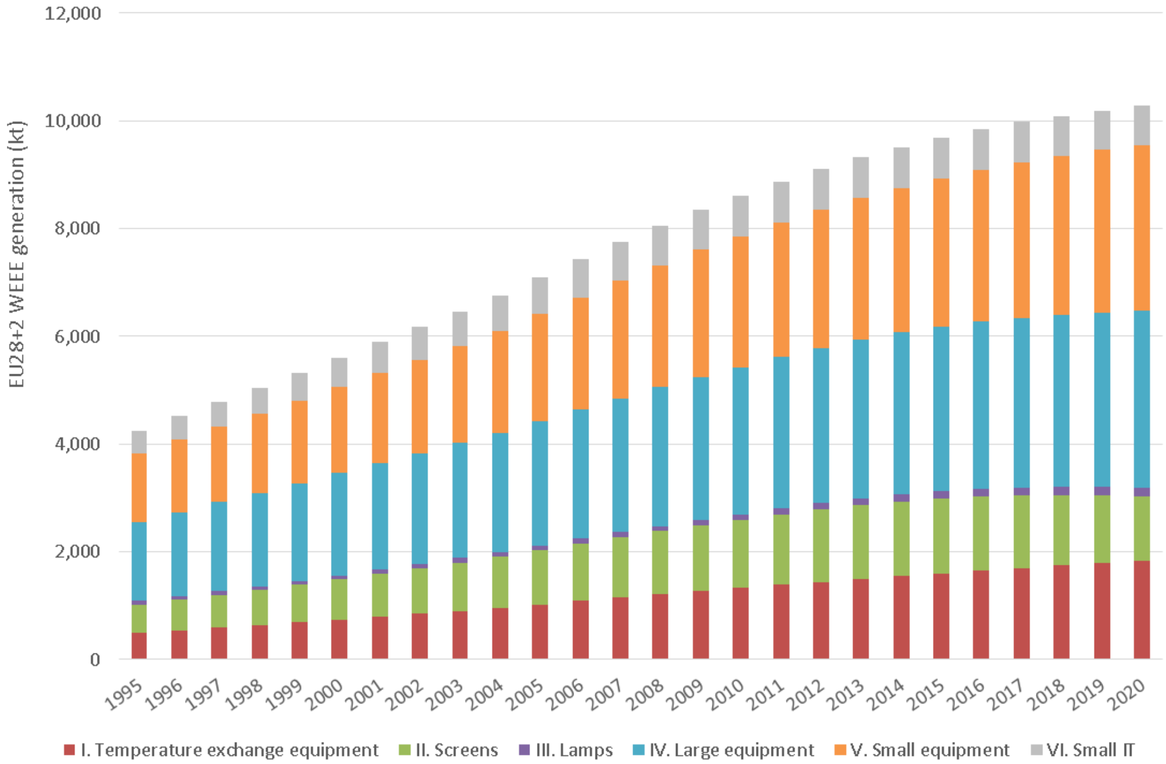


Figure 14. WEEE generation in kg/inh, 2015

4. Conclusion and Recommendations

This chapter concludes the model characteristics of BATT, ELV and WEEE using the methodologies described in section 1.2, followed by details in Chapter 2. This chapter also provides recommendations to improve the above described stocks and flows data models.

4.1. Batteries

For batteries, the data collected so far provide comprehensive information on the flows of batteries POM and the average weight of batteries. Compared to the status quo presented in March 2016 in Deliverable 3.1, the coverage of the collected data has been considerably expanded, and the modelling approach has been tested. Annex 1 shows preliminary results for laptops and tablets for the European Union.

Comprehensive data on the lifespan distribution are currently being collected by Eucobat and are expected to be available in February 2017 to finalise the stocks and flows modelling. As soon as the updated data on lifespan distribution is available, the modelling will be finalised for 50 combinations of keys, sub-keys and defined applications considering like portable PC, cell phones, e-bikes and BEV, considering data availability and the relevance of the battery types in terms of CRM content (Table 2). The results of the modelling will be data on batteries POM, battery stocks and estimated waste batteries generation for the 50 selected cases and the 28 member states of the European Union, plus Switzerland and Norway. After conducting data consolidation for instance by comparing the number of batteries POM in vehicles with the number of vehicles POM, as well as the number of batteries POM in EEE with the number of appliances POM, the data will be integrated into the harvesting database.

The next steps primarily concern data consolidation between the work packages. Based on the data collected in WP2, the flows of materials and elements contained in the batteries POM, stocks and the modelled waste generation will be estimated. The outcomes of the stocks and flows modelling in WP3 will be compared to the datasets on measured waste flows produced in Task 4.2 to get a better understanding of the gaps between generation of waste batteries and actual collection.

4.2. Vehicles

Since the D3.1 report, the model has been implemented and is now operational to the full data specification, although certain finalisation steps remain. These steps are described below and will be complete in 1st quarter of 2017. In terms of the project requirements, the model is capable of expressing stocks and flows of vehicles inside the EU, at a granular level of vehicle keys that is both novel and a prerequisite for linking the vehicle flows to the product (WP2) and waste stream composition (WP4) in the project.

The work focus is currently on correcting a few known miscalculations resulting from missing data, manual verification of the calculations and output, and on final integration with the other work packages. The model output is now available in the harvesting templates as a review-ready prototype with preliminary data that is complete. Once the output format is verified with the work packages directly using the output from the model, the format can be locked down with only numerical updates in the future. This means that going forwards, after any requests for format changes, other work packages may use the model output directly with future revisions not affecting format or data keys, thus fulfilling the ProSUM ambition for automated processes.

As per the status above, there are a few remaining steps to finalise the model and link it into the other work packages listed below.

1. The model has flagged the estimated mass of some vehicle keys in some countries, e.g. Italy, as falling outside the allowable range, e.g. an average mass of 990kg in the 1000-1249kg key. The cause is primary data missing for that particular country, and the fall-back condition being

the EU average mass, despite a clearly differing fleet composition. An improved calculation that accounts for difference in fleet composition is being implemented and verified. This step is important for improving the estimated error of fleet mass. This will help improve the mass calculations in other work packages but the primary link with this model is based on pieces, and thus will not directly benefit.

2. The estimated age distributions and ELV compositions are being compared to measured data from literature sources that exist for some data points. Discrepancies are being used to tune the loss function modelling, enabling better projections in the next iteration of the model.

3. A proprietary database for all electric (BEV, PHEV, HEV) vehicles sold in the EU, specified down to vehicle model, has been obtained. Work is being undertaken to update the input data for the vehicle stock-flow model, and to see how the data could be used to improve the CRM parameters for these types of vehicle.

4. Testing of the projection functionality to complete the data set out to 2020 is still being undertaken. After it is verified to work, harmonized scenarios will be discussed with the consortium before being included. This includes deciding on final scenario assumptions e.g. POM continues on trend with respect to GDP/capita, and verifying the projections themselves.

5. Once all other steps are complete (per April 2017), a final assessment of data quality will be undertaken.

6. We can now verify the output with the work packages linking to the results. There will, however, be some revisions to the numbers. As a final step in the workflow, the model code will be updated to generate the harvesting template spreadsheet directly, eliminating the last manual steps in the process. This also allows for further data reconciliation and programming as planned for WP5 in the coming months.

4.3. Waste Electrical and Electronic Equipment

The advanced and now publicly accessible WEEE data model provides comprehensive information on POM data), stock amounts) and waste generation from 1995-2020 for EU28+2. However the publicly available data model does not contain data from Norway and Switzerland due to lack of automation possibilities. The data is included in the provided datasets.

Compared to the status and data presented in Deliverable 3.1, PV panels (UNU key 0002) data has been updated. Furthermore, average weights per UNU key presented in Table 7 are being normalised over time by eliminating remaining outliers. Comprehensive data on product disposal age are currently being collected from WEEE Forum linked third parties such as Recupel and Wecycle.

4.4. Next steps

The next steps primarily concern the data consolidation between the work packages. Based on the composition data collected in WP2, the flows of materials and elements in POM, stocks and the waste generation will be estimated across the three product groups. The outcomes of the stocks and flows modelling in WP3 will be expanded to include multiplication of the (complementary) flows data from D3.2 and measured waste flows in WP4 with the compositional data from D2.5 to better describe the total flows of elements, materials, components and products within the scope of the project and the EU-UMKDP by Month 30. The use of meta data describing all used sources in this and the adjacent deliverables D2.5 and D4.2, as well as higher level summaries of the data consolidation process for completed datasets, are prepared and in an advanced stage for use in D5.6 Creation of the Meta Data System which is due for June 2017.

5. References

Araújo, M. G., Magrini, A., Mahler, C. F., & Bilitewski, B. (2012). A model for estimation of potential generation of waste electrical and electronic equipment in Brazil. Waste Management, 32(2), 335-342.

Avicenne. (2016). Battery Market Development for Consumer Electronics, Automotive, and Industrial. Batteries congresses, Nice.

BEBAT. (2014). How the battery life cycle influences the collection rate of battery collection scheme. (Möbius, Ed.). International Congress for Battery Recycling (ICBR).

Binder, C., Bader, H. P., Scheidegger, R., & Baccini, P. (2001). Dynamic models for managing durables using a stratified approach: the case of Tunja, Colombia. Ecological Economics, 38(2), 191-207.

Brunner, P. H., & Rechberger, H. (2004). Practical handbook of material flow analysis. *The International Journal of Life Cycle Assessment*, *9*(5), 337-338.

Chung, S. (2011). Projection of waste quantities: the case of e-waste of the People's Republic of China Waste Management & Research 0, 1–8. China.

Dwivedy, M., & Mittal, R. K. (2010). Estimation of future outflows of e-waste in India. *Waste Management*, *30*(3), 483-491.

EPBA. (2015). The collection of waste portable batteries in Europe in view of the achievability of the collection targets set by Batteries Directive 2006/66/EC. August 2013, update December 2015. Perchards study on behalf of European Portable Battery Association (EPBA). Retrieved from http://www.epbaeurope.net/documents/Reportontheportablebatterycollectionrates-UpdateDec-15-Exerpt.pdf

Eucobat. (2016). Key figures for the years 2011-2015.

Eurobat. (2013). Industrial Batteries Economic Outlook. EUROBAT IBC Committee. Retrieved from http://eurobat.org/statistics

Eurobat. (2016). Industrial Batteries Economic Outlook. Retrieved from http://eurobat.org/statistics

Huisman, J. (2008). WEEE recast: from 4kg to 65%: the compliance consequences, UNU Expert Opinion, United Nations University, Bonn, Germany.

Huisman, J. (2010). Eco-efficiency evaluation of WEEE take-back systems In: Goodship, V., Stevels, A. (Eds.), Part 1 in Waste Electrical and Electronic Equipment (WEEE) Handbook: Woodhead Publishing Ltd., Cambridge, the United Kingdom.

Huisman, J. (2010). Eco-efficiency evaluation of WEEE take-back systems In: Goodship, V., Stevels, A. (Eds.), Part 1 in Waste Electrical and Electronic Equipment (WEEE) Handbook: Woodhead Publishing Ltd., Cambridge, the United Kingdom.

Huisman, J. (2012). The Dutch WEEE flows. In M. van der Maesen, Eijsbouts, R.J.J., Wang, F., Baldé, C.P., Wielenga, C.A., (Ed.). NLD: United Nations University, ISP – SCYCLE, Bonn, Germany.

Huisman, J., Magalini, F., Kuehr, R., Maurer, C., Delgado, C.,Artim, E., Szlezak, J., Ogilvie, S., Poll, J., Stevels, A., (2008). Review of Directive 2002/96 on Waste Electrical and Electronic Equipment (WEEE). In (Eds.): European Commission DG ENV.

Huisman, J., Van der Maesen, M., Eijsbouts, R. J. J., Wang, F., Baldé, C. P., & Wielenga, C. A. (2012). The Dutch WEEE Flows. United Nations University, ISP–SCYCLE, Bonn, Germany, 15.

Jain, A., & Sareen, R. (2006). E-waste assessment methodology and validation in India. Journal of Material Cycles and Waste Management, 8(1), 40-45.

Kang, H. Y., & Schoenung, J. M. (2006). Estimation of future outflows and infrastructure needed to recycle personal computer systems in California. *Journal of Hazardous Materials*, *137*(2), 1165-1174.

Magalini, F. , Kuehr, R., Baldé, C.P., (2015a). eWaste in Latin America, Statistical analysis and policy recommendations.

Magalini, F. Wang, F., Huisman, J., Kuehr, R., Baldé, K., van Straalen, V., Hestin, M., Lecerf, L., Sayman, U., Akpulat, O., (2016). Study On Collection Rates Of Waste Electrical And Electronic Equipment (WEEE), possible measures to be initiated by the Commission as required by Article 7(4), 7(5), 7(6) and 7(7) of Directive 2012/19/EU On Waste Electrical And Electronic Equipment (WEEE). European Commission DG ENV.

Magalini, F., Baldé, C.P., Habib, H., (2015b). Quantifying waste of Electric and Electronic Equipment in Romania. United Nations University, ISP – SCYCLE, Bonn, Germany.

Magalini, F., Huisman, J., Mosconi, R., Gobbi, A., Manzoni, M., Pagnoncelli, N.,Scarcella, G., Alemanno, A., Monti, I., (2012). Households WEEE arising in Italy. Ecodom Consorzio Italiano Recupero e Ricidaggio Electtrodomestici.

Melo, M. T. (1999). Statistical analysis of metal scrap generation: the case of aluminium in Germany Resources, Conservation and Recycling 26, pp 91–113.

Monier, V., Hestin, M., Witte, F., Guilcher, S., Fangeat, E., Baudry,R., (2013). Study on the quantification of Waste of Electrical and Electronic Equipment (WEEE) in France. ADEME.

Müller, E., Schluep, M., Widmer, R., Gottschalk, F., & Böni, H. (2009). Assessment of e-waste flows: a probabilistic approach to quantify e-waste based on world ICT and development indicators. In R09. World Recycling Congress. Davos, Switzerland

Murakami, S., Oguchi, M., Tasaki, T., Daigo, I., & Hashimoto, S. (2010). Lifespan of commodities, Part I. Journal of Industrial Ecology, 14(4), 598-612.

Oguchi, M., Kameya, T., Yagi, S., & Urano, K. (2008). Product flow analysis of various consumer durables in Japan. Resources, Conservation and Recycling, 52(3), 463-480.

Oguchi, M., Murakami, S., Tasaki, T., Daigo, I., & Hashimoto, S. (2010). Lifespan of commodities, Part II. Journal of Industrial Ecology, 14(4), 613-626.

Peralta, G. L., & Fontanos, P. M. (2006). E-waste issues and measures in the Philippines. Journal of material cycles and waste management, 8(1), 34-39.

Polák, M., & Drápalová, L. (2012). Estimation of end of life mobile phones generation: the case study of the Czech Republic. Waste management, 32(8), 1583-1591.

ProdCom, (2016). Statistics on the production of manufactured goods. EU28: European Commission.

Robinson, B. H. (2009). E-waste: an assessment of global production and environmental impacts. Science of the total environment, 408(2), 183-191.

Steubing, B., Böni, H., Schluep, M., Silva, U., & Ludwig, C. (2010). Assessing computer waste generation in Chile using material flow analysis. Waste Management, 30(3), 473-482.

Streicher-Porte, M., Widmer, R., Jain, A., Bader, H. P., Scheidegger, R., & Kytzia, S. (2005). Key drivers of the e-waste recycling system: Assessing and modelling e-waste processing in the informal sector in Delhi. Environmental impact assessment review, 25(5), 472-491.

SYDEREP. (2015). 2014 annual report and summary. SYDEREP - French Battery producer Register, French Environment and Energy Management Agency ADEME. Retrieved from https://syderep.ademe.fr/en/commun/pa

TemaNord. (2009). Methods to measure the amount of WEEE generated - Report to the Nordic council's subgroup on EEE waste: Nordic council of Ministries, Copenhagen, Denmark.

UK Environment Agency. (2016). National Packaging Waste Database - Public Batteries Reports. UK Environment Agency. Retrieved from http://npwd.environment-agency.gov.uk/Public/Batteries/PublishedReports.aspx

Van der Voet, E., Kleijn, R., Huele, R., Ishikawa, M., & Verkuijlen, E. (2002). Predicting future emissions based on characteristics of stocks. Ecological Economics, 41(2), 223-234.

Van Schaik, A., & Reuter, M. A. (2004). The time-varying factors influencing the recycling rate of products. *Resources, Conservation and Recycling*, *40*(4), 301-328.

Van Straalen, V.M, Roskam, A.J., & Baldé, C.P. (2016). Waste over Time [computer software]. The Hague, The Netherlands: Statistics Netherlands (CBS). Retrieved from: http://github.com/Statistics-Netherlands/ewaste

Walk, W. (2004). Approaches to estimated future quantities of waste electrical and electronic equipment (WEEE): Proceedings of the Electronics Goes Green, Berlin, Germany, pp 263–268.

Walk, W. (2009). Forecasting quantities of disused household CRT appliances–A regional case study approach and its application to Baden-Württemberg. Waste management, 29(2), 945-951.

Wang, F. (2014). E-waste: collect more, treat better; Tracking take-back system performance for eco-efficient electronics recycling. TU Delft, Delft University of Technology.

Wang, F., Huisman, J., Stevels, A., & Baldé, C. P. (2013). Enhancing e-waste estimates: Improving data quality by multivariate input–output analysis. Waste management, 33(11), 2397-2407.

Wielenga, K., Huisman, J., (2013). (W)EEE Mass balance and market structure in Belgium. FFact Management Consultants and United Nations University, Institute for Sustainability and Peace.

Yang, J., Lu, B., & Xu, C. (2008). WEEE flow and mitigating measures in China. Waste Management, 28(9), 1589-1597.

Yu, J., Williams, E., Ju, M., & Yang, Y. (2010). Forecasting global generation of obsolete personal computers. Environmental science & technology, 44(9), 3232-3237.

Zhang, L., Yuan, Z., & Bi, J. (2011). Predicting future quantities of obsolete household appliances in Nanjing by a stock-based model. Resources, Conservation and Recycling, 55(11), 1087-1094.