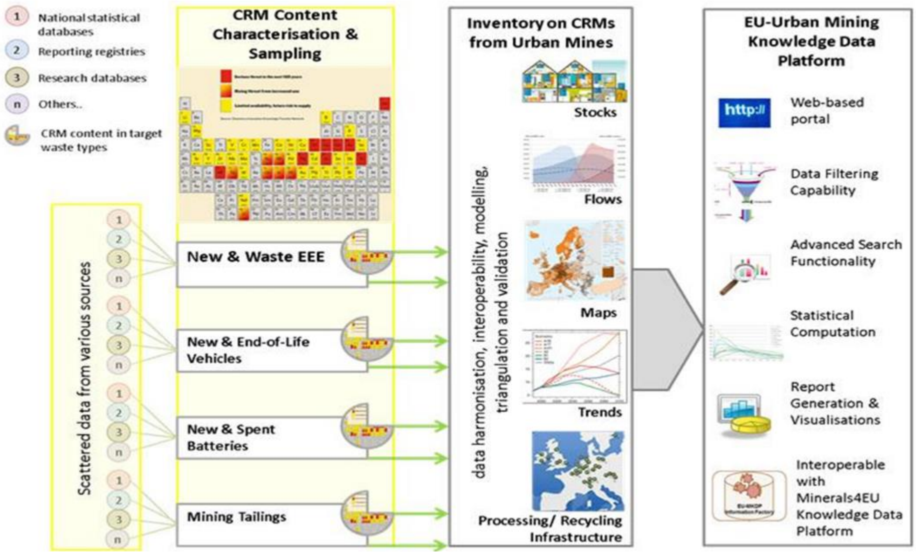
Report on consolidation of data into CRM database: Deliverable 2.5



Project	Prospecting Secondary raw materials in the Urban mine and Mining waste
Acronym	ProSUM
Grant Agreement	641999
Funding Scheme	Horizon 2020
Webpage	www.prosumproject.eu
Work Package	Work Package 2
Work Package Leader	Patrick Wäger, Empa
Deliverable Title	Report on consolidation of data into CRM database
Deliverable Number	2.5
Deliverable Leader	Amund N. Løvik
Version:	4.1
Status	Final
Authors	Amund N. Løvik (Empa), Patrick Wäger (Empa), Claude Chanson (RECHARGE), Jaco Huisman (UNU), Maria Ljunggren Söderman (Chalmers), Michelle Guzman Brechu (UNU), Arthur Haarman (Empa), Hina Habib (UNU), Paul Mählitz (TUB), Matthias Rösslein (Empa), Maximilian Ueberschaar (TUB)
Reviewed by	Project Management Team
E-mail	amund.loevik@empa.ch
Scientific Coordinators	Dr Jaco Huisman, Scientific Advisor, UNU – IAS SCYCLE Nikolaos Arvanitidis, Chair of the EGS Mineral Resources Expert Group
E-mail	Huisman@unu.edu Nikolaos.Arvanitidis@sgu.se

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 641999.

ProSUM
Prospecting Secondary raw materials in the Urban mine and Mining wastes

Document Control

Project Coordinator:	WEEE Forum
Work Package Leader:	Patrick Wäger
Deliverable leader	Amund N. Løvik
Due date:	M24 31 December 2016
Date of submission:	M25 06 January 2017
Dissemination level:	RESTRICTED

Version history			
Ver. no.	**Date**	**Reason for release**	**Responsible**
1.0	14.9.2016	Outline	AL
2.0	5.12.2016	Draft chapters on batteries and vehicles	AL, CC
2.2	7.12.2016	Review and revision of battery chapters	AL, CC
2.3	8.12.2016	Review on vehicles sections	MLS
3.0	9.12.2016	(almost) complete first draft	AL
3.2	9.12.2016	Added conclusions text for EEE (additional comments from JH in v3.1 on seafile)	JH
3.3	11.12.2016	Comments from PW + Added text on results for microwaves	PW, AL
3.5	12.12.2016	Integrated changes from MU, MB and HH	AL
3.6	12.12.2016	Integrated all changes and addressed comments from JH, PW and MLS	AL
3.7	14.12.2016	Comments and changes from Sarah addressed and included.	AL
3.8	14.12.2016	Added results for tablets (MU) and methods for laptops	AL
3.9	21.12.2016	PMT Review	JH
4.0	22.12.2016	Final revisions	AL
4.1	4.1.2017	Final proof read prior to submission	JHo

Contents

List of Figures

List of Tables

PURPOSE

This report (deliverable report D2.5) presents the work within task "T2.2: Consolidate data for integration into CRM database". The deliverable consists of this report, describing the methodology and highlights from the results, three annexes of Excel templates used in the work, and three datasets for representative composition of electric and electronic products (EEE), vehicles and batteries (BATT) placed on the market (POM). The datasets are only provided internally in the ProSUM project for use within WP5 to populate the ProSUM unified data model.

EXECUTIVE SUMMARY

The goal of this deliverable was to provide composition data that represent the average product placed on the market for all product keys within the scope of ProSUM. In detail, this meant to provide the mass, number or mass fraction of components, materials, and elements within these, as they occur in products, in such a way as to enable the calculation of the content of CRM (elements) in the product.

The work was conducted in five steps: 1) Describe and record *raw data* from original sources in a semi-structured format (spreadsheets). 2) Evaluate data quality of the raw data based on recorded information. 3) Estimate the representative composition of all product keys. 4) Evaluate data quality and estimate uncertainties for the representative composition. 5) Provide the representative composition data in templates (*data portrayals*) for harvesting into the ProSUM diffusion database.

The description and recording of data was done in spreadsheets, using previously developed code lists for products, components, materials and elements (D5.3), as well as additional code lists to describe various properties of the data that were relevant for evaluation of data quality. The evaluation of raw data was undertaken on the basis of five factors: *measurement method, modelling approach, sample size, temporal scope definition,* and *consistency of descriptions*. The data quality evaluation informed the subsequent calculation of average mass fractions and contents in representative products, but in practice the approach was tailored to each product category, taking advantage of the product-specific expert knowledge of the various persons working on the task.

The number of composition data available varies significantly between the different product groups: around 800 data were collected for batteries, 1,800 for vehicles and 27,000 for EEE. The work resulted in three internal project datasets of these raw data (one for each product category), as well as three corresponding datasets of consolidated average product composition to be harvested and uploaded to the ProSUM diffusion database. The sets of consolidated data are complete for vehicles and batteries. For EEE, data have been consolidated for three products (microwave ovens, tablet computers and flat panel display TVs). Due to the large number of data and complexity of the product category, the final consolidation for EEE is still ongoing, and will be completed by end of April 2017.

The resulting datasets embody the current state of knowledge on product composition with respect to CRM, and are, to our knowledge, the most comprehensive of their kind to date. That being said, the datasets rely on published information, which in some cases is too scarce to make reliable estimates of relevant parameters. In general, the most important gaps are related to changes in composition in recent years and elements that occur at very low mass fractions in the product or component.

The tables below neatly summarise the composition results for each of BATT, EEE and vehicles showing what is available and what the gaps in the data are.

Summary of BATT composition results

What is available	What is missing/ data gaps	Comments
POM compositions for all BATT sub-keys in e-p format, representing the BATT cell.	Reliable measurement of the variability of the composition within sub-keys.	The decisive factors for the development of the material composition of batteries are not changes of the composition of batteries with a specific electrochemical system, but market shifts from one electrochemical system to another.
Compositions of waste BATT are assumed to be the same as compositions of POM BATT per BATT sub-key.	Battery electronics are not included	
	Changes in composition over time.	

Summary of EEE composition results

What is available	What is missing/ data gaps	Comments
WEEE composition data for 2012-2014 which can be reconciled with market input years. Data is available for all WEEE categories except for lamps. EEE market input composition data are available for certain UNU keys from more recent literature sources (IT products and screens) and for lamps and some other UNU keys from "Ecodesign" studies.	Lamps data Detailed composition on the trends in absolute and relative weight of certain key components e.g. printed circuit boards For some UNU keys, there is no recent bill of materials data available. For many UNU keys, the construction of full time series composition is not possible or relies on assumptions.	In D2.4 a further attempt will be done to describe the trends over time of critical components. Especially for newer types of products, hardly any information will be available for very recent components like sensors, embedded electronics, lighting etc.

Summary of vehicle composition results

What is available	What is missing/ data gaps	Comments
Composition data from case studies based on producer data as well as some sampling studies on ELVs. Representative compositions have been estimated, including the base metals as well as the most commonly occurring scarce/critical metals. The following components and materials are included: catalytic converter, electric and electronic system (as 1 component), battery, standard steel, high strength steel, cast iron, cast aluminium, wrought aluminium, magnesium alloy.	Lack of data on individual components in electrical and electronic system (raw data exist, but cannot be consolidated due to difficulty of comparison between various sources). Lack of temporal data. Changes over time were only included in selected cases where data were available (e.g. catalytic converter).	Uncertainties are in general high due to a small number of studies, small sample sizes, and lack of representativeness (focus on individual vehicle models)

1 Introduction

1.1 Aim and scope of the Deliverable

According to the Description of Action, this deliverable (D2.5) comprises consolidation of “CRM parameter data” for integration into the CRM database. As defined in D2.2 (p.7), CRM parameters are “parameters that can be used to describe or calculate the composition of products and components with respect to CRM”. D2.5 comprises the work in Task 2.2, which is divided in two sub-tasks: Task 2.2.1: Evaluate, filter and complement the data collected in T2.1, and Task 2.2.2: Provide datasets for CRM database. Due to the close link between the two, these two sub-tasks are considered as one task throughout the rest of this report.

The goal of this deliverable is firstly to provide composition data that represent the average product put on the market for all product keys within the scope of ProSUM. In detail, this means to provide the mass, number or mass fraction of components, materials, as well as the elements within these, as they occur in products, in such a way as to enable the calculation of the content of CRM (elements) in the product. Changes over time shall be included as far as possible until present day. Scenarios for the future are dealt with in D2.4. While the main goal is to quantify the product composition with respect to CRM, components and materials are also included as far as possible.

Secondly, it is the aim of this deliverable to develop the methods necessary for achieving the first goal, including an approach for recording and describing raw data, evaluation of data quality (both for raw data and produced datasets), procedures for estimating representative composition, and procedures for estimating uncertainties of the produced datasets.

Figure 1 shows the relationship between D2.5 and other deliverables in ProSUM. In D2.2, around 140 sources of CRM parameter data were identified, collected and described with respect to their subject and the data they contain. In D2.5 data are processed and prepared for the database developed within WP5. The procedures for data quality assessment will feed into the work for D2.7 on update and quality assessment protocols.

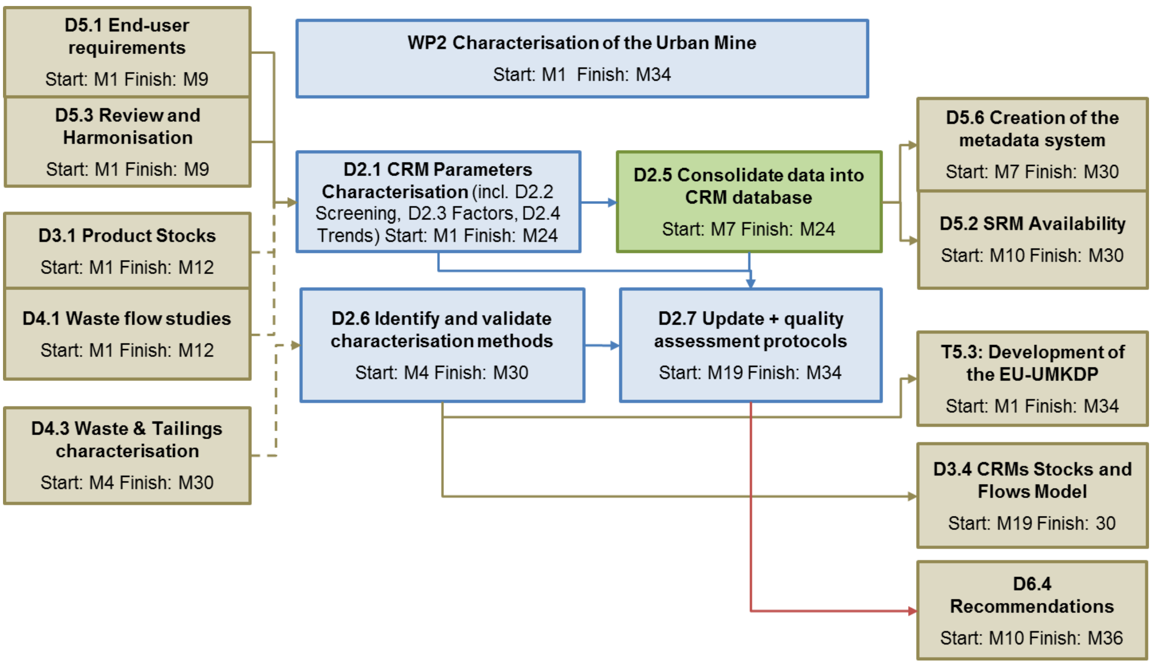


Figure 1 Pert chart of WP2, showing the relationship between D2.5 and other deliverables in ProSUM.

The work in D2.5 is closely related to the work in D3.3 (Review methods for analysing stocks and flows) and D4.2 (CRM assessment strategy for waste & tailings). Data on product mass and lifespan (which are sometimes needed for estimating changes in composition over time) are considered part of D3.3, while data on waste flow composition (e.g. mass fractions of elements or products in collected waste consisting of several product keys) are considered part of D4.2. D2.5 deals exclusively with the composition of products, components and materials as defined in ProSUM code lists developed in D5.3.

2 Methods

This chapter presents the general methods used for classifying, describing, evaluating and consolidating product composition data as well as product group-specific deviations from the general approach.

2.1 General methods

2.1.1 Overview

The practical steps of T2.2 were the following:

1. Describe and record *raw data* from original sources in a semi-structured format (spreadsheets);
2. Evaluate the data quality of the raw data based on recorded information;
3. Estimate representative composition for all product keys;
4. Evaluate data quality and estimate uncertainties for the representative composition; and
5. Provide the representative composition data in templates (*data portrayals*) for harvesting into the database

The starting point for task T2.2 were the data sources identified and collected in an EndNote library in task T2.1.1. The majority of these are scientific journal articles and reports that contain a relatively small number of data in an unstructured format. In addition, some structured data on EEE composition were obtained from a WEEE Forum member organization. The overall procedure is shown in Figure 3, and the details of each step are explained in the following subchapters.

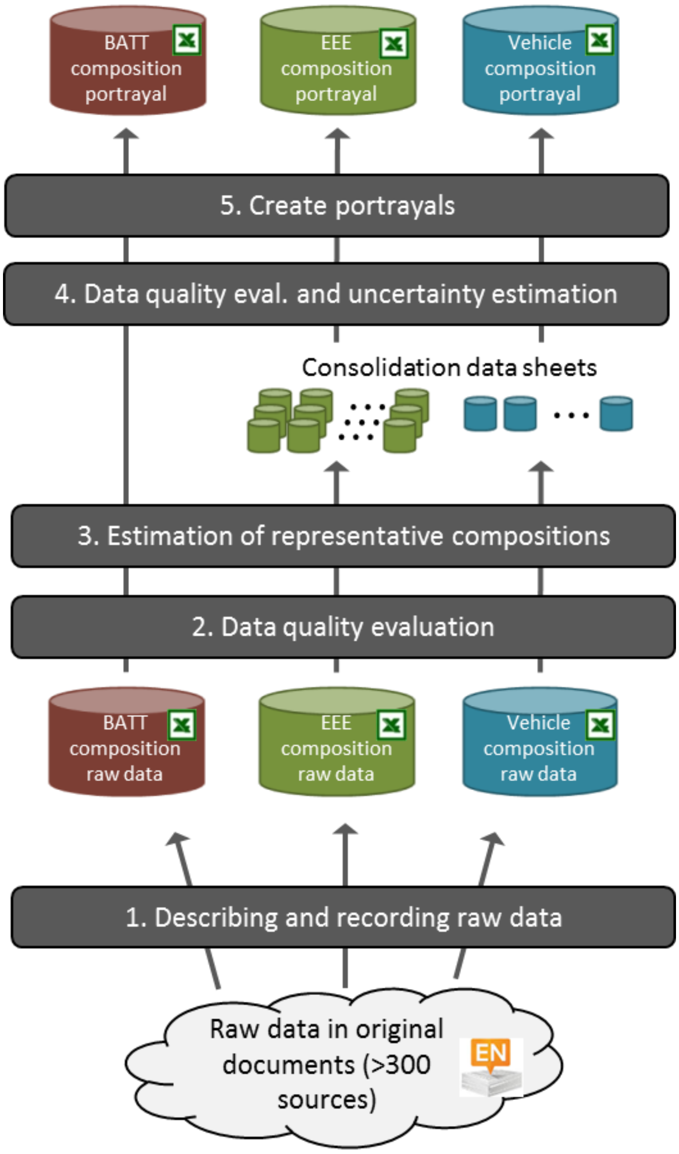


Figure 2 Overview of practical steps of D2.5 and the generated datasets.

2.1.2 Step 1: Describe and record raw data

Within ProSUM, the composition of a product is described in terms of four "levels": *product, component, material* and *element*, as illustrated in Figure 3. Any product can be described as a set of distinct components, every component can be described as consisting of a set of materials, and every material can be described in terms of its constituent chemical elements. Moreover, a product may contain other products (e.g. lead-acid battery in passenger vehicles) and components may contain other components (e.g. capacitor on a printed circuit board (PCB)). It is also possible to describe the content of an element or a material in a product directly, without going via the component or material level.

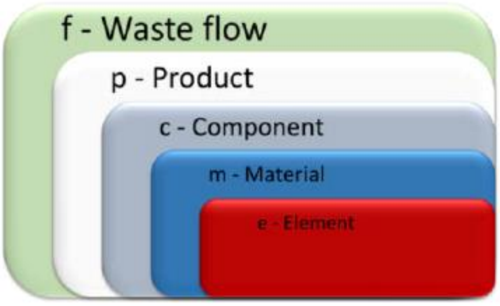


Figure 3 "Composition hierarchy" within ProSUM.

Available data on product composition reflect all these possibilities: some studies quantify the mass of elements directly at the product level, some include all the levels presented here, some include additional levels, and often components and materials are treated as the same level. To be able to put all relevant data into a consistent and structured format, codes and nomenclature were developed to describe the meaning of the data. The codes used for products, components, materials and elements were developed within D5.3; some additional codes for materials and components were added when required for the description and consolidation of data in D2.5.

The most relevant physical quantities for composition data are listed in Table 1.

Table 1 Physical quantities, symbols used within this report and their units.

Symbol	*Description*	*Code used in project databases*	*Units*
x	Mass content	MassContent	kg/piece, g/piece, mg/piece
M	Mass	Mass	kg/piece, g/piece, mg/piece
w	Mass fraction	MassFraction	kg/kg, mg/kg (ppm), m%
z	Number content	NumberContent	pieces/piece

Other properties such as length, area, concentration and density are also relevant, and were in some cases recorded, but are not included here because they were not used systematically in the estimation of representative composition.

For a meaningful description of the data, it is also necessary to describe the levels (in Figure 3) that the data refer to. The symbols used for the different levels are listed and described in Table 2.

Table 2 Levels used to describe the composition of entities in ProSUM. Used as subscripts for the physical quantities.

Symbol	*Name*
f	Flow
p	Product
c	Component
m	Material
e	Element

The parameters used to describe composition are then described using the symbols for physical quantities, and the symbols for the five levels as subscripts. The quantity *mass* in this context is only relevant by reference to a product or a component. The parameter is then designated M_p or M_c respectively. When recording data, the product or component must be specified by reference to the relevant code lists. The quantities *mass fraction*, *mass content* and *number content* are described by their appropriate symbol and a subscript of two letters connected with a dash, where the first letter indicates the part and the second letter indicates the whole. Hence, $w_{e\text{-}c}$ refers to the *mass fraction of an element in a component*, and $z_{c\text{-}p}$ refers to the *number of a component* (type) *in a product.* In all of these cases, the element, material, component and/or product must be specified by reference to the appropriate code lists. The code for the physical quantity, the parameter subscript, the units and a specification of the relevant levels (element, material, component, product) gives a full description of the meaning of the datum recorded.

In addition, the following information was recorded along with each datum, if available:

- Description of product in original reference;
- Similarity between description in original reference and ProSUM codes, for each level (code list);
- Number of products/components in batch;
- Production/model/design year;
- Uncertainties (as upper/lower limit or single value);
- Type of uncertainty (code list);
- Modelling method (code list);
- Digestion method (code list);
- Measurement method (code list);
- Original measurement: yes/no (code list);
- Measurement year;
- Measurement location (code list);
- Rights (code list);
- Reference;
- Original data source; and
- Person who recorded data

An Excel template was created for recording composition data, which allows for description of the data according to the procedure explained above. The unstructured data were manually extracted from the references and recorded in five data sheets (one per product category) using a common format. The Excel template is attached as “Annex 1 – Template for recording composition data”.

Data which are to be treated as confidential are clearly labelled so in the field “Rights”.

In practice, additional data were also obtained and recorded in step 3 when the original set of raw data was not sufficient. This meant identification of new references, description of them in the EndNote library and extraction of data (step 1).

2.1.3 Step 2: Evaluate quality of raw data

A procedure for data quality assessment was developed specifically for composition data. The procedure takes into account five factors: *measurement method, modelling approach, sample size, temporal scope definition,* and *consistency of descriptions*. In each category, a score is given based on the information recorded in the raw data sheets. These scores are added up to a total data quality score, which is finally used to assign a data quality rating: *highly confident, confident, less confident, and dubious*.

Different criteria were used depending on the type of data. Three types of data were distinguished:

- Element mass content or mass fractions (e-c, e-m, e-p);
- Component or material mass content, number content or mass fraction in components or products (m-c, c-c, m-p, c-p); and
- Product or component mass

The following table shows the application of different criteria to the evaluation of the three different types of data. *Measurement method* was only included for measurements of chemical elements (e-c, e-m, e-p) because for the remaining types of data, the measurement method is always weighing or producer data, both of which are considered highly accurate. While the details of the dismantling approach could be relevant, such information was not recorded and could therefore not be taken into account. *Modelling approach* was in practice only used to distinguish between a so-called "hot-spot" approach, where only a subset of the components in a product are measured to arrive at an estimate of the total mass or mass fraction of an element in the product. Although not relevant for e-m data, it was nevertheless included (with the highest score), which simply reflects the higher reliability of these data.

Table 3 Criteria applied in evaluation of raw data

Evaluation category	*e-c, e-m, e-p*	*m-c, c-c, m-p, c-p, c, p*
Measurement method	X	
Modelling approach	X	
Sample size	X	X
Temporal scope definition	X	X
Consistency of descriptions	X	X

Measurement method

The following measurement methods were distinguished while recording data.

Table 4 Measurement methods included in description of data

Code used in template	*Name of method*
AAS	Atomic Absorption Spectrometry
conductivity	Conductivity
EDX	Energy dispersive X-ray spectroscopy
FMD	Full materials declarations
gammaRadiation	Gamma Radiation
gammaRaySpectrometry	Gamma-ray Spectrometry
ICP-AES	Inductively coupled plasma atomic emission spectroscopy
ICP-MS	Inductively Coupled Plasma Emission Spectrometry
ICP-OES	Inductively Coupled Plasma-Optical Emission Spectrometry
INAA	Instrumental Neutron Activation Analyses
LECO	Combined combustion and infrared detection (LECO)
ProducerData	Data from producer
mossbauerSpectroscopy	Mössbauer spectroscopy
NiS-INAA	Nickel Sulphide Fire Assay - Instrumental Neutron Activation Analysis
Pb-ICP-ES	Lead Fire Assay - Inductively Coupled Plasma Emission Spectrometry
Pb-ICP-OES	Lead Fire Assay - Inductively Coupled Plasma-Optical Emission Spectrometry
Pb-ICP-S	Lead Fire Assay - Inductively Coupled Plasma Spectrometry
PortableXRF	Portable XRF analyzer
Pu-XRF	Plutonium-isotope excited X-Ray Fluorescence Spectrometry
SEM-EDX	Scanning electron microscopy with energy dispersive X-ray spectroscopy
XRD	X-Ray Diffraction
XRF	X-Ray Fluorescence Analysis
MarketData	Data from market analysis
Weighing	Weighing, after dismantling components or materials

A detailed evaluation of the impact of measurement method on data quality and uncertainty was not included, because it is highly dependent on sample preparation, digestion method and which element is measured, as well as the measurement method. Sufficient information was usually only available per reference, if at all. Nevertheless, the following distinction was made to account for the higher uncertainty of XRF.

Table 5 Scoring for measurement methods

Measurement method	$q_{MeasurementMethod}$
XRF	2
Unknown	1
All other methods	5

Modelling method

This category was included to distinguish between studies that use a "hot-spot" approach, i.e. investigating a subset of the component/product believed to contain most of the element mass of interest, and those that perform a "full material balance". The distinction made is shown in Table 6.

Table 6 Scoring for modelling methods

Modelling method	$q_{ModellingMethod}$
HotSpot	3
FullMaterialBalance	5
Other	3
Unknown	1

Sample size

Sample size was included as a criterion with the following function:

$$q_{SampleSize} = 1 + log_2(n)$$

Where *n* is the sample size of the relevant component or product. If sample size is unknown it was set equal to 1. The example values in Table 7 illustrate the function.

Table 7 Scoring for sample size

Sample size	$q_{SampleSize}$
Unknown	1
1	1.00
2	2.00
3	2.58
4	3.00
5	3.32
10	4.32
50	6.64
100	7.64
1000	10.97

The maximum observed sample size was 700.

Temporal scope definition

The category "temporal scope definition" includes a score that is higher where more knowledge about temporal information of the sample is available. Table 8 explains the four levels.

Table 8 Scoring for temporal scope

Description of temporal scope/age of object	$q_{Temporal}$
Unknown	1
Sample or collection year specified	2
Age specified as a range of years	3
Age specified as a specific year	5

Consistency of description

The correspondence with ProSUM code lists was evaluated for every material, component and product described by the data, using three levels: "low", "medium" and "high". The purpose of this factor is to account for the fact that the ProSUM code lists sometimes do not match to the descriptions of the raw data. Entries with a good match (i.e. the product/component/material is clearly within the specified product key) scored "high", entries that could possibly be partly outside the scope of the product/component/material code scored "medium" and entries that were known to be partly outside the scope scored "low". Entries that are entirely outside the scope necessarily had to be recorded with a different code, introducing new codes when necessary. When two entities were specified (m-c, c-c, c-p and m-p), the lowest correspondence level was used for the evaluation.

The following figure illustrates the meaning of the different terms.

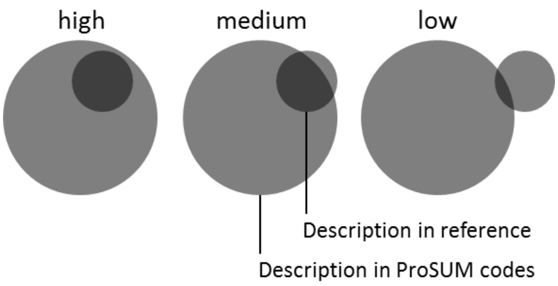


Figure 4 The three levels of "consistency of descriptions" used in data quality evaluation of raw data.

Table 9 shows the scores which were applied.

Table 9 Scoring for consistency of description

Correspondence of description with ProSUM codes	$q_{Correspondence}$
Unknown	1
Low	1
Medium	3
High	5

Calculation of data quality score and data quality level

The above sub-scores were used to calculate an overall "data quality score", *Q*, using the following formulas:

e-m, e-c, e-p data

$$Q1 = q_{MeasurementMethod} + q_{ModellingMethod} + q_{SampleSize} + q_{Correspondence} + q_{Temporal}$$

For a sample size of 1000, the maximum data quality score is this 30.97. The following table explains the assignment of a data quality level based on the data quality score.

Table 10 Data quality scores and levels for e-m, e-c and e-p data

Data quality score, Q1	*Data quality level*
>=22	Highly confident
16-22	Confident
10-15.99	Less confident
< 10	Dubious

m-c, c-c, m-p, c-p, c and p data

$$Q2 = q_{SampleSize} + q_{Correspondence} + q_{Temporal}$$

For a sample size of 1000, the maximum data quality score is thus 20.97. The following table explains the assignment of a data quality level based on the data quality score for m-c, c-c, m-p, c-p, c and p data.

Table 11 Data quality scores and levels for m-c, c-c, m-p, c-p, c and p data

Data quality score, Q2	*Data quality level*
>=13	Highly confident
10-12.99	Confident
5-9.99	Less confident
< 5	Dubious

With the approach described above, it is more difficult to obtain a high data quality level for the former type of data (e-m, e-c, e-p). This is intentional, as measurements of element mass content or mass fractions are in general less certain than dismantling and weighing of components and materials.

2.1.4 Step 3: Estimate representative composition

Goal and general approach

The guiding goal of the consolidation process was to produce representative data that could be used to calculate the element mass fractions or mass contents in each product over time. Ideally, this should be done in three steps, working down from a complete list of components and their mass content/mass fraction in the product (c-p), through a complete list of materials in each component (m-c) to the chemical composition of each material (e-m). In practice, this was rarely possible due to a lack of complete data sets. For batteries, estimation was done directly on e-p; for EEE and vehicles, materials and components were treated as the same level.

The estimation of representative composition was done differently between the different product categories, taking advantage of the product-specific expert knowledge of the various persons working on the task. Despite the systematic description and quality evaluation of raw data, it was found that many case-specific decisions had to be made throughout the consolidation, so that an automated procedure was not feasible. In practice, the data quality evaluation does not capture all relevant information. For example, many e-p raw data for vehicles were used to estimate e-c values, because it is known that a given component carries the majority of a given element's mass in the product. On the other hand, some data were excluded from the consolidation, not because of the assigned data quality, but because detailed knowledge of the measurement methods justified it. Nevertheless, the assigned data quality guided the use of raw data in the consolidation process e.g. “dubious” data were usually discarded.

When several data were available for the same parameter, the average was usually calculated to estimate the representative value. In some cases the weighted average was used, where the weights were either the sample size (when data originated from the same source with the same measurement method), or the data quality (“highly confident” = 4, “confident” = 3, “less confident” = 2, “dubious” = 1).

Calculations of compositions

A calculation procedure for composition data was created to enable quickly reproducible comparison of produced datasets for e-m, e-c, m-p and c-p data with e-p data. This is particularly useful for EEE, where the same steps have to be taken for all 54 UNU keys analysed.

The following notation is used:

n_m – number of different materials

n_c – number of different components

n_e – number of different elements

a – vector of mass fractions of materials m_i and components c_j in the product p:

$$\mathbf{a} = \begin{matrix} w_{m_1-p} \\ w_{m_2-p} \\ \vdots \\ w_{m_{n_m}-p} \\ w_{c_1-p} \\ w_{c_2-p} \\ \vdots \\ w_{c_{n_c}-p} \end{matrix}$$

B – matrix of mass fractions of materials and components in other materials and components

$$\mathbf{B} = \begin{bmatrix} w_{m_1-m_1} & \cdots & w_{m_1-c_{n_c}} \\ \vdots & \ddots & \vdots \\ w_{c_{n_c}-m_1} & \cdots & w_{c_{n_c}-c_{n_c}} \end{bmatrix}$$

In B, some materials and components will contain data on their content of other materials and components, while others will not. For those that do not have such data, the corresponding element on the diagonal of **B** will be 1 (applies to all materials). For those components that do have such data, the diagonal element should be equal to zero.

C – matrix of mass fractions of elements in components and materials

$$\mathbf{C} = \begin{bmatrix} w_{e_1-m_1} & \cdots & w_{e_1-m_{n_m}} \\ \vdots & \ddots & \vdots \\ w_{e_{n_e}-m_1} & \cdots & w_{e_{n_e}-m_{n_m}} \end{bmatrix}$$

We can then calculate a new vector of mass fractions of materials and components in the product, **d**, as:

$$\mathbf{d} = \mathbf{Ba}$$

The mass fraction of elements in the product ($w_{e\text{-}p}$) can be calculated as:

$$\mathbf{x} = \mathbf{Cd}$$

The contribution of each material and component to an element's mass fraction in the product is:

$$\mathbf{X} = \mathbf{C} \cdot \mathrm{diag}(\mathbf{d})$$

where diag(**d**) is a n_e x n_e matrix with the elements of **d** on the northwest-southeast diagonal and zero elsewhere.

2.1.5 Step 4: Evaluate data quality and uncertainty of representative compositions

Data quality

The following procedure was used to evaluate the produced datasets for composition of products and components.

Scores were given in three categories: number of references, q_n, "representativeness", q_r, and "temporal change", q_t. They are scored as follows:

Representativeness

- Large set of representative products/components → $q_r = 0$
- Small set of representative products/components → $q_r = -1$
- Not representative → $q_r = -3$

Number of references

- Number of references > 3 → $q_n = 0$
- Number of references = 1-3 → $q_n = -1$

Temporal change

- Temporal change relevant and included OR not relevant → $q_t = 0$
- Temporal change relevant but not included → $q_t = -1$

The *data quality score* is then calculated as:

$$q_{tot} = 4 + q_n + q_r + q_t$$

The data quality is determined by the following table:

Table 12 Data quality scores and levels for estimated representative composition data

q_{tot}	*Data quality*
4	Highly confident
3	Confident
2	Less confident
<=1	Dubious

Table 13 gives a qualitative description of the four data quality levels.

Table 13 Data quality levels and their descriptions

Data quality	Estimate based on
Highly confident	Large representative set of products/components Many observations
Confident	Large representative set of products/components Few observations OR Small representative set of products/components Many observations
Less confident	Small representative set of products/components Few observations
Dubious	Notrepresentative set of products/components

Uncertainties

The uncertainties of the produced data sets were estimated based on the data quality evaluation. The procedure takes into account that the same data quality level should be interpreted differently depending on the parameter for which it applies. Thus, the uncertainty, as estimated here, is a function of the value of the parameter *and* its data quality. Moreover, when uncertainties are large (as is often the case for composition data) and the quantity in question is bounded (e.g. a mass fraction cannot be less than 0), asymmetric uncertainty intervals give a more realistic representation of the uncertainty. The approach taken here uses "uncertainty factors" as introduced by Hedbrant and Sörme (2001). If μ is our estimate of the quantity of interest, and f is its uncertainty factor, then the lower limit, μ-, and upper limits, μ+, are defined as:

$$\mu^{-} = \frac{\mu}{f}$$

and

$$\mu^{+} = f\mu$$

As an example, an uncertainty factor of 2 means that we expect the true value to lie between one half and twice our "best estimate", μ. A factor 5 means that we expect it to lie between one fifth and five times μ.

Quantities with small values, such as the mass fraction of Au or Pt, are more difficult to measure and generally show a much higher variation between individual measurements than large quantities, such as the mass fraction of steel in a product. We account for this by assigning higher uncertainty factors to data with smaller absolute values for the same data quality level. Table 14 shows the factors for the four data quality levels and four value ranges for mass fraction and mass content.

Table 14 Uncertainty factors used for the four data quality levels

Mass fraction lower limit (ppm)	Mass content lower limit (g)		Highly confident	Confident	Less confident	Dubious
100000	100	*/	1.01	1.05	1.2	1.5
10000	10	*/	1.05	1.2	1.5	2
1000	1	*/	1.2	1.5	2	5
0	0	*/	1.5	2	5	10

For quantities of number content, the upper row of factors was used. However, this parameter is often known with certainty (e.g. a vehicle always has exactly one electrical and electronic system as this component is defined in ProSUM), in which case the uncertainty is set to zero (f = 1).

In practice, the data model does not work with uncertainty factors, so they were converted to lower and upper limits. The resulting range should be interpreted as a triangular probability density function with the mode at the best estimate, μ, and the lower and upper limits at μ- and μ+ respectively. Due to the asymmetry of the distribution, the lower part of the distribution will always have a steeper gradient than the upper one. However, for small uncertainties the distribution approaches a symmetric triangular distribution.

2.1.6 Step 5: Provide portrayals

An Excel "harvest template" was created for providing the data portrayals. The data were extracted from consolidation data sheets (EEE and vehicles) and put into the harvest templates using MATLAB scripts. Batteries data were pasted manually due to a much smaller number of data.

2.2 Product-specific methods

2.2.1 Methods for batteries

In the case of batteries, the general principle described in 2.1.4 is applicable for consolidation. Nevertheless, due to a rather limited number of raw data, application of a statistical calculation was only possible for a few elements in the composition.

However, a rather complete description of the batteries composition was available in different documents originating from the battery industry:

- Batteries Material Safety Data Sheets;
- Handbook of batteries, based on scientific and historical description of the batteries compositions; and
- Published data from the industry including recyclers' data

The estimated representative values for CRM and main valuable material content has been based on these documents, providing the composition of the main battery designs. For each battery sub-key, a representative value and a confidence interval for each of the selected elements have been calculated based on these data sources. It is important to note that the estimated battery composition only include the mass fractions of elements in the battery cell. Battery electronics are not included due to a complete lack of data.

When possible, a weighted average of the product composition, according to the market share, has been applied e.g. for the usage of natural graphite (identified as CRM) in the cathode of Li-ion batteries. Based on published market share data (Avicenne 2016), natural graphite represents 63% , and artificial graphite 37% of all the graphite used in batteries. As the different type of graphite are generally not identified in the composition or analysis data, a ratio of 63% has been applied by default to assess the quantity of natural graphite used in batteries.

Chemical composition normally evolves slowly within each battery technology. Major product design changes are linked to new applications: consequently, the compositions assessed are assumed to be stable over the period 2000-2015.

A comparison test between the representative value and the statistical average of various analysis was done with the Lithium content for one of the Li-batteries BATT sub-keys, battLiCoO2, where 8 values were available.

The results of the data treatment are presented in paragraph 3.1.

2.2.2 Methods for EEE

2.2.2.1 General approach for EEE data

EEE is distinguished from the other product groups by much better data availability (around 27,000 data available from almost 300 references) as well as a much larger diversity of product composition within the group. A distinction is made between 54 different UNU keys, as well as further distinction between "sub-keys" within some UNU keys. For example, laptops and tablet computers belong to the same UNU key (0303), but the estimation of representative composition was done separately (sub-keys 030301 and 030302).

To facilitate a common approach for all UNU keys, an Excel template was developed for gathering all relevant data and estimating representative composition. Each UNU key/sub-key with distinct composition estimated has its own Excel file, where all steps of the consolidation are done separately in individual sheets (p, m-p/c-p, e-m/e-c, e-p) and appropriately documented to enable tracking to the original data and references. An automatic procedure (MATLAB script), was used for extracting raw data from the "EEE composition raw data" template and pasting it into the key-specific consolidation template.

The main starting point for estimating EEE compositions is a comprehensive dataset from Eco-systèmes on w_{m-p}, w_{c-p}, w_{m-c} and w_{c-c}, originating from dismantling campaigns (Eco-systèmes 2013, Eco-systèmes 2014, Eco-systèmes 2014, Eco-systèmes 2015). These data were compared and consolidated with data from other sources when available.[1] In addition, a variable number of data (depending on the product key) were available for w_{e-c} and w_{e-m} from a large number of references. For each product, a distinction was made between "general" and "product-specific" data for w_{e-c} and w_{e-m}. General data were used across several products for common materials and components meeting at least one of the two following conditions: i) no product-specific data were available, ii) no significant variation between products is believed to exist. Examples of using such general assumptions include most materials (e.g. steel alloys, aluminium alloys, brass, copper) as well as common components (e.g. electric motors, LEDs, cables). Data for these were taken from various sources including producer data, dismantling studies, chemical analyses, and alloy specification standards (Osram 2007, Lim et al. 2011, Rotter 2013, Eco-systèmes 2014, Böni et al. 2015, Sun et al. 2015, Widmer et al. 2015).

It has not been possible to complete the consolidation process for all of the UNU keys/sub-keys due to the complexity of the procedures developed above, the large number of data, and the high level of individual expert checking required. So far, it has been completed for three rather different UNU keys: microwave ovens (0114), tablet computers (030302) and flat screen TVs (0408). The consolidation process will be completed for the remaining products by the end of April 2017 (M30).

The main data sources and procedure are explained below for the four example products. They were chosen for different reasons: microwave ovens were a good starting example since the product key has limited complexity and a small number of data sources; the remaining two

---

[1] The original confidential data are clearly labelled as such in all project datasets and databases, and will not be made publicly available (neither in this report nor the EU-UMKDP). They were however used in calculations to estimate the representative compositions of products and components.

products are highly complex products with a large number of data available, allowing for a full testing and demonstration of the approach.

Table 15 Overview of calculation method and data available for composition of EEE

UNU key	Calculation method	Number of sources	Org. resp. for data consolidations	Structured data available?
0114	e-m-p/e-c-p	7	Empa	m-p, c-p, e-p
030302	e-m-p/e-c-p	4	TUB	m-p, c-p, e-p
0408	e-m-p/e-c-p	24	UNU	m-p, c-p, e-p

2.2.2.2 Microwave ovens (0114)

$w_{m\text{-}p}$ and $w_{c\text{-}p}$

Data from Eco-systèmes were used to estimate an average microwave composition as put on the market in 1999 (Eco-systèmes 2013, Eco-systèmes 2014, Eco-systèmes 2015), relying on the D3.3 outcome indicating an average disposal age of 13 years. It is assumed the collected and analysed data is representative and has the same disposal age as the D3.3 outcome for microwaves collected and measured between 2011 and 2014 (with most measurements in 2012). Additional c-c and m-c data for the magnetron, electric motor and capacitor were used to represent these in terms of other materials and components e.g. including magnets. For changing composition over time, it was assumed that the mass of the printed circuit board (PCB) stays the same over time. Due to the increasing mass of the product, this leads to a reduction in mass fraction of PCB over time while the mass fraction other components and materials increase slightly. Other changes over time were not included due to lack of data. Within the scope of D2.4, it will be attempted to gather sufficient information on the absolute and relative change of circuit boards in 0114 products over time.

$w_{e\text{-}c}$ and $w_{e\text{-}m}$

Mass fractions in materials were set equal to general assumptions about the common alloys used (explained in section 2.2.2.1). Mass fractions in components were taken from different studies (Osram 2007, Lim et al. 2011, Rotter 2013, Eco-systèmes 2014, Böni et al. 2015, Sun et al. 2015, Widmer et al. 2015). For magnets and PCBs, microwave-specific data were used. For other components, e.g. LEDs, lamps, cables, general data were used. No changes over time were included due to lack of data.

2.2.2.3 Tablets (030302)

$w_{m\text{-}p}$ and $w_{c\text{-}p}$

For tablets, highly confident m-p and c-p data were available from the project UPgrade (Rotter et al. 2016), Eco-systèmes (Eco-systèmes 2013) and other sources. Almost 50 disassembled products showed a detailed overview of almost all applied materials and components in tablets in various disassembly levels. The components obtained from dismantling were further investigated to provide additional compositional data.

Tablets represent a very young generation of electronic devices. Devices investigated were dated back to the years 2010-2013. Most information was available for the years 2011 and 2013. The depiction of a trend over time is possible for the overall product masses as well as for the applied materials and components.

$w_{e\text{-}c}$ and $w_{e\text{-}m}$

The primary data source was the project UPgrade (Rotter et al. 2016). In this project, components identified as CRM carrier (Chancerel et al., 2013) were chemically analysed with appropriate techniques (ICP-MS, ICP-OES and AAS). Measurements were undertaken for In, Cu, Sn, As, Sb, Pb, and Sr in LCD panels, including separate measurements for the polarizer foils and glass substrate (e-m)(Ueberschaar et al. 2016). Moreover, Ta, PM, Cu, and other elements were measured in tantalum capacitors and printed circuit boards (Ueberschaar et al. 2016). Confident and less confident e-c, e-m data were obtained through handheld XRF measurements for magnets from microphones, loudspeakers and vibration alert motors as well as for other materials/components such as screws and casing materials. (Rotter et al., 2016).

The materials and components which were chemically characterised were specific to a product and, therefore, related to the product's manufacturing date. A depiction of a possible time trend might be possible with these data.

2.2.2.4 Flat display panel TVs (0408)

$w_{m\text{-}p}$ and $w_{c\text{-}p}$

Data from Eco-systèmes were used to estimate the average LCD TV composition as put on the market in 2000 (Eco-systèmes 2014). The assumption being that the median residence time is 9 years, which corresponds with a 4 year average disposal age for LCD TV observed in the return stream collected and measured between 2011 and 2014 (with most measurements in 2012). For changing composition over time, it was assumed that the mass of the PCB stays the same over time. Due to the increasing mass of the product, this leads to a reduction in mass fraction of PCB over time while the mass fraction of other components and materials increase slightly.

$w_{e\text{-}c}$ and $w_{e\text{-}m}$

Mass fractions of elements in materials were set equal to general assumptions about the common alloys used (explained in section 2.2.2.1). Mass fractions for components were taken from different studies. For magnets and TFT displays, data specific for flat screen TVs were used (Eco-systèmes 2014). For other components e.g. LEDs, lamps, and cables), general data were used.

2.2.3 Methods for vehicles

2.2.3.1 General approach for vehicles

Due to the variable level of detail for composition data on vehicles, a combined approach was used, where one element (Cu) was estimated directly on the product level (e-p), some estimated via components (e-c, c-p), and some estimated through materials (e-m, m-p). In general, no full material balances are given for vehicle composition, meaning that the sum of mass fractions of elements in a component do not add up to 100%, and the total mass of components and materials included does not add up to the mass of the vehicle. This approach follows from the fact that selected elements only constitute parts of total mass, and consequently that the provision of complete material balances were outside the scope. Moreover, due to the complexity of vehicles and lack of data, it was necessary to focus on "hot-spots", i.e. components that are known to contain CRM and valuable materials for recycling.

To be able to consolidate data from different sources, many components were aggregated and represented by the component EESystem (electrical and electronic system), which includes all devices powered by or generating electricity, except the vehicle battery cell. This was necessary because some key data sources only include aggregated data (Alonso et al. 2012, Cullbrand and Magnusson 2012, Andersson et al. 2016). In addition, the catalytic converter, battery, magnet from the electric drive motor, cast aluminium, wrought aluminium, standard steel, high strength steel, cast iron and magnesium were included as separate components and materials. In total 30 elements are included in the data set: Ag, Al, Au, C, Ce, Co, Cr, Cu, Dy, Fe, Ga, Gd, In, La, Mg, Mn, Mo, Nb, Nd, Pd, Pr, Pt, Rh, Si, Sm, Ta, Tb, Y, Zn, Zr. Among these, C and Si are included only as part of steel and aluminium alloys and the data therefore do not represent their content in an entire vehicle.

Table 16 shows the estimation approach for each element, including those that were excluded due to a lack of data.

Table 16 Calculation method and number of data for elements in components and materials considered for vehicles. Note that "Steel alloys" include three materials (standard steel, high strength steel and cast iron), and "Aluminium alloys" include cast and wrought aluminium. Separate data are provided for these five materials (not shown in this table).

Element	*Number of e-p data*	*Calculation method*	**PRODUCT (e-p)**	EESystem (e-c)	CatalyticConverter (e-c)	BatteryCell (e-c)	ElectricDriveMotorMagnet (e-c)	MagnesiumAlloyUnspecified (e-m)	Steel alloys (e-m)	Aluminium alloys (e-m)	*Comment*
Ag	4	**e-c-p**		■							
Al		**e-m-p**						■		■	
As	1	EXCLUDE									Too few observations
Au	4	**e-c-p**		■							
Be		EXCLUDE									Too few observations
Bi		EXCLUDE									
Cd	1	EXCLUDE									Too few observations
Ce	10	**e-c-p**			■						
Co	6	**e-m-p/e-c-p**		■		■					Steel alloys and superalloys not included
Cr	2	EXCLUDE									Too few observations
Cu	5	**e-p**	■								
Dy	12	**e-c-p**		■			■				
Er	4	EXCLUDE									Too few observations and low values
Eu	2	EXCLUDE									Too few observations and low values
Fe		**e-m-p**							■		
Ga	6	**e-c-p/e-m-p**		■						■	
Gd	6	**e-c-p**		■		■					
Ge		EXCLUDE									Too few observations and low values
Hg	2	EXCLUDE									Too few and unreliable observations
Ho	1	EXCLUDE									Too few observations
In	6	**e-c-p**		■							
La	12	**e-c-p**		■	■	■					
Li	4	**e-c-p**				■					
Lu	4	EXCLUDE									Not detected
Mg	4	**e-m-p**						■		■	
Mn	6	**e-m-p**							■	■	
Mo	6	**e-m-p**							■		
Nb	6	**e-m-p**							■		
Nd	12	**e-c-p**		■	■	■	■				
Ni	2	EXCLUDE									Too few observations

Table 16 cont.

Element	Number of e-p data	Calculation method	PRODUCT (e-p)	EESystem (e-c)	CatalyticConverter (e-c)	BatteryCell (e-c)	ElectricDriveMotorMagnet (e-c)	MagnesiumAlloyUnspecified (e-m)	Steel alloys (e-m)	Aluminium alloys (e-m)	Comment
Os		EXCLUDE									Too few observations
Pb	2	**e-c-p**				■					
Pd	6	**e-c-p**		■	■						
Pm		EXCLUDE									Too few observations
Pr	11	**e-c-p**		■		■	■				
Pt	6	**e-c-p**			■						
Rb		EXCLUDE									Too few observations
Re		EXCLUDE									Too few observations
Rh	4	**e-c-p**			■						
Ru		EXCLUDE									Too few observations
Sb	2	EXCLUDE									Too few and unreliable observations
Sc	6	EXCLUDE									Too few observations
Se	1	EXCLUDE									Too few observations
Si		**e-m-p**								■	
Sm	8	**e-c-p**		■							
Sn		EXCLUDE									Too few observations
Sr	2	EXCLUDE									Too few and unreliable observations
Ta	6	**e-c-p**		■							
Tb	7	**e-c-p**		■							
Tc		EXCLUDE									
Te		EXCLUDE									Too few and unreliable observations
Ti		EXCLUDE									Too few observations
Tl		EXCLUDE									Too few observations
Tm	4	EXCLUDE									Not detected
V	2	EXCLUDE									Too few observations
W	2	EXCLUDE									Too few observations
Y	6	**e-c-p**		■							Nickel alloys not included
Yb	6	EXCLUDE									Too few observations and low values
Zn		EXCLUDE									Too few observations
Zr	2	EXCLUDE									Too few observations

The vehicle keys are defined according to four properties:

- *type* (car, van);
- *motor energy type* (petrol, diesel, compressed natural gas (CNG), liquid petroleum gas (LPG), hybrid-electric, plug-in hybrid-electric, battery electric/fuel cell, and others);
- *engine displacement range* (< 1400 cm3, 1400-1999 cm3, > 2000 cm3, no cylinder); and
- *weight range* (< 1000 kg, 1000-1249 kg, 1250-1499 kg, > 1500 kg)

These vehicle keys, which are based on the Eurostat classification system, were found appropriate for describing the material composition of vehicles, and allow for a direct linkage to available data for stock and flow modelling in ProSUM. In contrast, vehicle segment classes, commonly referred to in vehicle industry, were not deemed suitable to use in ProSUM, because the classification (1) is relative to the most commonly sold vehicles at a certain point in time (thus, models can shift class over time) and (2) lack a strict and uniform definition (classes as well as classification of specific models can therefore differ between countries and actors).

In the consolidation process, differences in vehicle composition between different vehicle keys were included to variable degrees depending on the material parameter. Generally, a distinction based on properties and over time was included whenever they were believed to correlate with composition differences and sufficient data were available.

Depending on the material and component of interest, one or several vehicle key properties were used as predictors for its mass content in vehicles. For example, the mass of steel used is highly correlated with the weight of the car, while the type of battery used is clearly dependent on the motor energy type. Engine displacement is used in relation to several materials and components: (1) for data dependent on engine size (such as catalytic converter), (2) as a proxy for segment classes for data available by such classes (e.g. aluminium).

Table 17 shows, for each parameter, the properties that determine its value in the produced data set.

Table 17 Properties determining the value of parameters in produced dataset for vehicles.

Parameter		Type (car/van)	Motor energy	Engine displacement	Weight	Year put on market
e-p	Cu		x			
e-c	EESystem (16 elements)		x [a]			x [b]
c-p	CatalyticConverter		x			x
e-c	CatalyticConverter (5 elements)		x	x		
c-p	BatteryCell (6 battery sub-keys)		x			
c	BatteryCell (6 battery sub-keys)		x			
c-p	ElectricDriveMotorMagnet		x			
c	ElectricDriveMotorMagnet		x		x	
e-c	ElectricDriveMotorMagnet					x
m-p	Aluminium (2 materials)			x		x
e-m	Aluminium (2 materials, 9 elements)					
m-p	Steel and iron (3 materials)				x	X
e-m	Steel and iron (3 materials, 7 elements)					
m-p	Magnesium					
e-m	Magnesium (4 elements)					

[a] – Was used only for Ag
[b] – Was used only for Ag, Au, Co, Dy, La, Nd, Pd

2.2.3.2 *Elements estimated directly on product level: Cu*

Only one element, Cu, was estimated directly on the product level. This was done because insufficient data were available to estimate the content of each of the relevant materials (e.g. copper alloys, brass, bronze).

For vehicles with internal combustion engines as the only power source (ICEV), i.e. the following motor types: petrol, diesel, compressed natural gas and liquid petroleum gas, the estimated mass content of Cu is the average of the three diesel cars from Cullbrand and Magnusson (2012) and the ICEV from Burnham et al. (2006). For hybrid-electric vehicles (HEV), battery electric vehicles

(BEV) and plug-in hybrid-electric vehicles (PHEV) the estimated mass content of Cu is the average of a PHEV from Cullbrand and Magnusson (2012) and a HEV from Burnham et al. (2006).

2.2.3.3 EESystem

The mass content of elements in the electrical and electronic (EE) system was estimated from several sources (Ministry of Environment Japan 2009, Alonso et al. 2012, Cullbrand and Magnusson 2012, Widmer et al. 2015, Restrepo et al. 2016). Two of these have an explicit focus on the EE system (Widmer et al. 2015, Restrepo et al. 2016), while the others quantify elements on the vehicle level. Nevertheless, the former data can for many elements be used for the EE system since the majority of the mass occurs in the EE system, as indicated by Andersson et al. (2016). For one element, Ag, a differentiation between different motor energy types was included. Changes over time (by cohort year) for vehicles POM, estimated by Restrepo et al. (2016), were included for Ag, Au, Co, Dy, La, Nd and Pd.

2.2.3.4 Catalytic converter

The number of catalytic converters per vehicle was estimated based on timeline of legislations in Europe. According to Hagelüken et al. (2006) the first catalytic converters were used in petrol vehicles around 1985. From 1993, all new petrol vehicles were required to have catalytic converters to meet emission standards (European Environment Agency 2001). The number of catalytic converters per new petrol-fuelled vehicle introduced on the market was assumed to be 0 until 1984, followed by a linear increase up to 1 in 1993, and 1 thereafter.

Light duty diesel vehicles started employing catalytic converters around the year 2000 with the introduction of the Euro III regulation on emissions. From the Euro IV regulation in 2004, all light duty diesel vehicles were required to have catalytic converters to meet emissions standards (European Environment Agency 2001). The number of catalytic converters per new diesel-fuelled vehicle introduced on the market was assumed to be 0 until 1999, followed by a linear increase up to 1 in 2004 and 1 thereafter.

BEV do not need a catalytic converter. It was assumed that 80% of PHEV and HEV are petrol-electric and the remaining 20% diesel-electric, based on information from Auto-i-Dat AG (2015). The number of catalytic converters per vehicle was then estimated as 80% of the number for petrol cars + 20% times the number for diesel cars. However, since HEVs and PHEVs barely existed before catalytic converters became standard equipment in all ICEV (2004), these assumptions will have nearly no influence in further calculation steps.

Regarding platinum group metals in catalytic converters, a distinction was made between catalytic converters in petrol and diesel vehicles. Catalytic converters for petrol engines contain less Pt due to substitution with Pd (Johnson Matthey 2013). Change in composition over time was not estimated due to lack of data. The available data focuses on newer vehicles. This may lead to an underestimate of platinum content, since older catalytic converters tend to contain more platinum.

2.2.3.5 Battery

The share of battery types and their mass per average vehicle were consolidated using data from Avicenne (2016), and are based on specific technology information on the most commonly sold HEV, PHEV and BEV models.

Four main battery types are used for vehicles:

- Lead-acid: 100% of ICEV
- Nickel-metal hydride: estimated to 85% of HEV;
- Lithium nickel manganese cobalt oxide (Li-NMC): estimated to 15% of HEV, 90% of PHEV and 5% of BEV; and

- Lithium manganese oxide (Li-Mn): estimated to 10% of PHEV and 95% of BEV.

2.2.3.6 Electric drive machine magnet

The number of electric drive machine magnets were estimated based on information about individual vehicle models, provided by Elwert et al. (2016) and de Santiago et al. (2012). About half of BEV use permanent magnets, while all HEV and PHEV use permanent magnets. This considers all the permanent magnets found in the motor/generator as one component, although in reality there are many individual pieces. The quantity therefore represents the share of vehicles that employ permanent magnet drive motor technology.

The mass of magnets was first estimated for a HEV representing the 1000-1249 kg weight class. This estimate was obtained as the average of six values from Elwert et al. (2016), Zepf (2013), Glöser-Chahoud et al. (2016) and Yano et al. (2015). Magnet mass for BEV, PHEV and other weight classes were then estimated by scaling with the same factors as given by Glöser-Chahoud et al. (2016).The difference between BEV and HEV is similar to that estimated by Elwert et al. (2016). Yano et al. (2015) showed some change in magnet mass over time for different Toyota Prius models. However, data was deemed too specific to represent all HEV.

For the composition of the drive motor magnet, estimates were taken from the only measured data available, from Yano et al. (2015). These data include mass fractions of Pr, Nd and Dy in hybrid transmission generator and motor magnets from three Toyota Prius models (1998, 2003, 2009). The estimates from Zepf (2013) and Elwert et al. (2016) are slightly higher for Nd and Dy (compared to the 1998 Toyota Prius) but do not include Pr and were not used. Between 1998 and 2009, a linear increase was assumed, while before 1998 and after 2009, the composition was assumed constant.

2.2.3.7 Aluminium alloys

Aluminium content in vehicles was taken from estimates by Ducker Worldwide (2014), which are based on information about a representative selection of models from different vehicle segments[2]. The vehicle segments were used as proxies for engine displacement (one of four properties describing vehicle keys in ProSUM), assuming the following correlation: i) <1400 cm3: A/B segment, ii) 1400-1999 cm3: C segment, iii) >2000 cm3: weighted average of C, D, E, F, J and S segments, where the weights were the market shares of the segments in Europe in 2011. The resulting average aluminium content of new vehicles put on the market in Europe in 2011, obtained by multiplying with the share of each engine displacement category, was 142 kg, compared to 138 kg as estimated by Ducker Worldwide (2012).

It was assumed that within each engine displacement range, the relative change over time is equal to the relative change over time for the average vehicle. This may lead to a slightly underestimated aluminium content in older vehicles, since part of the change seen for the average vehicle can be explained by a shift towards segments with higher aluminium content. Vehicles without combustion engine cylinder were assumed to contain the same amount of aluminium as those with engine displacement <1400 cm3, but with 50% lower cast aluminium content, due to the lack of engine blocks and cylinder heads. Vehicles with unknown engine displacement were assumed equal to the category 1400-1999 cm3.

[2] Segments are used by Ducker Worldwide and others to classify cars. In ProSUM, segments are not used, mainly since Eurostat statistics do not provide this information for data on stocks and flows of vehicles. The segments referred to here are: A – mini cars, B – small cars, C – medium cars, D – large cars, E – executive cars, F – luxury cars, J – sport utility cars, M – multipurpose cars, S – sports cars

Composition of aluminium alloys was estimated from two publications. Modaresi et al. (2014) provide an estimate of the share of different automotive alloy types. Løvik et al. (2014) provide representative alloys and their compositions for the categories used by Modaresi et al. This information was combined to estimate the average composition of wrought and cast alloys as two distinct materials. It was further assumed that all aluminium contain at least 0.01% Ga, 0.03% Si and 0.1% Fe by mass. The Ga mass fraction was taken from Widmer et al. (2015), while Si and Fe mass fractions were taken from Løvik et al. (2014).

2.2.3.8 Steel and iron alloys

Steel content was estimated using a combination of data sources. Modaresi et al. (2014) provide the average content of cast iron, standard steel and high strength steel (HSS) in vehicles from 1980 to 2015 (however with no change assumed after 2010, which may lead to an underestimate of HSS content in recent vehicle cohorts). This content was assumed to apply for a car of average mass (1377 kg) POM in 2014, where the average mass was estimated using the ProSUM stocks and flows model for vehicles. To find the steel and iron content per mass range of vehicle keys, the values for a 1377 kg vehicle were scaled by the average mass within each mass range as estimated by the ProSUM stocks and flows model.

There is little information available about the average composition of steel alloys in vehicles. The estimated content of Fe, C, Cu, Mn, Si, Mo and Nb were obtained by a combination of assumptions and literature sources. It was assumed that standard steel has the typical composition of A36 steel, as given by AZOM (2012). High strength steel was assumed to be mainly high-strength low-alloy (HSLA) steel with small additions of Nb and Mo. The Mo content was estimated from data from Cullbrand and Magnusson (2012), Widmer et al. (2015) and Ministry of Environment Japan (2009). It was assumed that all the Mo observed by these authors originated from high-strength steel. Nb content in HSLA steel was assumed to be 0.02% on average, as indicated by Mohrbacher (2006). This Nb content is in the same range as observed by Ministry of Environment Japan (2009), Cullbrand and Magnusson (2012) and Widmer et al. (2015). For cast iron, it was assumed a typical grey iron composition, as given by AZOM (2001), since this is usually used for engine blocks. Other alloying elements, such as Ni, Cr, Ti, V and Zr were not included due to a lack of data.

2.2.3.9 Magnesium alloys

The estimated mass of magnesium alloys per vehicle is based on an average North American vehicle in 2009 (Lutsey 2010). Due to lack of data, no distinction is made over time or between different vehicle keys. It is however known that the use of magnesium has increased in the last decade. It was assumed that AZ91 is used, as it is the most common die-cast alloy (Dynacast 2016).

3 Results

3.1 Composition of batteries

The treatment of the data for batteries has led to the following results. A large number of single point analysis data are in the range of the calculated representative data. However, many data are not coherent, and cannot be taken into account. The reasons are:

- Steel/iron may be mixed (lack of precision of the steel type). As a result, the Cr content is often incorrectly assessed.
- Some of the batteries analysed are obsolete, for example, Zn batteries containing mercury (except button cells) have not been permitted on the European market since 2008.
- Some data provided do not correspond to the battery sub-key selected: they represent the composition of batteries with limited use, or even prototypes.
- Some data are not based on the same reference perimeter of the analysis: for example analysis of the composition of a component (like the electrode) or a part of the battery (such as "battery without can"). This information requires an assessment of the weight percentage of this component per battery and as it is not always supplied, it reduces the data comparability.
- Finally, some data are unreliable due to quality issues or incorrect analytical methodologies:
  - Incorrect preparation of the sample (presence of electrolyte in the material analysis of electrodes);
  - Analysis of traces and impurities, not representative for the product;
  - Graphite not identified or differentiated from other types of carbon; and
  - Incoherent values (unrepresentative samples or incorrect analysis)

The verification of the approach for battLiCoO2 is illustrated in Figure 5, which shows the estimated confidence intervals for the ProSUM data as well as the independent measurements (Lain 2001, Shin et al. 2005, Fisher et al. 2006, Broussely and Pistoia 2007, Li et al. 2009, Kang et al. 2010, Petrániková et al. 2011, Georgi-Maschler et al. 2012, Nogueira and Margarido 2012). The representative calculated value for the Li content is 2.5%, with a 90% confidence interval of 1.2-3.8%. The average of the 8 analyses identified is 2.4%, with a standard deviation of 0.6%.

This verification shows an excellent fit for the average value and the calculated value. Assuming a normal distribution, 95% of measurements are expected to lie within two standard deviations from the mean, i.e. between 1.2% and 3.6%, which again fits with the estimated confidence interval for the representative composition. The verification confirms the appropriateness of the approach, particularly in the majority of the cases where no statistical approach is possible.

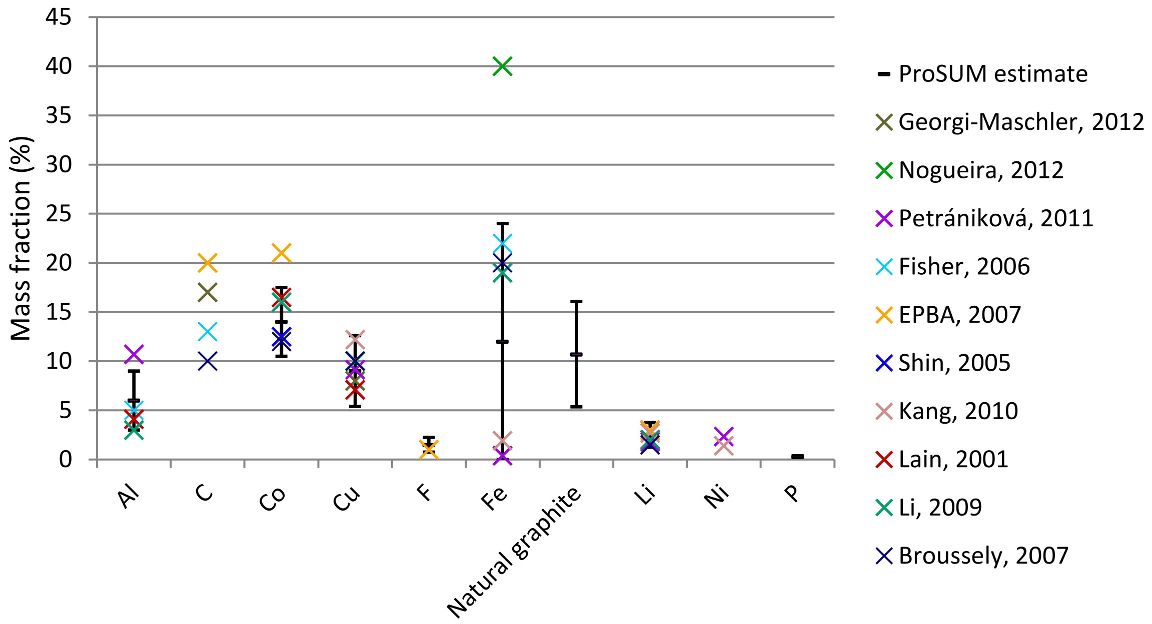


Figure 5 Estimated composition of battLiCoO2 and independent measurements.

The estimated representative compositions for batteries are presented in the following figures. Figure 6 shows the composition of lithium carbon mono-fluoride batteries. The lithium mass fraction in the cell is estimated to 5-9%.

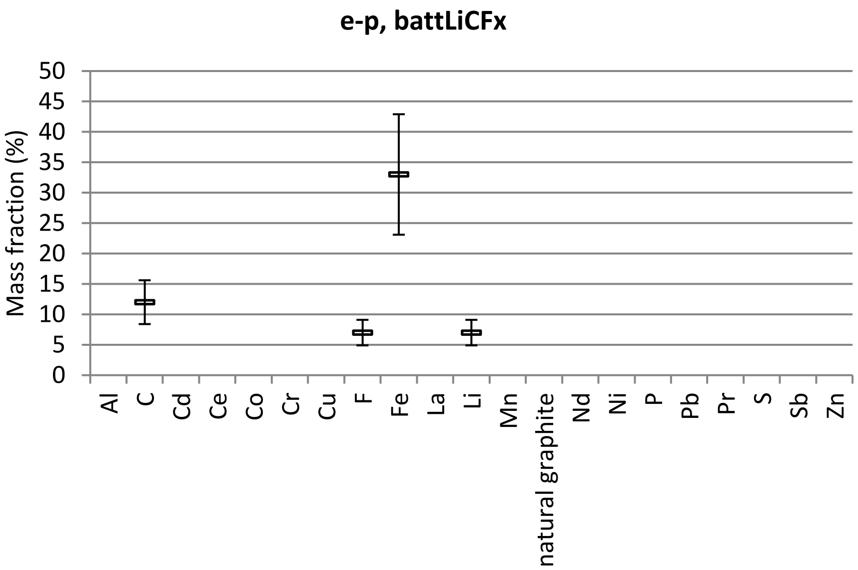


Figure 6 Estimated representative composition for LiCFx batteries.

Figure 7 Shows the estimated representative composition for lithium cobalt dioxide batteries. It contains around 2.5% Li and 14% Co by mass.

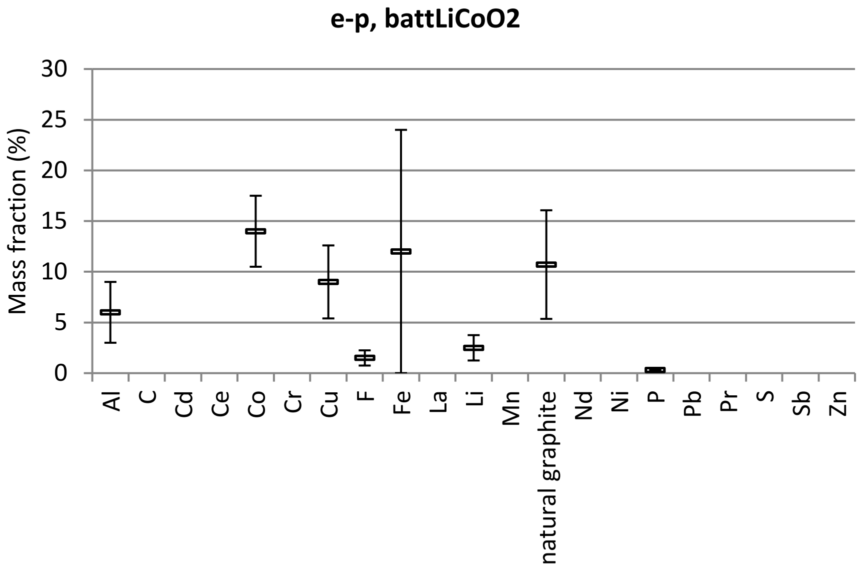


Figure 7 Estimated representative composition for LiCoO2 batteries.

Figure 8 shows the estimated representative composition of lithium iron phosphate batteries. The composition is similar to that of lithium cobalt dioxide batteries, without Co and with a reduced mass fraction of natural graphite.

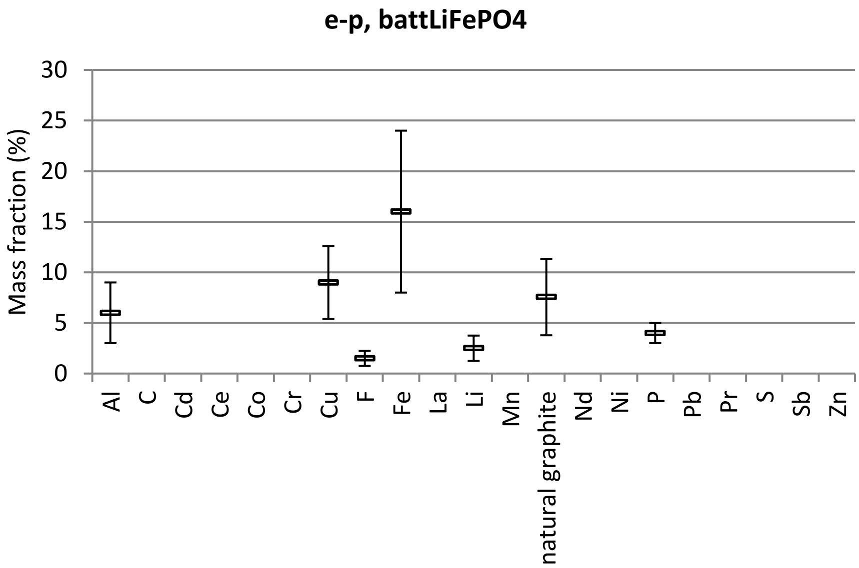


Figure 8 Estimated representative composition for LiFePO4 batteries.

Figure 9 shows the estimated representative composition of lithium manganese batteries. The composition is essentially the same as for lithium cobalt dioxide batteries, only with Co replaced by Mn (at a somewhat higher mass fraction).

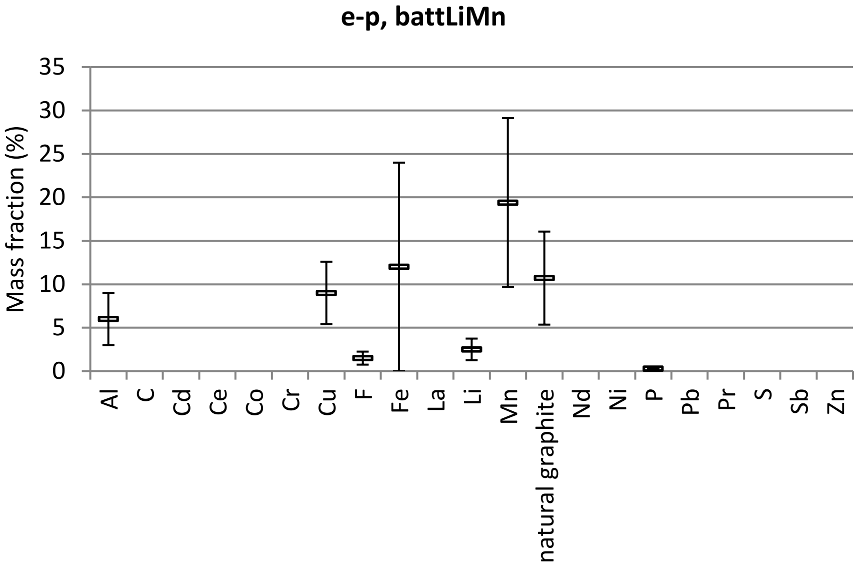


Figure 9 Estimated representative composition for LiMn batteries.

Figure 10 shows the estimated representative composition of lithium manganese dioxide batteries. The estimated lithium content is 2.5% of the mass, as for most other lithium batteries.

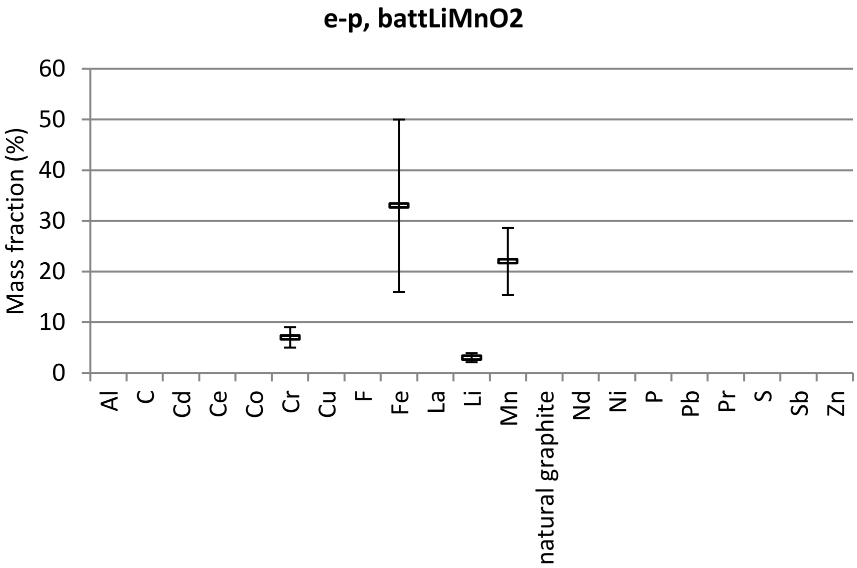


Figure 10 Estimated representative composition for LiMnO2 batteries.

Figure 11 shows the estimated representative composition of lithium nickel manganese cobalt batteries. The composition is largely the same as for lithium cobalt dioxide and lithium manganese batteries, only with a mixture of Ni, Co and Mn instead of only Co or Mn.

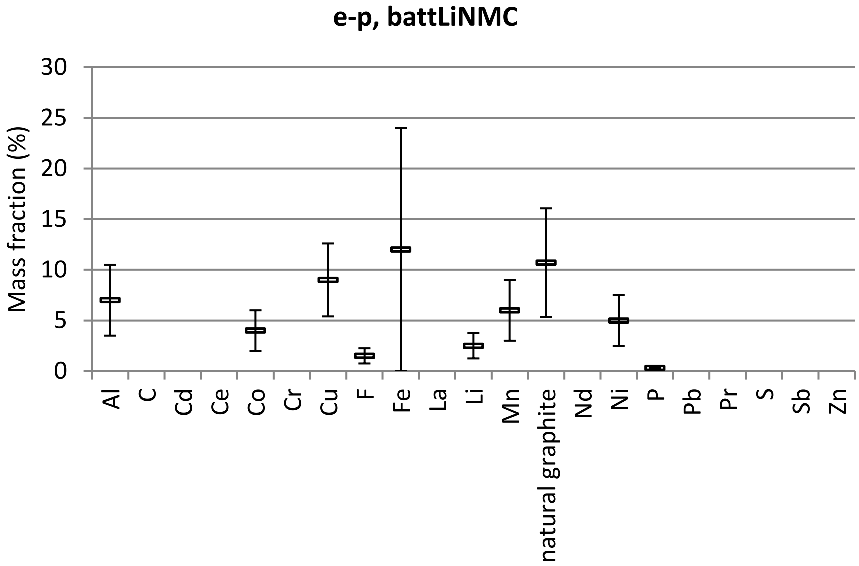


Figure 11 Estimated representative composition for LiNMC batteries.

Figure 12 shows the estimated representative composition of lithium sulphur dioxide batteries. The lithium content is estimated to 3% of the mass.

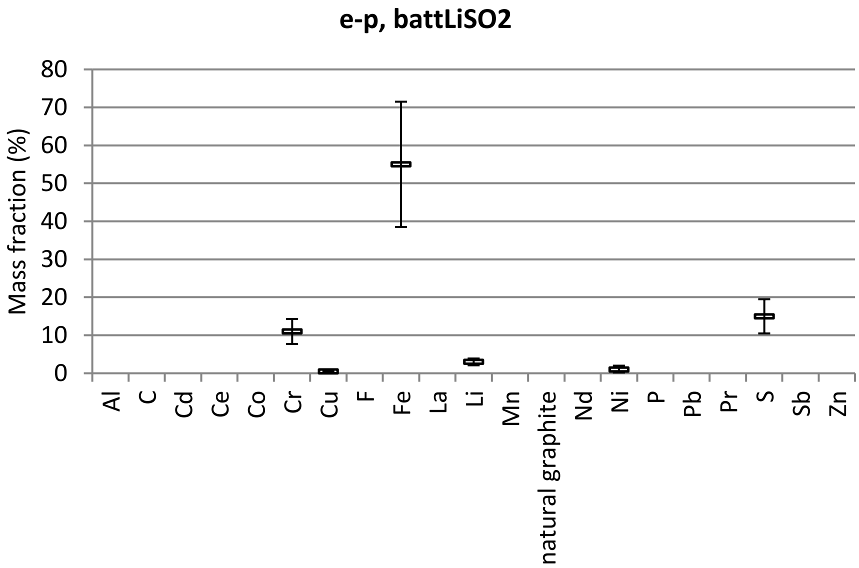


Figure 12 Estimated representative composition for LiSO2 batteries.

Figure 13 shows the estimated representative composition of lithium thionyl chloride batteries. The lithium content is estimated to around 4% of the mass.

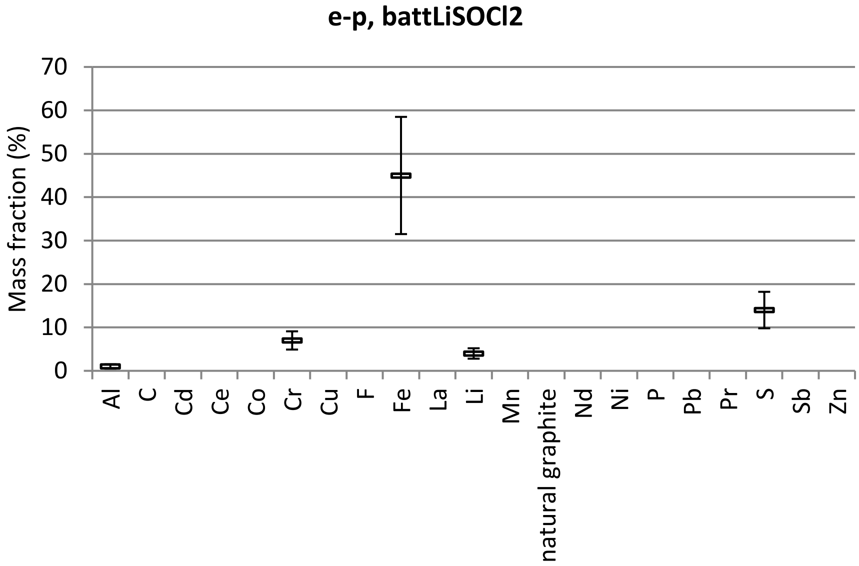


Figure 13 Estimated representative composition for LiSOCl2 batteries.

Figure 14 and Figure 15 show the estimated representative composition of sealed and vented nickel cadmium batteries respectively. The main constituents are Cd, Fe, Ni and Cr, all with higher mass fractions in the sealed type.

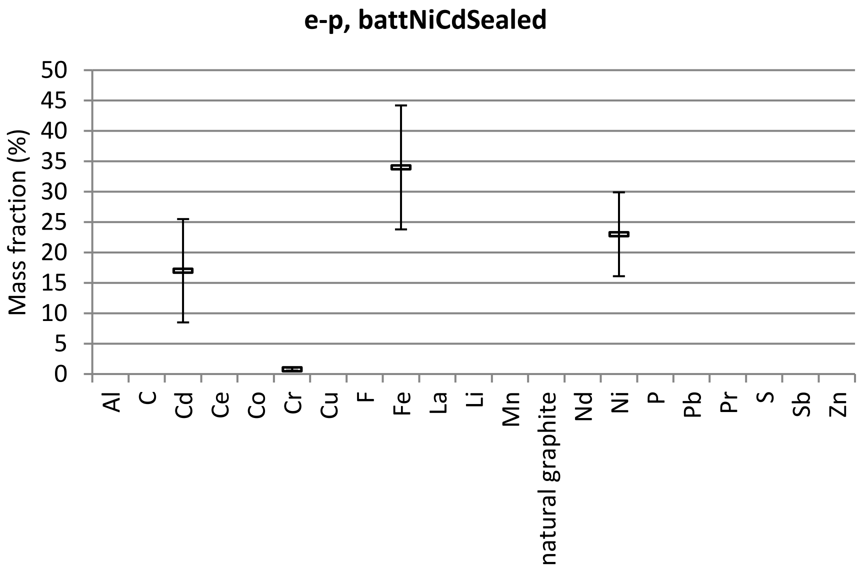


Figure 14 Estimated representative composition for sealed NiCd batteries.

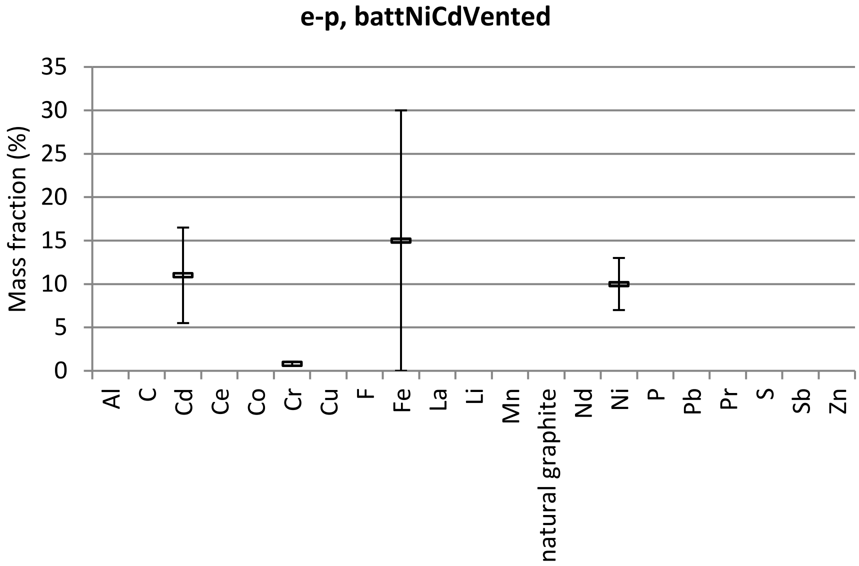


Figure 15 Estimated representative compositions for vented NiCd batteries.

Figure 16 and Figure 17 show the estimated representative composition of sealed and vented nickel metal hydride batteries respectively. These batteries contain a larger number of CRM, due to the use of rare earths. Only Ce, La, Nd and Pr are included here, although it is known that other rare earths are also being used (substituting for each other).

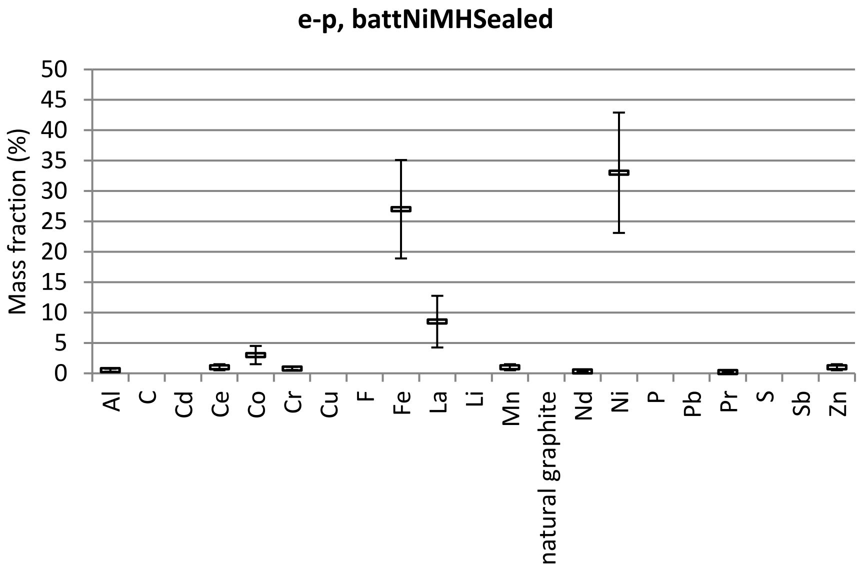


Figure 16 Estimated representative composition for sealed NiNH batteries

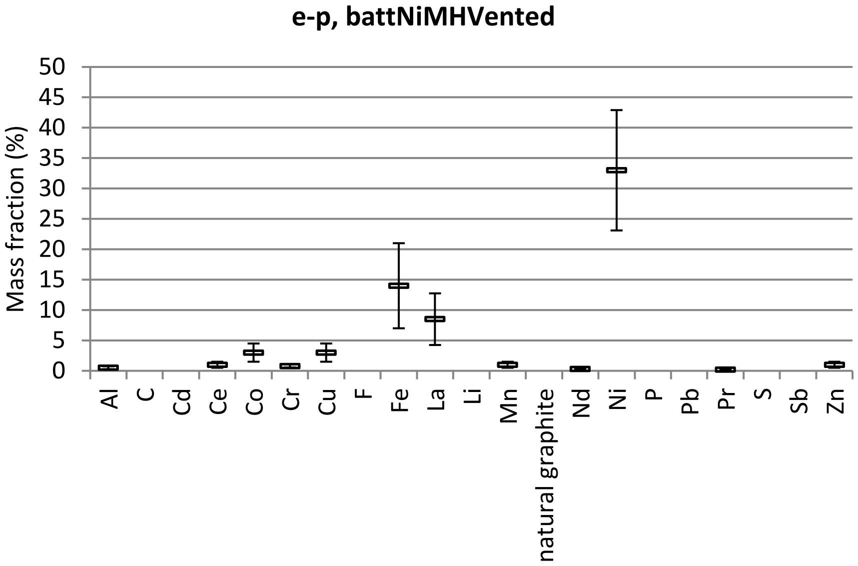


Figure 17 Estimated representative composition for vented NiMH batteries.

Figure 18 and Figure 19 show the estimated representative composition of sealed and vented lead-acid batteries respectively. The vented version is estimated to contain more Sb on average.

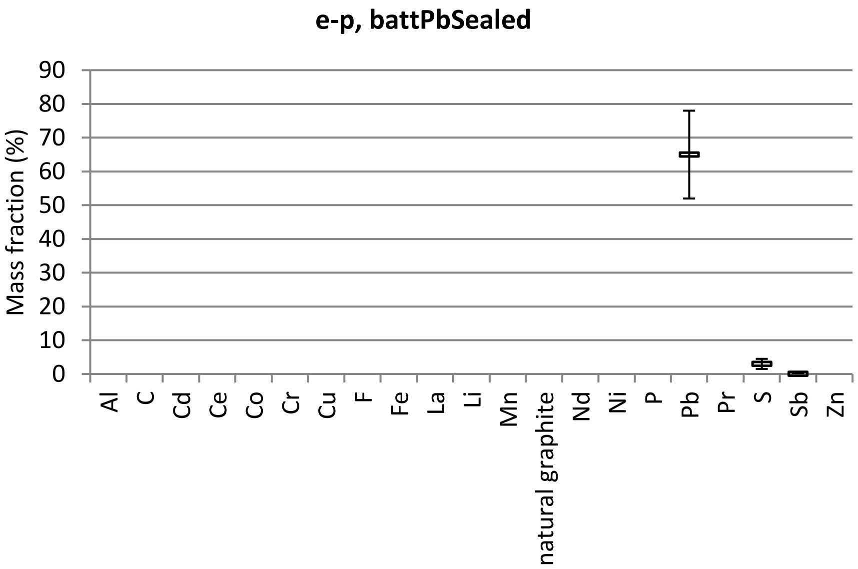


Figure 18 Estimated representative composition for sealed Pb batteries.

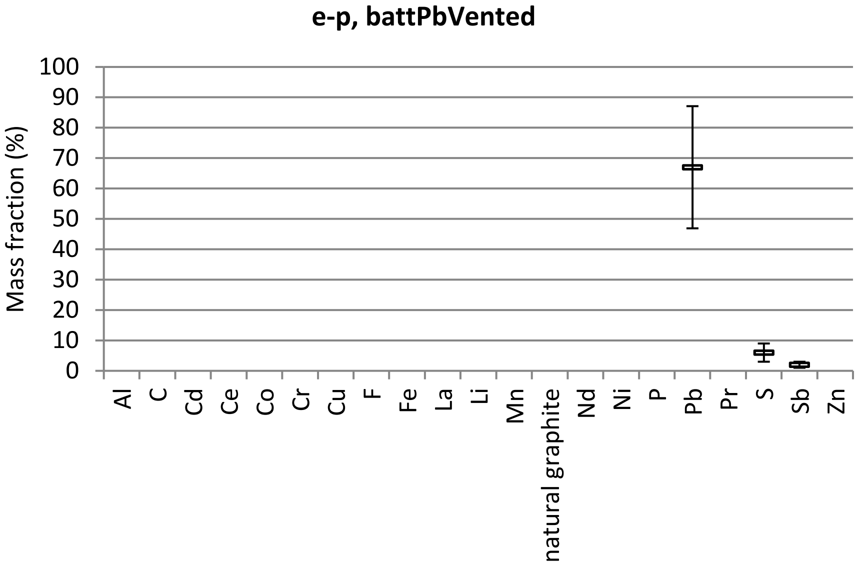


Figure 19 Estimated representative compositions for vented Pb batteries.

Figure 20 shows the estimated representative composition of zinc batteries, with Fe, Mn and Zn as the main constituents.

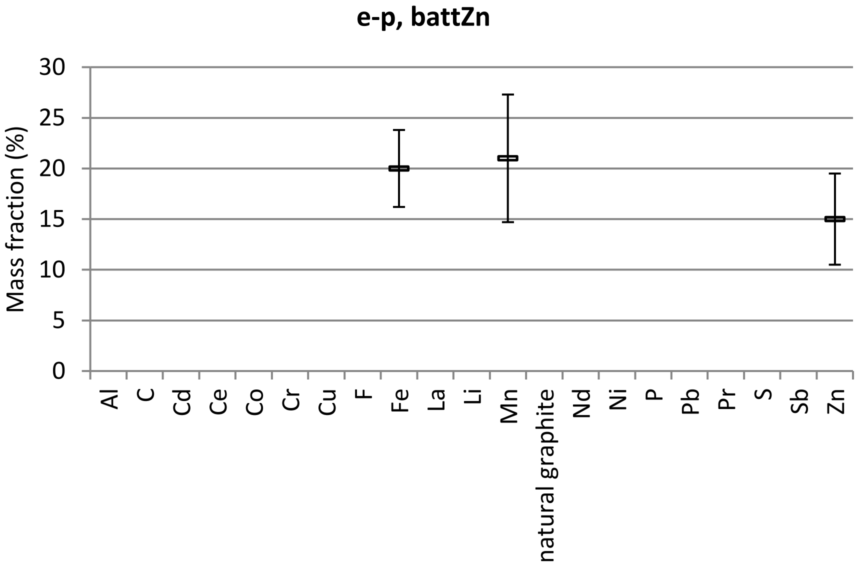


Figure 20 Estimated representative composition for Zn batteries.

3.2 Composition of EEE

In the following sub-chapters, the estimated representative composition for the three example EEE products are presented.

3.2.1 Microwave ovens (0114)

The following four figures show the estimated composition of microwave ovens as placed on the market in 2013. The main findings are:

- The composition is dominated by non-critical materials such as steel alloys, polymers, glass and aluminium (Figure 21);
- PCB and magnets give the main contribution for precious metals and CRM such as gold, silver, gallium, indium and neodymium (Figure 24);
- However, mass fractions of CRM and precious metals are very low, owing to the low content of permanent magnets and PCBs in the product and the relatively low content of precious metals and CRM in these. The high Sr content and low rare earth content in magnets indicate that permanent magnets in microwave ovens are usually ferrite magnets without rare earth alloys.

The main limitations and uncertainties of the estimates are related to the following:

- Raw data originate from end-of-life products sampled between 2011 and 2014, and recent changes in technology have therefore not been taken into account. The exception here is the mass fraction of PCBs, which is assumed to have declined steadily along with an increasing size of microwave ovens. It was assumed that the mass of the circuit boards remained the same.
- The mass fractions of elements in magnets and PCBs are uncertain, both due to a lack of recent data, and because the estimates mainly rely on one source with an unknown sample size and unknown measurement method.

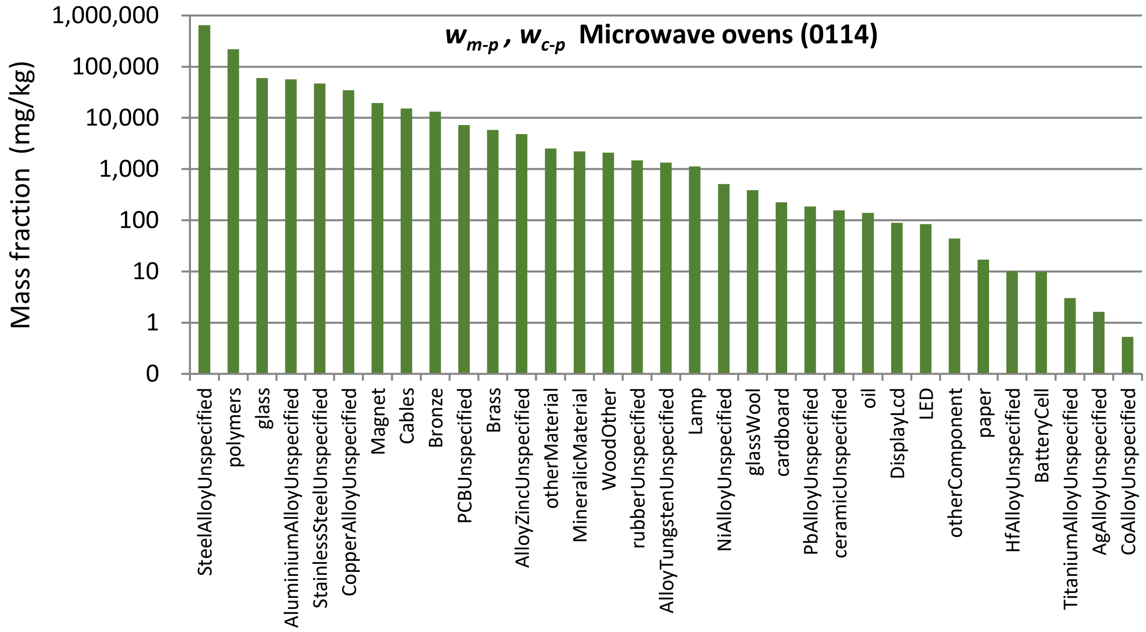


Figure 21 Estimated mass fraction of materials and components in microwave ovens as placed on the market in 2013. (m-p, c-p)

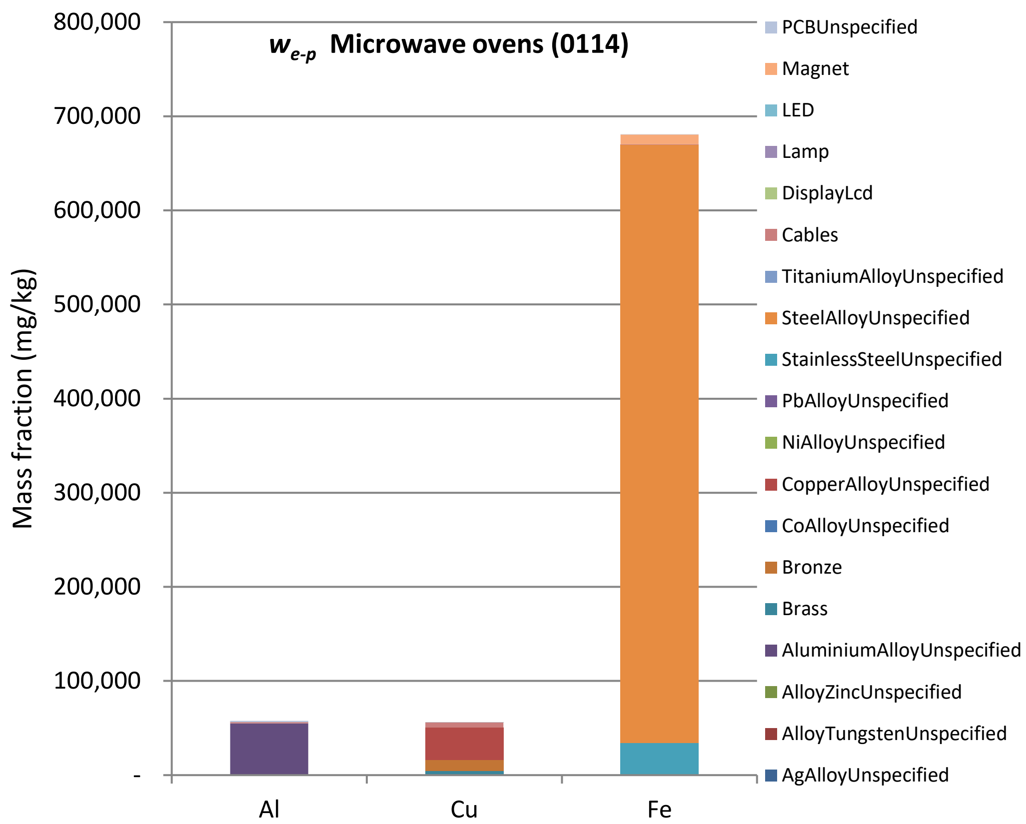


Figure 22 Estimated mass fraction of top 3 elements in microwave ovens. Coloured areas show contribution from different materials and components (e-c,e-p).

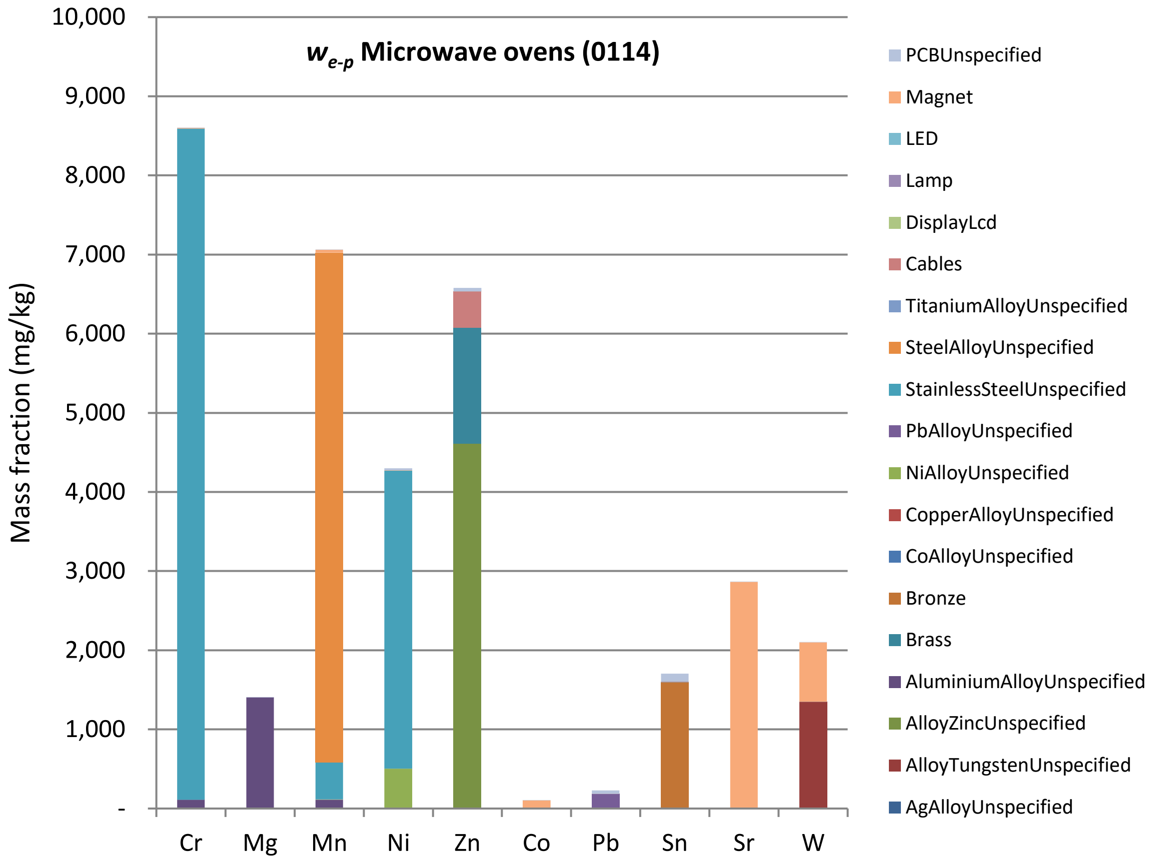


Figure 23 Estimated mass fractions of elements in microwave ovens (4th to 14th highest mass fractions). Colours show contribution from different materials and components (e-c,e-p).

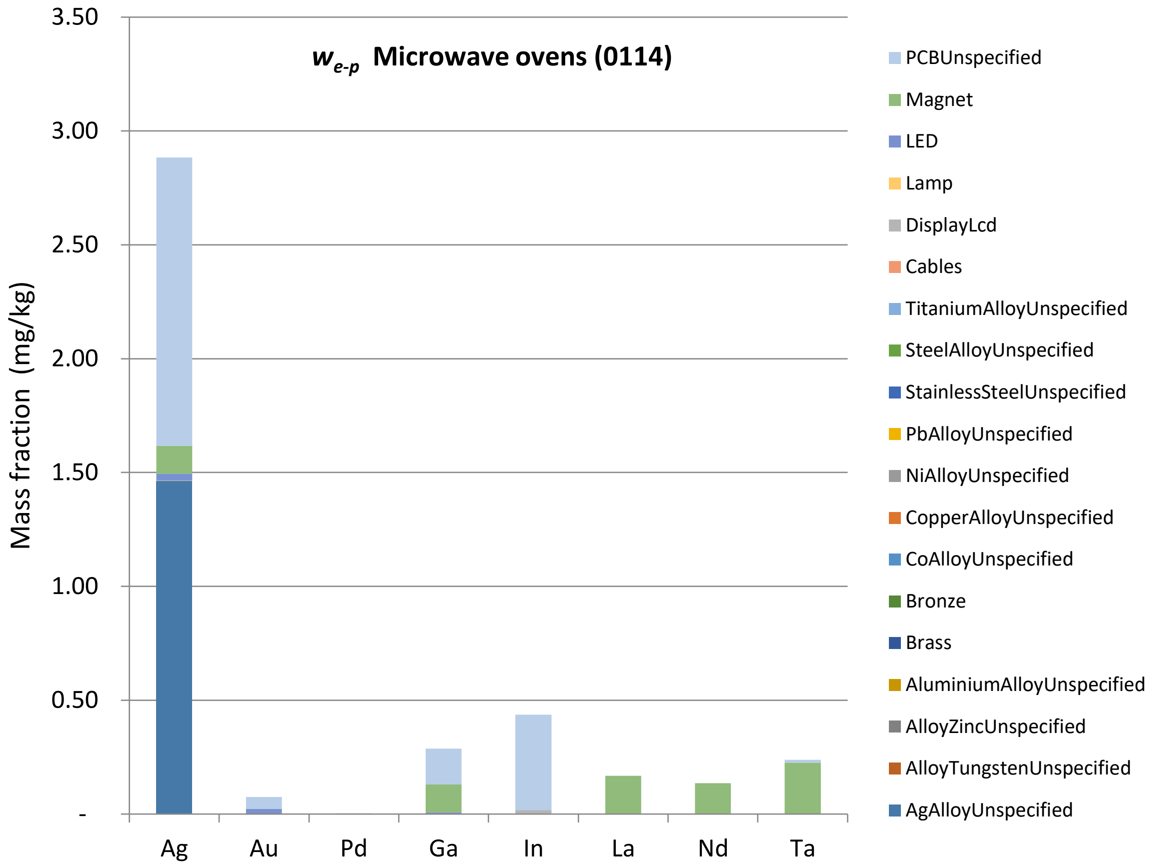


Figure 24 Estimated mass fractions of minor elements in microwave ovens. Colours show contribution from different materials and components (e-c, e-p).

3.2.2 Tablets (030302)

The following four figures show the estimated composition of tablets placed on the market between 2010 - 2013. The main findings are:

- The composition is dominated by CRM carrying components such as LCD displays (In), printed circuit boards (Ta, and other), and batteries (e.g. Co in $LiCoO_2$)
- Further major non-critical materials are polymers, ferrous metals, aluminum, and glass (see Figure 25)
- Figure 26 and Figure 27 show the elements with highest mass fraction present in tablets. These estimated mass fractions relate to the chemical composition of single investigated components and materials. Not all components and materials were chemically analyzed. Thus, the chemical composition depicted here is not complete for all elements.
- This applies to Figure 28 and Figure 29 as well, which depict minor metals such as precious metals, further CRM, and contaminants. With precious metals Ag and Au, the CRMs In, Ta, and Co represent the highest mass fractions among minor constituents.
- Among minor constituents, arsenic has one of the highest mass fractions. This is due to its application in the heatsink and the LCD panel glass.
- Mass fractions of CRMs and precious metals are low. Compared to other electronic devices, tablets in particular have noticeable low contents of CRMs and precious metals although carrying high shares of printed circuit boards, LCD panels, and batteries.

The main limitations and uncertainties of the estimates are related to the following:

- Raw data originate from end-of-life products manufactured from 2000 on, but mostly between 2010 and 2013. A time trend is noticeable for the overall product mass, but not for single applied elements. A fundamental change in technology within the investigated years is not expected.

- e-p data originates from chemical characterization of single dismantled components and materials.
    - This approach provides a very detailed level of information
    - Various analytical methods were used. Uncertainties related to the measurement method used is expressed with the data quality
    - Elements can be traced back to the host material or component
    - Not all materials and components have been chemically analyzed. Thus, the e-p data is not complete. The estimated e-p data relates to the investigated materials only and should therefore be used carefully

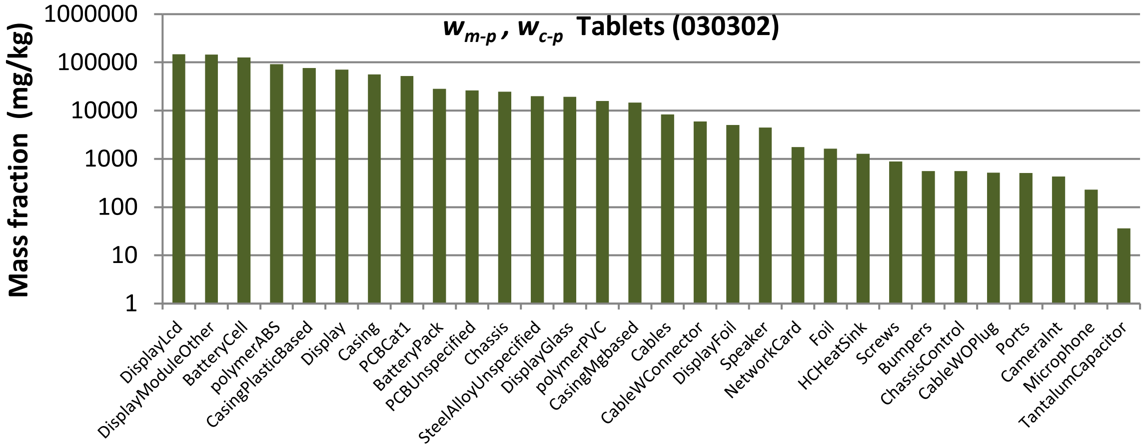


Figure 25 Estimated mass fraction of materials and components in tablets as placed on the market in 2010 – 2013

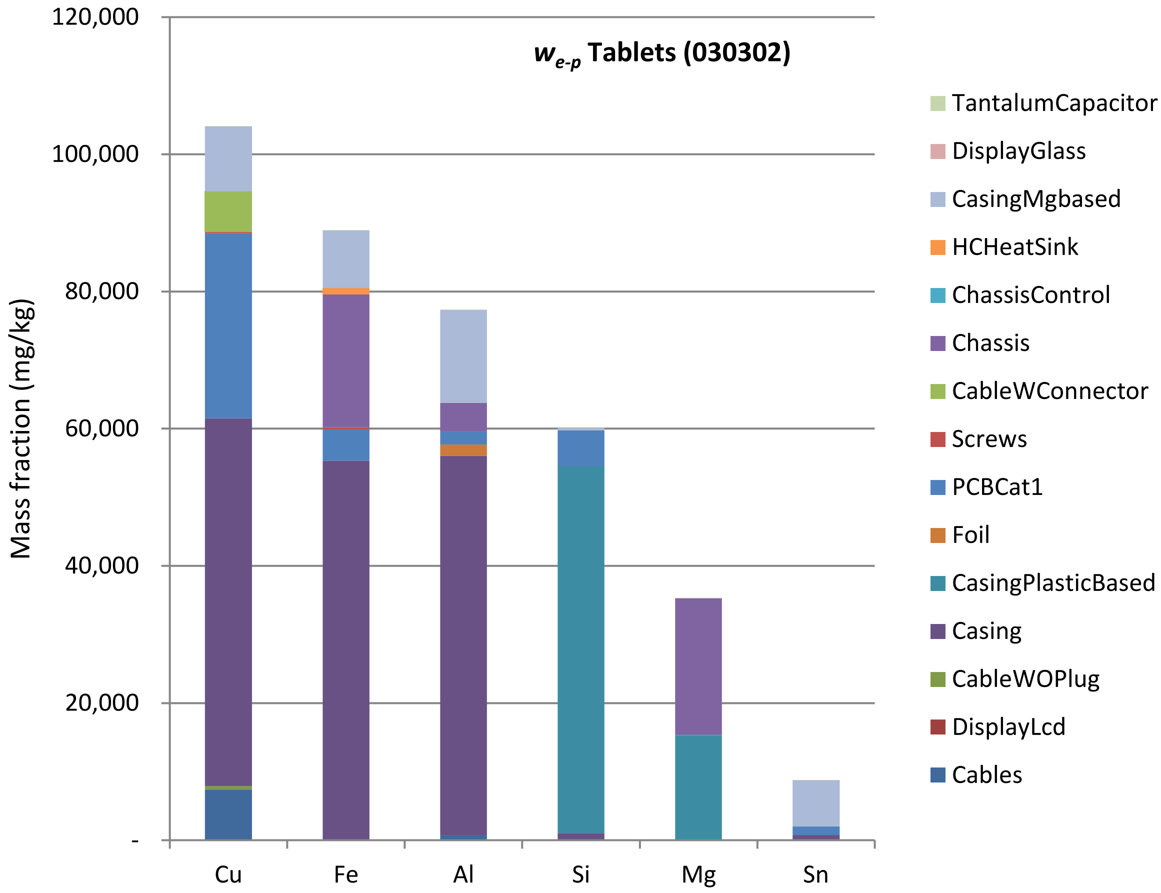


Figure 26 Estimated mass fraction of top 5 elements in tablets based on available elemental composition. Coloured areas show contribution from different materials and components.

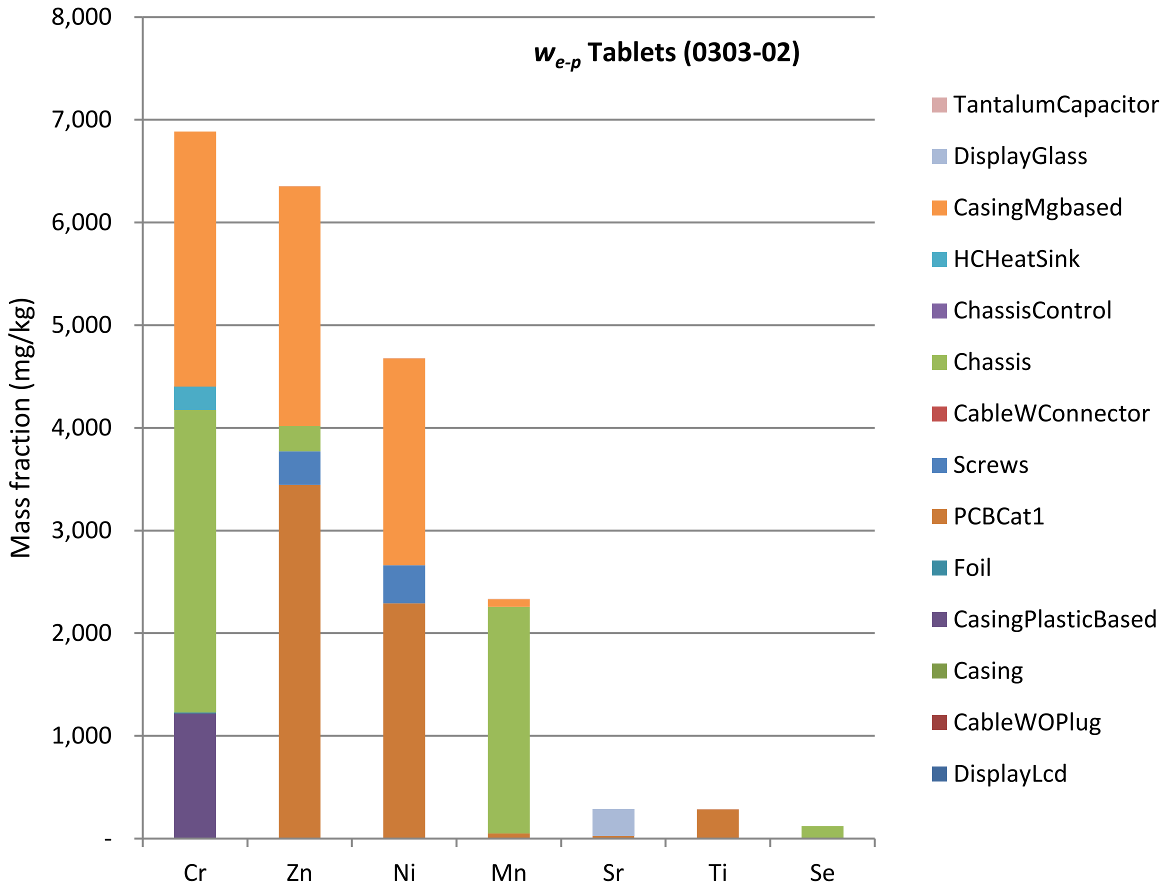


Figure 27 Estimated mass fractions of elements in tablets (7th to 13th highest mass fractions) based on available elemental composition. Colours show contribution from different materials and components.

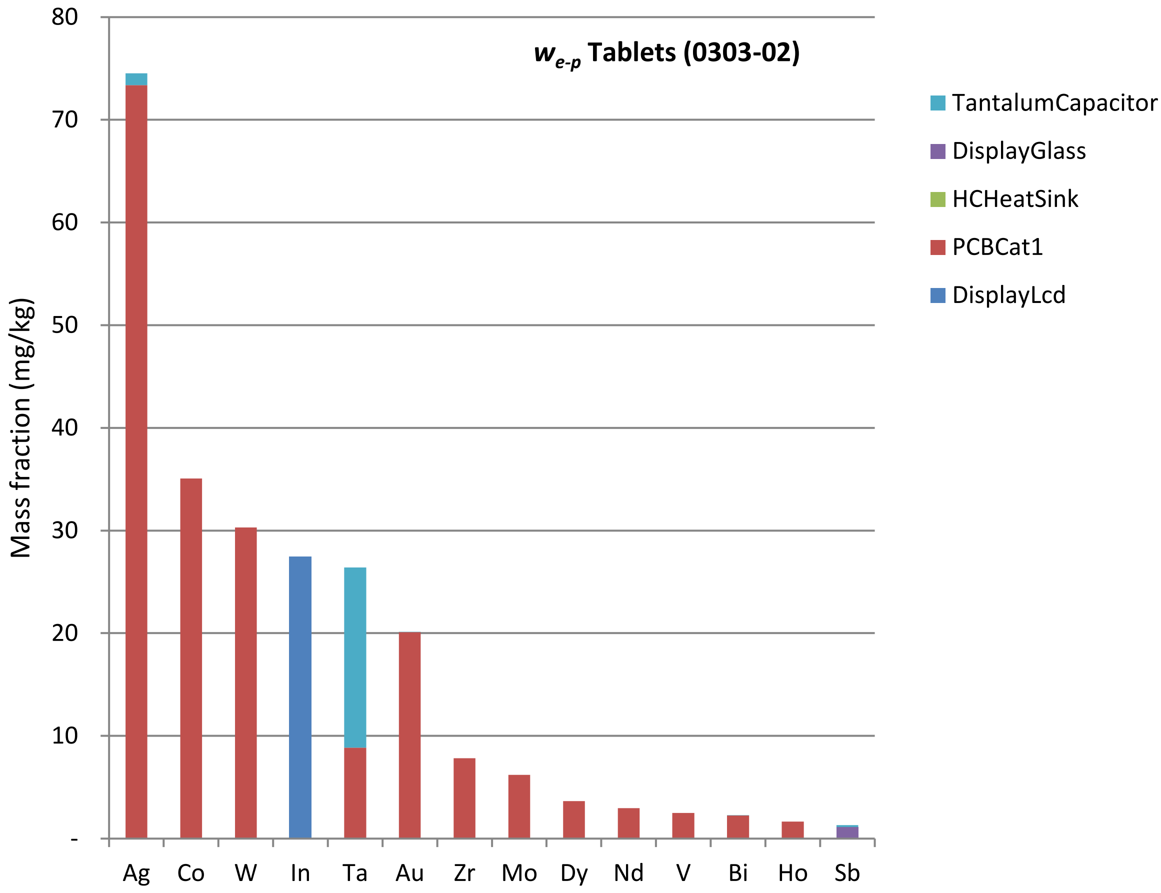


Figure 28 Estimated mass fractions of minor elements between 1.2 and 80 ppm in tablets based on available elemental composition. Colours show contribution from different materials and components.

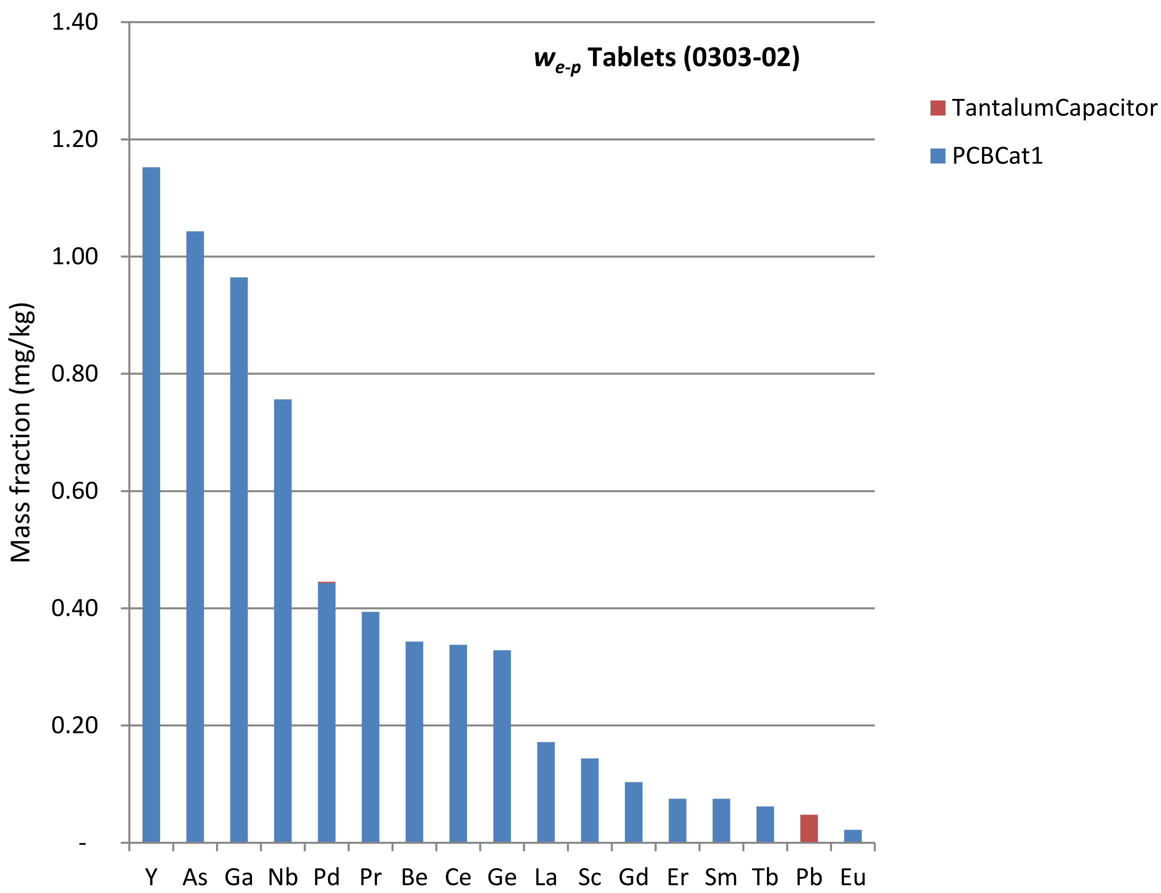


Figure 29 Estimated mass fractions of minor elements up to 1.2 ppm in tablets based on available elemental composition. Colours show contribution from different materials and components.

3.2.3 Flat panel display TVs (0408)

The following four figures show the estimated composition of flat panel display TVs as placed on the market in 2000, The main findings are:

- As seen in Figure 30 the composition of flat panel display TVs is dominated by steel alloys, plasma display, PCBs and glass.
- From the mass fraction contribution, the three main elements found in flat display panel TVs are aluminium, copper and iron (Figure 31).
- PCB and magnets found in flat panel display TVs give the main contribution for precious metals and CRM such as gold, silver, palladium, indium, gallium and neodymium (Figure 33).
- It can be said that the mass fractions of CRM and precious metals found in flat panel display TVs are substantial, mainly due to the liquid crystal display (LCD) itself and the amount of PCB found in the product

The main limitations and uncertainties of the estimates are related to the following:

- Raw data originate from end-of-life products sampled between 2011 and 2014, and recent changes in technology have therefore not been taken into account with the exception of the mass fraction of PCB. It is assumed that the PCB mass fraction declined due to market trend for increased product mass.
- It was assumed that the median residence time is 9 years, equivalent to 4 years average disposal age for flat panel display TVs observed in the return stream.

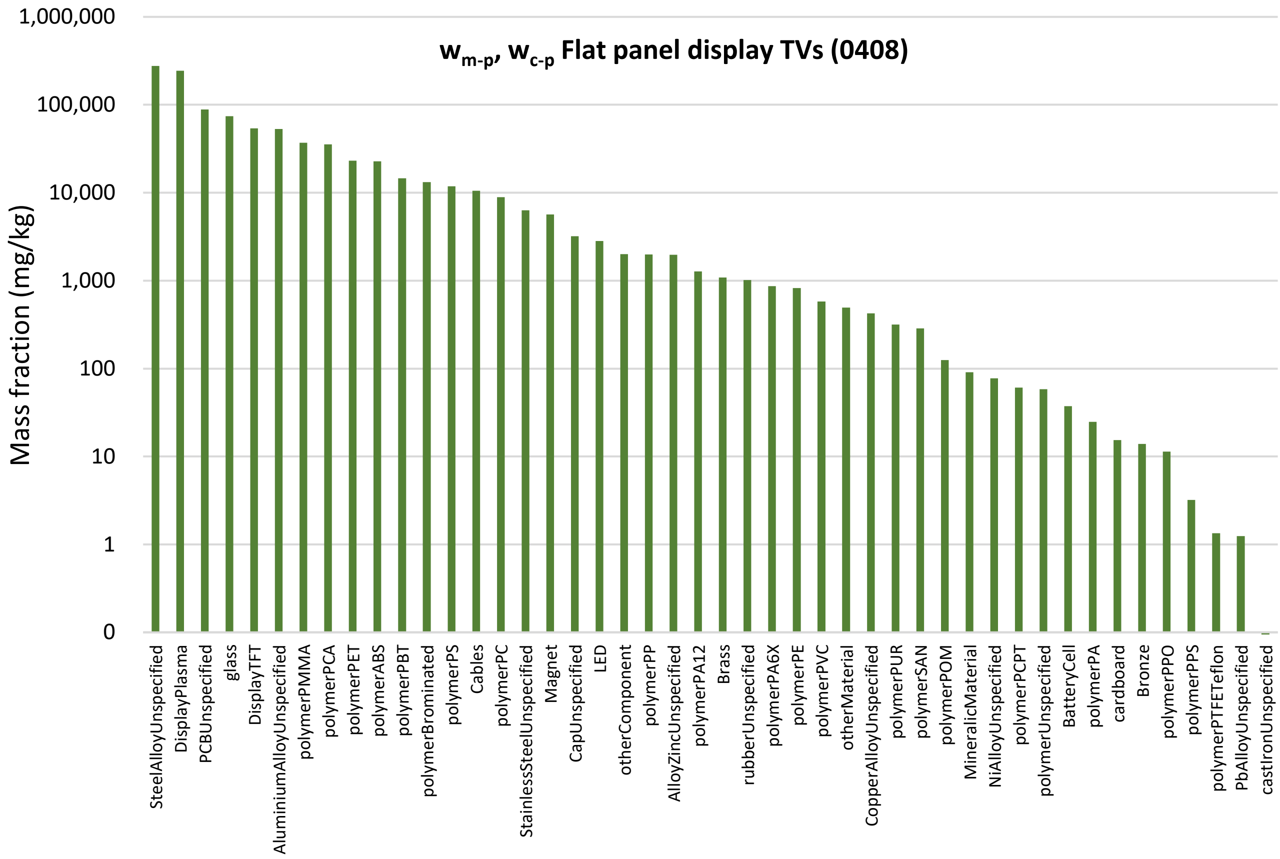


Figure 30 Estimated mass fraction of materials and components in flat panel display TVs as placed on the market in 2000.

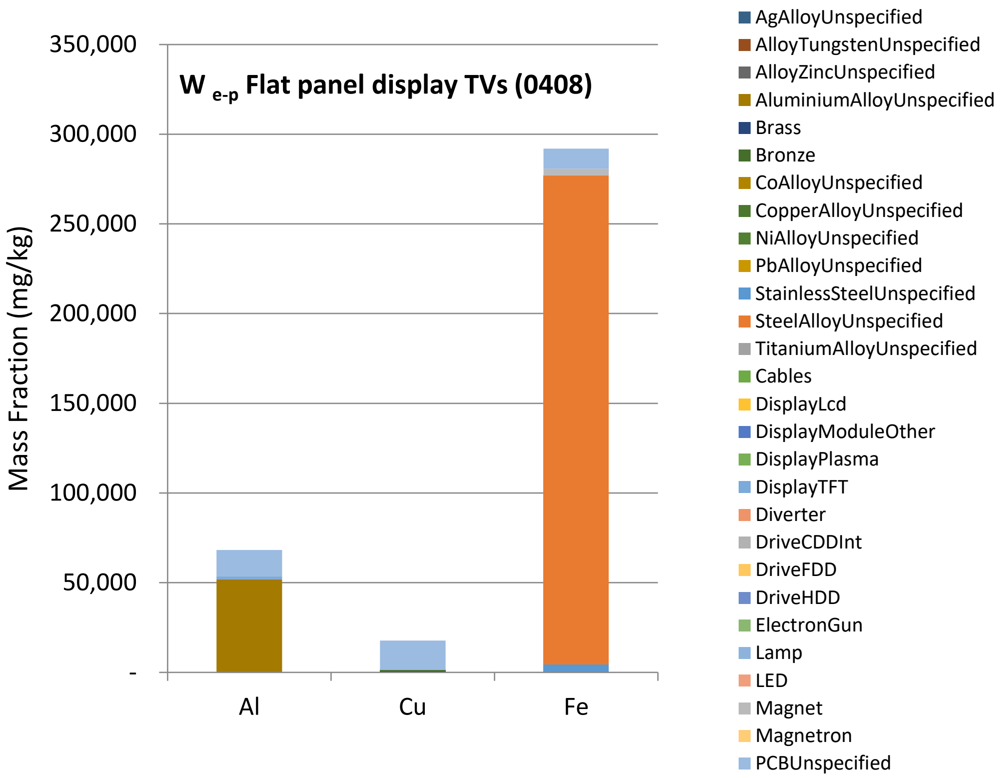


Figure 31 Estimated mass fraction of top 3 elements in Flat panel display TVs. Coloured areas show contribution from different materials and components.

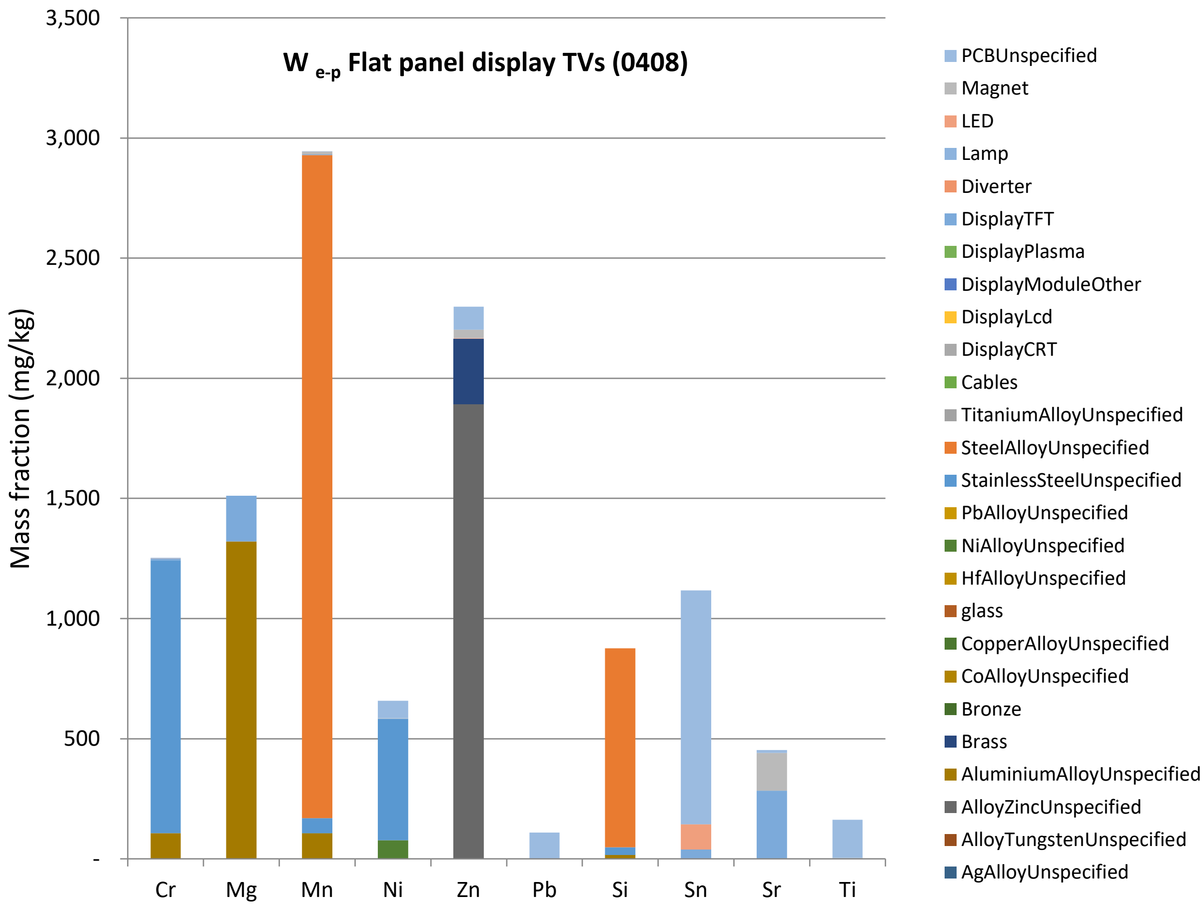


Figure 32 Estimated mass fractions of elements in flat panel display TVs (4th to 14th highest mass fractions). Colours show contribution from different materials and components.

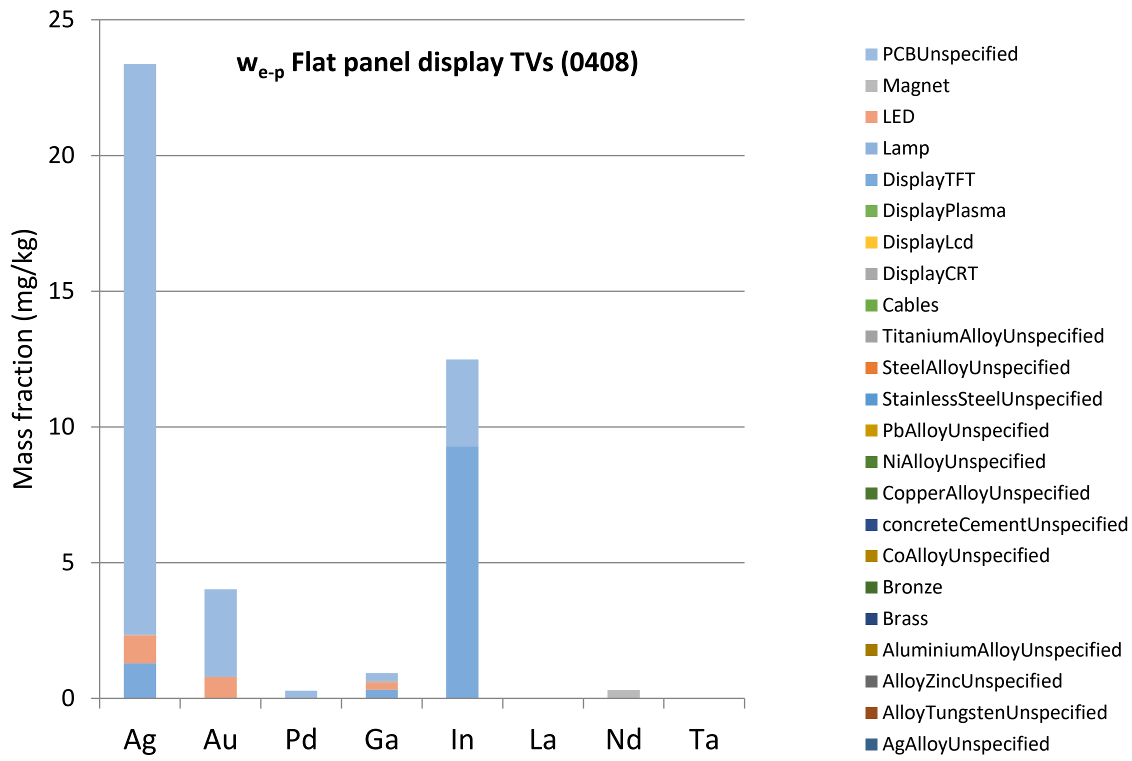


Figure 33 Estimated mass fractions of minor elements in flat panel display TVs. Colours show contribution from different materials and components.

3.3 Composition of vehicles

The estimated compositions for vehicles are considered the best possible estimate given the available data. All data are provided on an individual vehicle key level due to the structure of the data model developed for the EU-UMKDP within WP5. However, this does not necessarily mean that the data are accurate at the individual key level. Rather, the aim was to produce a dataset that will give the best possible representation of the overall fleet in each member state. In Figure 34 to Figure 39, some of the key parameters and their estimated values are presented. Figure 35 to Figure 39 contain examples of parameters where a distinction was made for certain vehicle properties. For example, the estimated mass of platinum group metals (PGM) per catalytic converter is shown for the motor energy types petrol and diesel vehicles, and for different engine displacement ranges, but the different mass ranges are not shown because no distinction was made here.

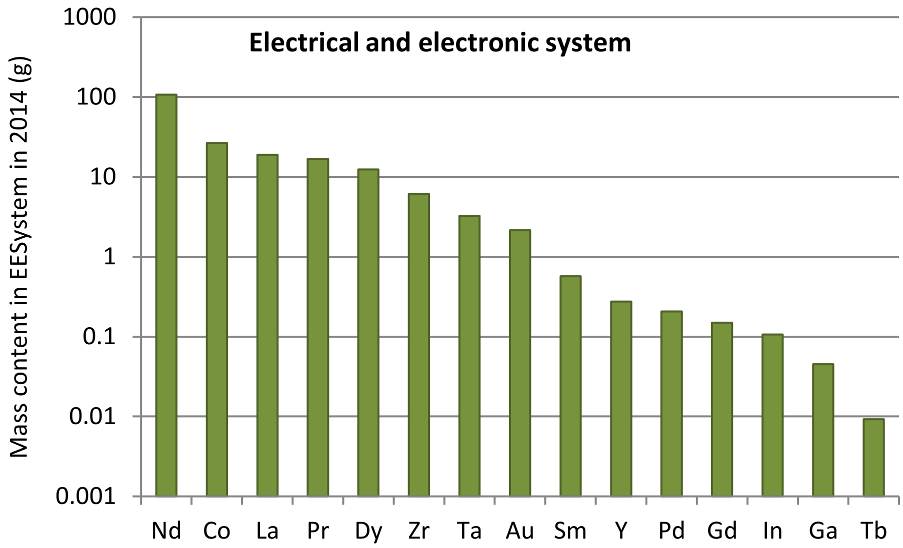


Figure 34 Estimated mass of selected elements in all electrical and electronic and electronic components in vehicles POM in 2014. Note that Au, Co, Dy, La, Nd and Pd are assumed to vary over time.

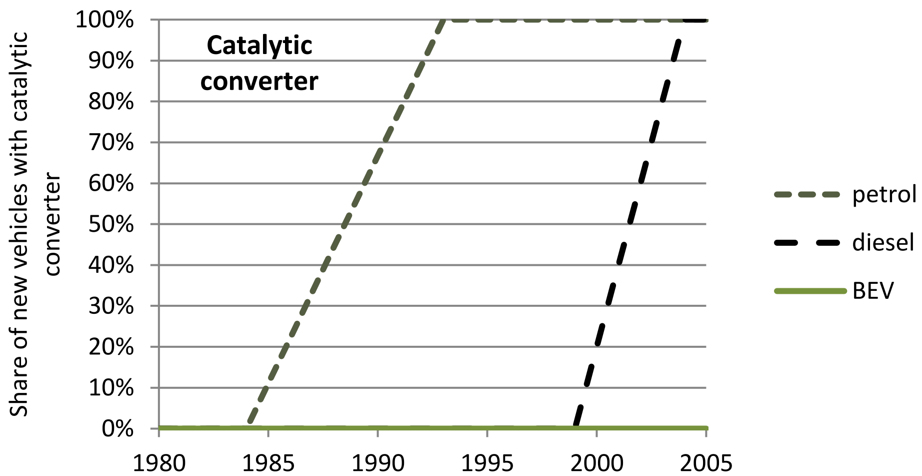


Figure 35 Estimated share of vehicles POM with a catalytic converter over time and for different motor energy types.

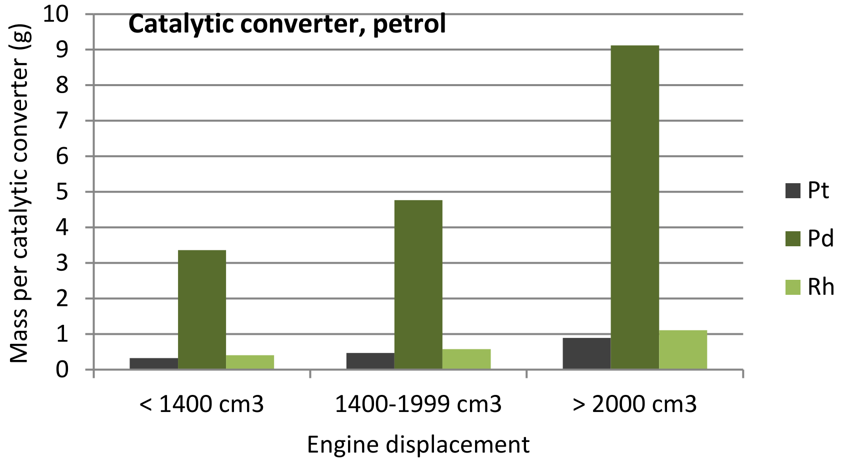


Figure 36 Estimated mass of platinum group metals per catalytic converter for the motor energy type petrol.

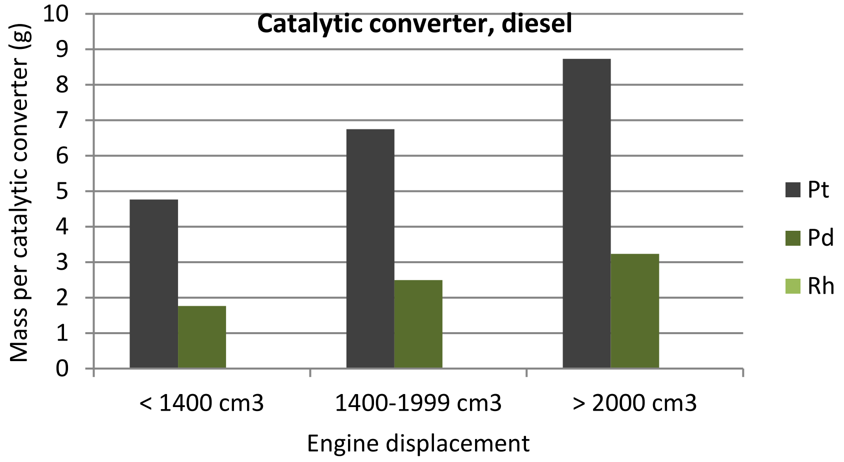


Figure 37 Estimated mass of platinum group metals per catalytic converter for the motor energy type diesel.

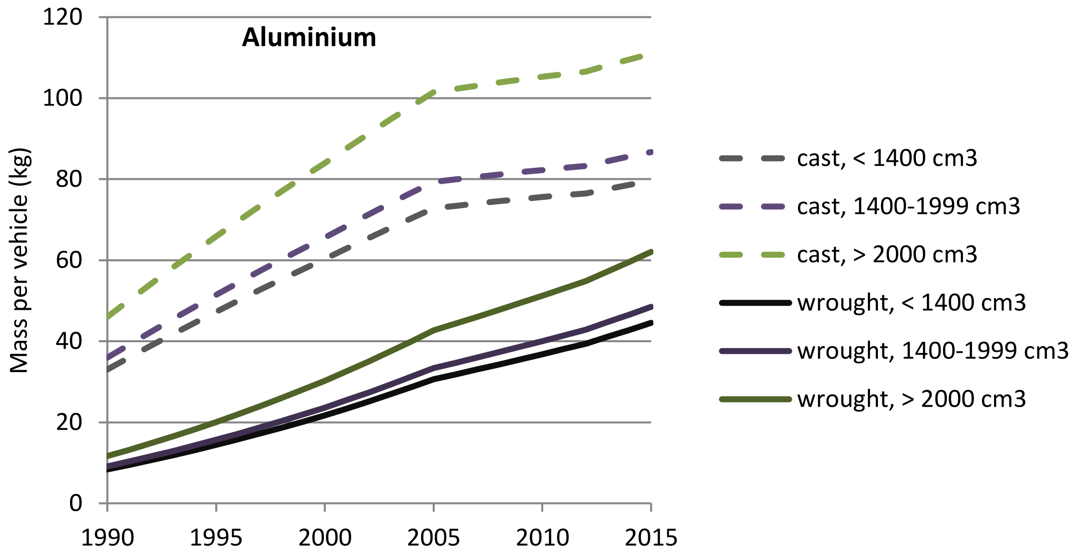


Figure 38 Estimated mass of cast and wrought aluminium per vehicle POM market over time and for different engine displacement ranges.

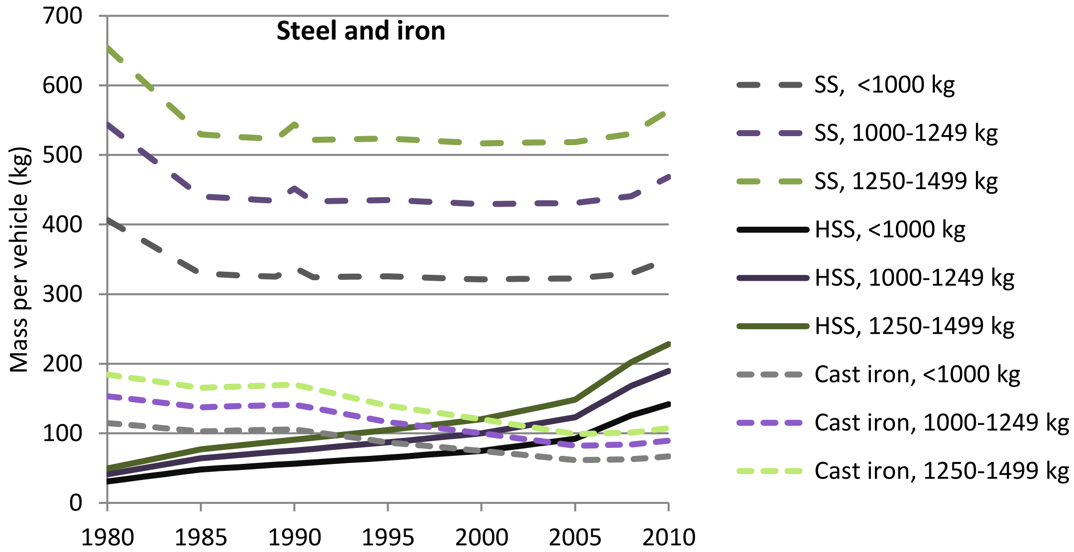


Figure 39 Estimated mass of standard steel (SS), high strength steel (HSS) and cast iron per vehicle POM over time and for different vehicle weight ranges.

4 Conclusions

Data from more than 300 sources were collected, put into a structured format, evaluated and consolidated in order to estimate the average composition of batteries, EEE and passenger vehicles put on the market. The work resulted in three project datasets of raw data (one for each product category) for internal use, as well as three datasets of estimated average product compositions to be harvested and uploaded to the ProSUM diffusion database. The three project datasets of raw data and the two average composition datasets for vehicles and batteries are complete. Due to the large number of data and complexity of the product category, the final consolidation for EEE is still ongoing, and will be completed by the end of April 2017.

The resulting datasets embody the current state of knowledge on product composition with respect to CRM, and are, to our knowledge, the most comprehensive of their kind to date. That being said, the datasets rely on published information, which in some cases is too scarce to make reliable estimates of relevant parameters. In general, the most important gaps are related to changes over time and elements that occur at very low mass fractions in the product/component e.g. Eu, Ga, Ge, Sm.

Meta data describing all sources used for this and the adjacent deliverables D3.3 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

A summary of the most important findings and limitations follows for each of the product categories.

4.1 Batteries

The provided dataset will be used as representative batteries composition data for the ProSUM diffusion database. Although the method used requires a good knowledge of the battery technologies placed on the market, it achieved more complete information about the elemental analysis of batteries, more precise than statistical analysis would have provided (often impossible because of a lack of data). Nevertheless, further acquisition of measured data may allow for more statistical comparisons in the future.

The main limitations of the data are:

- Changes over time are not included: because of lack of traceability and conflict with proprietary information, changes in product composition within the defined battery sub-keys have not been taken into account. For example, it is well known that the mixture of rare earth metals used in NiMH batteries has changed over time with fluctuations in prices. Nevertheless, the most important change is the relative share of different technologies in the market, which is taken into account through the data and models of stocks and flows within ProSUM. Further work on future development of battery compositions will be undertaken within D2.4.
- Battery electronics are not included. Although these parts represent a rather small weight portion of the battery, sometimes negligible or not existing at all (in the case of small portable batteries), they may be significant for large industrial batteries.
- Certain minor elements are not included due to a lack of data: again, the elements used in the battery electronics are not specifically identified. The impact of this may be mitigated by the assessment of the battery electronic as a part of the equipment or vehicle in which the battery is used. This has been done for Ag in electric vehicles, where the battery electronics are considered part of the EE system in the vehicle.

Table 18 Summary of BATT composition results

What is available	What is missing/ data gaps	Comments
POM compositions for all BATT sub-keys in e-p format, representing the BATT cell. Compositions of waste BATT are assumed to be the same as compositions of POM BATT per BATT sub-key.	Reliable measurement of the variability of the composition within sub-keys. Battery electronics are not included Changes in composition over time.	The decisive factors for the development of the material composition of batteries are not changes of the composition of batteries with a specific electrochemical system, but market shifts from one electrochemical system to another.

4.2 EEE

Compared with batteries and vehicles, for EEE there is a large amount of both structured and unstructured data sources available. All EEE data is now well structured and harmonised. The most important achievement at this stage is that the evaluation, filtering and complementing of all data is completed. For three UNU keys, the data consolidation procedure including the handling of data gaps, data quality description and uncertainty approach has been demonstrated successfully. The result is three readily available datasets available for WP5 for further programming and development of the portal. In addition, these consolidated datasets have also been aligned against product average weight and lifespan information from D3.3. In particular, data on the average product weight development over time has been used when describing the changing mass fraction of components in the product over time. In addition, the lifespan information from D3.3 has been used to compare measured composition data from the return streams with the original market input years.

Finally, the consolidated datasets are ready for connecting with the product count data at least for the official collection flow. In short the well-structured datasets allow multiplication with the p-f values derived for EEE in D4.2 and ultimately allow for e-f computations as illustrated in the adjacent D4.2 report.

This work will be continued and finalised in the same manner for all remaining UNU keys by the end of April 2017. This will enable data reconciliation with cross-sectoral comparisons until June 2017.

Table 19 Summary of EEE composition results

What is available	What is missing/ data gaps	Comments
WEEE composition data for 2012-2014 which can be reconciled with market input years. Data is available for all WEEE categories except for lamps. EEE market input composition data are available for certain UNU keys from more recent literature sources (IT products and screens) and for lamps and some other UNU keys from “Ecodesign” studies.	Lamps data Detailed composition on the trends in absolute and relative weight of certain key components e.g. printed circuit boards For some UNU keys, there is no recent bill of materials data available. For many UNU keys, the construction of full time series composition is not possible or relies on assumptions.	In D2.4 a further attempt will be done to describe the trends over time of critical components. Especially for newer types of products, hardly any information will be available for very recent components like sensors, embedded electronics, lighting etc.

4.3 Vehicles

A best estimate for the content of components, materials and elements in vehicles was obtained from the limited number of data available. A total of 28 references were used in the parameter estimation. Only 8 of these focus explicitly on a larger set of critical raw materials in vehicles, while the rest concern single materials, components or elements. In general, the data situation for CRM in vehicles is poor compared to other product categories, likely owing to the complexity of the product and the consequent lack of practically implementable sampling and measurement methods. A large number of data exist among vehicle and parts manufacturers, but these are generally confidential.

The main limitations of the data are:

- Lack of data on individual components. Due to the different level of detail and classification of components, an aggregation of most components of interest into one group (electrical and electronic system) was necessary to enable comparison and averaging between different studies.
- Lack of temporal data. Changes over time were included in some cases, but for most parameters the data were insufficient. Especially for the electrical and electronic system, changes over time are believed to be very important, but could only be estimated for 7 elements.

Uncertainties were estimated as high for most of the parameters due to:

- Small number of studies
- Lack of representativeness. Studies with producer data for CRM only consider individual vehicles from a single manufacturer.
- Lack of appropriate sampling and measurement techniques. Studies based on sampling and measurement of ELVs lack appropriate techniques for representative sampling of a highly complex waste stream when the goal is to measure elements with very low mass fractions.

For the most uncertain parameters (e.g. Ta content in electrical and electronic system), individual observations vary by 1-2 orders of magnitude.

Table 20 Summary of vehicle composition results

What is available	What is missing/ data gaps	Comments
Composition data from case studies based on producer data as well as some sampling studies on ELVs. Representative compositions have been estimated, including the base metals as well as the most commonly occurring scarce/critical metals. The following components and materials are included: catalytic converter, electric and electronic system (as 1 component), battery, standard steel, high strength steel, cast iron, cast aluminium, wrought aluminium, magnesium alloy.	Lack of data on individual components in electrical and electronic system (raw data exist, but cannot be consolidated due to difficulty of comparison between various sources). Lack of temporal data. Changes over time were only included in selected cases where data were available (e.g. catalytic converter).	Uncertainties are in general high due to a small number of studies, small sample sizes, and lack of representativeness (focus on individual vehicle models)

4.4 Next steps

Future work will focus on finalising the datasets for EEE, supporting the harvesting of data, developing the mathematical models needed for calculating composition data and combining it with stocks and flows data, and defining procedures for uncertainty. Finally, in task 2.4 (D2.7), protocols for updating the composition data will be developed, based on the methods for data quality evaluation and uncertainties presented here.

5. References

Alonso, E., T. Wallington, A. Sherman, M. Everson, F. Field, R. Roth and R. Kirchain (2012). "An Assessment of the Rare Earth Element Content of Conventional and Electric Vehicles." SAE International Journal of Materials & Manufacturing, SAE International Journal of Materials & Manufacturing.

Andersson, M., M. Ljunggren Söderman and B. A. Sandén (2016). "Are scarce metals in cars functionally recycled?" Waste Management.

Auto-i-Dat AG (2015). "Autohandel Database." Auto-i-Dat AG.

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

AZOM (2001). "Grey Iron."

AZOM (2012). "ASTM A36 Mild/Low Carbon Steel." AZOM.

Böni, H., P. Wäger, E. Thiébaud, X. Du, R. Figi, O. Nagel, R. Bunge, A. Stäubli, A. Spörry, M. Wolfensberger-Malo, M. Brechbühler-Peskova and S. Grösser (2015). Rückgewinnung von kritischen Metallen aus Elektronikschrott am Beispiel von Indium und Neodym. CHE.

Broussely, M. and G. Pistoia (2007). "Industrial Applications of Batteries - From Cars to Aerospace and Energy Storage."

Burnham, A., M. Wang and Y. Wu (2006). "Development and Applications of GREET 2.7 - The Transportation Vehicle-Cycle Model." Energy Systems Division, Argonne National Laboratory.

Cullbrand, K. and O. Magnusson (2012). "The Use of Potentially Critical Materials in Passenger Cars." Chalmers University of Technology.

de Santiago, J., H. Bernhoff, B. Ekergård, S. Erikson, S. Ferhatovic, R. Waters and M. Leijon (2012). "Electrical Motor Drivelines in Commercial All-Electric Vehicles: A Review." IEEE Transactions on Vehicular Technology.

Ducker Worldwide (2012). "EAA Aluminium penetration in cars. Final report. Public version.", Ducker Worldwide.

Ducker Worldwide (2014). "2015 North American Light Vehicle Aluminum Content Study: Executive Summary."

Dynacast (2016). "AZ91D."

Eco-systèmes (2013). "PROGRAMME Eco-systèmes DT9 Flux PAM 2013." Eco-systèmes.

Eco-systèmes (2014). "DT9 2 CRM." Eco-systèmes.

Eco-systèmes (2014). "PROGRAMME Eco-systèmes DT9.1 Flux Ecrans Plats 2014." Eco-systèmes.

Eco-systèmes (2014). "PROGRAMME Eco-systèmes DT9.1 Flux GEM HF 2014." Eco-systèmes.

Eco-systèmes (2015). "Composition des complexes." Eco-systèmes.

Elwert, T., D. Goldmann, F. Roemer and S. Schwartz (2016). "Recycling of NdFeB Magnets from Electric Drive Motors of (Hybrid) Electric Vehicles." Journal of Sustainable Metallurgy, The Minerals, Metals & Materials Society (TMS).

European Environment Agency (2001). "Fleet composition."

Fisher, K., E. Wallén, P. P. Laenen and M. Collins (2006). "Battery Waste Management Life Cycle Assessment." UK Department for Environment, Food and Rural Affairs (DEFRA).

Georgi-Maschler, T., B. Friedrich, R. Weyhe, H. Heegn and M. Rutz (2012). "Development of a recycling process for Li-ion batteries." Journal of Power Sources 207.

Glöser-Chahoud, S., M. Pfaff, L. Tercero Espinoza and M. Faulstich (2016). "Dynamische Materialfluss-Analyse der Magnetwerkstoffe Neodym und Dysprosium in Deutschland." Symposium Rohstoffeffizienz und Rohstoffinnovationen, Tutzing.

Hagelüken, C., M. Buchert and P. Ryan (2006). "Materials Flow of Platinum Group Metals in Germany." 13th CIRP International Conference on Life Cycle Engineering.

Hedbrant, J. and L. Sörme (2001). "Data vagueness and uncertaninties in urban heavy metal data collection." Water, Air, Soil Pollut.: Focus, Kluwer Academic Publishers, Department ofWater and Environmental studies, Linköping University.

Johnson Matthey (2013). "Platinum 2013: Interim review." Johnson Matthey Public Limited Company.

Kang, J., G. Senanayake, J. Sohn and S. M. Shin (2010). "Recovery of cobalt sulfate from spent lithium ion batteries by reductive leaching and solvent extraction with Cyanex 272." Hydrometallurgy 100.

Lain, M. J. (2001). "Recycling of lithium ion cells and batteries." Journal of Power Sources 97-98, p. 736-738.

Li, J., P. Shi, Z. Wang, Y. Chen and C. C. Chang (2009). "A combined recovery process of metals in spent lithium-ion batteries." Chemosphere 77, p. 1132-1136.

Lim, S.-R., D. Kang, O. A. Ogunseitan and J. M. Schoenung (2011). "Potential Environmental Impacts of Light-Emitting Diodes (LEDs): Metallic Resources, Toxicity, and Hazardous Waste Classification." Environmental Science & Technology, American Chemical Society.

Løvik, A. N., R. Modaresi and D. B. Müller (2014). "Long-term strategies for increased recycling of automotive aluminum and its alloying elements." Environmental science & technology, Environmental science & technology.

Lutsey, N. (2010). "Review of technical literature and trends related to automobile mass-reduction technology." California Air Resources Board.

Ministry of Environment Japan (2009). "Report on FY2009 Survey to Promote Streamlining of End-of-Life Vehicle Recycling (使用済み自動車再資源化の効率化及び合理化推進調査)." Ministry of the Environment, Japan.

Modaresi, R., A. N. Løvik and D. B. Müller (2014). "Component- and Alloy-Specific Modeling for Evaluating Aluminum Recycling Strategies for Vehicles." JOM, The Minerals, Metals & Materials Society.

Modaresi, R., S. Pauliuk, A. N. Løvik and D. B. Müller (2014). "Global Carbon Benefits of Material Substitution in Passenger Cars until 2050 and the Impact on the Steel and Aluminum Industries." Environmental Science & Technology, American Chemical Society.

Mohrbacher, H. (2006). "Niobium Alloyed High Strength Steels for Automotive Applications." International Journal of ISSI.

Nogueira, C. A. and F. Margarido (2012). "Battery Recycling by Hydrometallurgy: Evaluation of Simultaneous Treatment of Several Cell Systems." Energy Technology 2012: Carbon Dioxide Management and Other Technologies, TMS (The Minerals, Metals & Materials Society).

Osram (2007). "Material Declaration Sheet and RoHS Compliance Declaration."

Petrániková, M., A. Miskufová, T. Havlík, O. Forsén and A. Pehkonen (2011). "Cobalt recovery from spent portable lithium accumulators after thermal treatment." Acta Metallurgica Slovaca, Vol. 17, No. 2, p. 106-115.

Restrepo, E., A. N. Løvik, P. Wäger, R. Widmer, R. Lonka and D. B. Müller (2016). "Stocks, flows and distribution of critical metals in embedded electronics in passenger vehicles." submitted to: Environmental Science & Technology.

Rotter, S., M. Ueberschaar, G. Walter, S. Flamme, P. Chancerel and M. Marwede (2016). "Final report - UPgrade." Technische Universität Berlin, Institute of Environmental Technology, Chair of Circular Economy and Recycling Technology.

Rotter, V. S. (2013). Rückgewinnung von Spurenmetallen aus Elektroaltgeräten. M. Ueberschaar and P. Chancerel, Proceedings of conference Electronics Goes Green 2012+.

Shin, S. M., N. H. Kim, J. S. Sohn, D. H. Yang and Y. H. Kim (2005). "Development of a metal recovery process from Li-ion battery wastes." Hydrometallurgy 79, p. 172-181.

Sun, Z. H. I., Y. Xiao, J. Sietsma, H. Agterhuis, G. Visser and Y. Yang (2015). "Characterisation of metals in the electronic waste of complex mixtures of end-of-life ICT products for development of cleaner recovery technology." Waste Management, Elsevier Ldt.

Ueberschaar, M., D. Jalalpoor, N. Korf and S. Rotter (2016). "Potentials and barriers for tantalum recovery from Waste Electric and Electronic Equipment (WEEE)." Submitted to Journal of Industrial Ecology.

Ueberschaar, M., M. Schlummer, D. Jalalpoor, N. Kaup and V. S. Rotter (2016). "Potential and recycling strategies for indium in LCD displays from WEEE." Work in progress.

Widmer, R., X. Du, O. Haag, E. Restrepo and P. A. Wager (2015). "Scarce Metals in Conventional Passenger Vehicles and End-of-Life Vehicle Shredder Output." Environmental science & technology, American Chemical Society.

Yano, J., T. Muroi and S.-i. Sakai (2015). "Rare earth element recovery potentials from end-of-life hybrid electric vehicle components in 2010-2030." Journal of Material Cycles and Waste Management, Springer Japan.

Zepf, V. (2013). "Rare earth elements: A new approach to the nexus of supply, demand and use: exemplified along the use of neodymium in permanent magnets." Springer Theses, Springer Heidelberg New York Dordrecht London.

Annex 1 – Template for recording composition data

The template for recording composition data is provided as a separate file, “D2.5_Annex1_CRM_parameter_template.xlsx”.

Annex 2 – Template for consolidating EEE data

The template for consolidating EEE composition data is attached as a separate file "D2.5_Annex2_consolidationTemplateEEE.xlsx". The following screenshots give an overview of its contents.

ProSUM product composition consolidation template

UNU Key	**0114**
Originator	Amund N. Løvik
Person responsible for key	Amund N. Løvik
Date of first version	16. Nov 16
Current version	23. Nov 16
Contact	amund.loevik@empa.ch

Version history

Date	***Last edits***
17.11.2016	Data exported from CRM parameter template

Contents

Default sheets

Sheet name	***Contents***
Summary	Summary of data consolidation steps and data quality for given key/sub-key
Figures	Figures of the data
p	Data on product mass
p raw data	Raw data and calculations of product mass
e-p	e-p mass fractions calculated from data in sheets "m-p, c-p" and "e-m, e-c"
e-p raw data	e-p key-specific raw data
m-p, c-p	i. estimated m-p and c-p mass fractions ii. m-p and c-p mass fractions adjusted with m-c and c-c mass fractions iii. m-p and c-p raw data from Eco-systèmes
m-p, c-p (t)	Mass fraction of materials and components in the product as a function of time (must be entered manually)
m-c, c-c	Matrix of m-c and c-c mass fractions used for adjusting m-p and c-p (must be entered manually)
m-c, c-c ES data	m-c and c-c mass fractions from Eco-systèmes. Not key-specific.
e-c, c-c other data	e-c and c-c mass fractions and mass contents from other sources. Not key-specific
e-m, e-c	e-m and e-c mass fractions used in calculations, and to be harvested (must be entered manually)
e-c key-specific data	e-c mass fractions raw data (key-specific)
e-m, e-c general data	e-c mass fractions raw data (not key-specfic; must be copied manually from CRM parameter template when relevant)
Portrayal	Portrayal of data to be harvested
CRM data	Data for given key as recorded in CRM template
CRM references	List of references for all data

About this file

This template contains raw data and consolidated data for one UNU key or sub-key, indicated by the file name. Sheets with brighter shade contain raw data, while sheets with darker shade contain consolidated data, calculations and in one case also raw data ("m-p, c-p"). Custom sheets may be added to work with changes over time for e-c and e-m data.

Figure 40 Screenshot of contents in consolidation template m-p, c-p (t) (mg/kg)

References	
Data quality	

POM year / Material/component	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
Product mass	16.36	16.36	16.36	16.36	16.36	16.36	16.36	16.36	16.36	16.36	16.36
AgAlloyUnspecified	2	2	2	2	2	2	2	2	2	2	2
AlloyTungstenUnspecified	1'339	1'339	1'339	1'339	1'339	1'339	1'339	1'339	1'339	1'339	1'339
AlloyZincUnspecified	4'774	4'774	4'774	4'774	4'774	4'774	4'774	4'774	4'774	4'774	4'774
AluminiumAlloyUnspecified	56'240	56'240	56'240	56'240	56'240	56'240	56'240	56'240	56'240	56'240	56'240
Brass	5'799	5'799	5'799	5'799	5'799	5'799	5'799	5'799	5'799	5'799	5'799
Bronze	13'222	13'222	13'222	13'222	13'222	13'222	13'222	13'222	13'222	13'222	13'222
cardboard	223	223	223	223	223	223	223	223	223	223	223
castIronUnspecified	-	-	-	-	-	-	-	-	-	-	-
ceramicUnspecified	155	155	155	155	155	155	155	155	155	155	155
CoAlloyUnspecified	1	1	1	1	1	1	1	1	1	1	1
concreteCementUnspecified	-	-	-	-	-	-	-	-	-	-	-
CopperAlloyUnspecified	34'343	34'343	34'343	34'343	34'343	34'343	34'343	34'343	34'343	34'343	34'343
dust	-	-	-	-	-	-	-	-	-	-	-
glass	59'800	59'800	59'800	59'800	59'800	59'800	59'800	59'800	59'800	59'800	59'800
glassWool	383	383	383	383	383	383	383	383	383	383	383
HfAlloyUnspecified	10	10	10	10	10	10	10	10	10	10	10
MineralicMaterial	2'191	2'191	2'191	2'191	2'191	2'191	2'191	2'191	2'191	2'191	2'191
NiAlloyUnspecified	504	504	504	504	504	504	504	504	504	504	504
oil	139	139	139	139	139	139	139	139	139	139	139
otherMaterial	2'496	2'496	2'496	2'496	2'496	2'496	2'496	2'496	2'496	2'496	2'496
paper	17	17	17	17	17	17	17	17	17	17	17
PbAlloyUnspecified	184	184	184	184	184	184	184	184	184	184	184
polymerABS	23'001	23'001	23'001	23'001	23'001	23'001	23'001	23'001	23'001	23'001	23'001
polymerAPVC	3	3	3	3	3	3	3	3	3	3	3
polymerBrominated	7'204	7'204	7'204	7'204	7'204	7'204	7'204	7'204	7'204	7'204	7'204
polymerOther	-	-	-	-	-	-	-	-	-	-	-
polymerPA	41	41	41	41	41	41	41	41	41	41	41
polymerPA12	1'121	1'121	1'121	1'121	1'121	1'121	1'121	1'121	1'121	1'121	1'121
polymerPA6X	6'432	6'432	6'432	6'432	6'432	6'432	6'432	6'432	6'432	6'432	6'432
polymerPBT	1'822	1'822	1'822	1'822	1'822	1'822	1'822	1'822	1'822	1'822	1'822
polymerPC	6'635	6'635	6'635	6'635	6'635	6'635	6'635	6'635	6'635	6'635	6'635
polymerPCA	1'871	1'871	1'871	1'871	1'871	1'871	1'871	1'871	1'871	1'871	1'871
polymerPCPT	374	374	374	374	374	374	374	374	374	374	374
polymerPE	315	315	315	315	315	315	315	315	315	315	315
polymerPET	863	863	863	863	863	863	863	863	863	863	863
polymerPMMA	2'650	2'650	2'650	2'650	2'650	2'650	2'650	2'650	2'650	2'650	2'650
polymerPOM	5'675	5'675	5'675	5'675	5'675	5'675	5'675	5'675	5'675	5'675	5'675
polymerPP	16'779	16'779	16'779	16'779	16'779	16'779	16'779	16'779	16'779	16'779	16'779
polymerPPE	1'137	1'137	1'137	1'137	1'137	1'137	1'137	1'137	1'137	1'137	1'137
polymerPPO	199	199	199	199	199	199	199	199	199	199	199
polymerPPS	155	155	155	155	155	155	155	155	155	155	155
polymerPS	1'543	1'543	1'543	1'543	1'543	1'543	1'543	1'543	1'543	1'543	1'543
polymerPTFETeflon	231	231	231	231	231	231	231	231	231	231	231
polymerPUR	274	274	274	274	274	274	274	274	274	274	274
polymerPVC	158	158	158	158	158	158	158	158	158	158	158
polymerSAN	234	234	234	234	234	234	234	234	234	234	234
polymerUnspecified	33	33	33	33	33	33	33	33	33	33	33
rubberUnspecified	1'479	1'479	1'479	1'479	1'479	1'479	1'479	1'479	1'479	1'479	1'479
StainlessSteelUnspecified	46'793	46'793	46'793	46'793	46'793	46'793	46'793	46'793	46'793	46'793	46'793
SteelAlloyUnspecified	639'640	639'640	639'640	639'640	639'640	639'640	639'640	639'640	639'640	639'640	639'640
TitaniumAlloyUnspecified	3	3	3	3	3	3	3	3	3	3	3
WoodOther	2'077	2'077	2'077	2'077	2'077	2'077	2'077	2'077	2'077	2'077	2'077
BatteryCell	10	10	10	10	10	10	10	10	10	10	10
Cables	15'086	15'086	15'086	15'086	15'086	15'086	15'086	15'086	15'086	15'086	15'086
CapUnspecified	-	-	-	-	-	-	-	-	-	-	-
CathodeRayTubes	-	-	-	-	-	-	-	-	-	-	-
DisplayCRT	-	-	-	-	-	-	-	-	-	-	-
DisplayLcd	89	89	89	89	89	89	89	89	89	89	89
DisplayModuleOther	-	-	-	-	-	-	-	-	-	-	-
DisplayPlasma	-	-	-	-	-	-	-	-	-	-	-
DisplayTFT	-	-	-	-	-	-	-	-	-	-	-
Diverter	-	-	-	-	-	-	-	-	-	-	-
DriveCDDInt	-	-	-	-	-	-	-	-	-	-	-
DriveFDD	-	-	-	-	-	-	-	-	-	-	-
DriveHDD	-	-	-	-	-	-	-	-	-	-	-
ElectronGun	-	-	-	-	-	-	-	-	-	-	-
Lamp	1'124	1'124	1'124	1'124	1'124	1'124	1'124	1'124	1'124	1'124	1'124
LED	83	83	83	83	83	83	83	83	83	83	83
Magnet	19'302	19'302	19'302	19'302	19'302	19'302	19'302	19'302	19'302	19'302	19'302
Magnetron	-	-	-	-	-	-	-	-	-	-	-
MotorMagneticApp	-	-	-	-	-	-	-	-	-	-	-
otherComponent	44	44	44	44	44	44	44	44	44	44	44
PCBUnspecified	13'700	13'700	13'700	13'700	13'700	13'700	13'700	13'700	13'700	13'700	13'700
TonerCartridge	-	-	-	-	-	-	-	-	-	-	-

POM year / Material/component	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Product mass	16.36	16.36	16.36	16.36	15.90	16.30	16.73	16.62	17.90	17.56	18.68
AgAlloyUnspecified	2	2	2	2	2	2	2	2	2	2	2
AlloyTungstenUnspecified	1'339	1'338	1'337	1'337	1'336	1'338	1'339	1'342	1'343	1'346	1'347
AlloyZincUnspecified	4'774	4'770	4'767	4'764	4'763	4'767	4'771	4'783	4'787	4'797	4'799
AluminiumAlloyUnspecified	56'240	56'187	56'155	56'125	56'106	56'157	56'210	56'350	56'391	56'509	56'539
Brass	5'799	5'793	5'790	5'787	5'785	5'790	5'796	5'810	5'814	5'826	5'830
Bronze	13'222	13'210	13'202	13'195	13'190	13'202	13'215	13'248	13'257	13'285	13'292
cardboard	223	223	223	223	223	223	223	224	224	225	225
castIronUnspecified	-	-	-	-	-	-	-	-	-	-	-
ceramicUnspecified	155	155	155	155	155	155	155	156	156	156	156
CoAlloyUnspecified	1	1	1	1	1	1	1	1	1	1	1
concreteCementUnspecified	-	-	-	-	-	-	-	-	-	-	-
CopperAlloyUnspecified	34'343	34'311	34'291	34'273	34'261	34'293	34'325	34'410	34'435	34'507	34'526
dust	-	-	-	-	-	-	-	-	-	-	-
glass	59'800	59'743	59'709	59'677	59'657	59'711	59'768	59'916	59'960	60'085	60'118
glassWool	383	383	382	382	382	382	383	384	384	385	385
HfAlloyUnspecified	10	10	10	10	10	10	10	10	10	10	10
MineralicMaterial	2'191	2'189	2'187	2'186	2'185	2'187	2'190	2'195	2'197	2'201	2'202
NiAlloyUnspecified	504	503	503	503	503	503	504	505	505	506	506
oil	139	138	138	138	138	138	139	139	139	139	139
otherMaterial	2'496	2'493	2'492	2'491	2'490	2'492	2'494	2'501	2'502	2'508	2'509
paper	17	17	17	17	17	17	17	17	17	17	17
PbAlloyUnspecified	184	184	183	183	183	183	184	184	184	185	185
polymerABS	23'001	22'979	22'966	22'954	22'946	22'967	22'989	23'046	23'062	23'111	23'123
polymerAPVC	3	3	3	3	3	3	3	3	3	3	3
polymerBrominated	7'204	7'197	7'193	7'189	7'187	7'193	7'200	7'218	7'223	7'238	7'242
polymerOther	-	-	-	-	-	-	-	-	-	-	-
polymerPA	41	41	41	41	41	41	41	41	41	41	41
polymerPA12	1'121	1'120	1'119	1'119	1'118	1'119	1'120	1'123	1'124	1'126	1'127
polymerPA6X	6'432	6'426	6'422	6'419	6'417	6'423	6'429	6'445	6'449	6'463	6'466
polymerPBT	1'822	1'820	1'819	1'818	1'818	1'819	1'821	1'826	1'827	1'831	1'832
polymerPC	6'635	6'629	6'625	6'622	6'620	6'626	6'632	6'648	6'653	6'667	6'671
polymerPCA	1'871	1'870	1'868	1'867	1'867	1'869	1'870	1'875	1'876	1'880	1'881
polymerPCPT	374	374	374	373	373	374	374	375	375	376	376
polymerPE	315	315	315	315	315	315	315	316	316	317	317
polymerPET	863	862	861	861	861	861	862	864	865	867	867
polymerPMMA	2'650	2'647	2'646	2'644	2'643	2'646	2'648	2'655	2'657	2'662	2'664
polymerPOM	5'675	5'669	5'666	5'663	5'661	5'666	5'672	5'686	5'690	5'702	5'705
polymerPP	16'779	16'763	16'754	16'745	16'739	16'754	16'770	16'812	16'824	16'859	16'868
polymerPPE	1'137	1'136	1'136	1'135	1'135	1'136	1'137	1'140	1'140	1'143	1'143
polymerPPO	199	199	199	199	198	199	199	199	200	200	200
polymerPPS	155	155	155	155	155	155	155	155	156	156	156
polymerPS	1'543	1'541	1'540	1'539	1'539	1'540	1'542	1'546	1'547	1'550	1'551
polymerPTFETeflon	231	231	231	231	231	231	231	232	232	232	232
polymerPUR	274	274	273	273	273	273	274	274	275	275	275
polymerPVC	158	158	157	157	157	157	158	158	158	158	159
polymerSAN	234	234	234	234	234	234	234	235	235	236	236
polymerUnspecified	33	33	33	33	33	33	33	33	33	33	33
rubberUnspecified	1'479	1'478	1'477	1'476	1'476	1'477	1'479	1'482	1'483	1'486	1'487
StainlessSteelUnspecified	46'793	46'748	46'721	46'696	46'681	46'723	46'767	46'883	46'918	47'016	47'041
SteelAlloyUnspecified	639'640	639'037	638'670	638'327	638'110	638'693	639'298	640'884	641'353	642'693	643'040
TitaniumAlloyUnspecified	3	3	3	3	3	3	3	3	3	3	3
WoodOther	2'077	2'075	2'074	2'073	2'072	2'074	2'076	2'081	2'083	2'087	2'088
BatteryCell	10	10	10	10	10	10	10	10	10	10	10
Cables	15'086	15'072	15'063	15'055	15'050	15'064	15'078	15'115	15'126	15'158	15'166
CapUnspecified	-	-	-	-	-	-	-	-	-	-	-
CathodeRayTubes	-	-	-	-	-	-	-	-	-	-	-
DisplayCRT	-	-	-	-	-	-	-	-	-	-	-
DisplayLcd	89	89	89	89	89	89	89	89	89	90	90
DisplayModuleOther	-	-	-	-	-	-	-	-	-	-	-
DisplayPlasma	-	-	-	-	-	-	-	-	-	-	-
DisplayTFT	-	-	-	-	-	-	-	-	-	-	-
Diverter	-	-	-	-	-	-	-	-	-	-	-
DriveCDDInt	-	-	-	-	-	-	-	-	-	-	-
DriveFDD	-	-	-	-	-	-	-	-	-	-	-
DriveHDD	-	-	-	-	-	-	-	-	-	-	-
ElectronGun	-	-	-	-	-	-	-	-	-	-	-
Lamp	1'124	1'123	1'122	1'122	1'121	1'122	1'123	1'126	1'127	1'129	1'130
LED	83	83	83	83	83	83	83	84	84	84	84
Magnet	19'302	19'284	19'272	19'262	19'256	19'273	19'291	19'339	19'353	19'394	19'404
Magnetron	-	-	-	-	-	-	-	-	-	-	-
MotorMagneticApp	-	-	-	-	-	-	-	-	-	-	-
otherComponent	44	44	44	44	44	44	44	44	44	44	44
PCBUnspecified	13'700	14'630	15'197	15'726	16'059	15'161	14'227	11'783	11'059	8'993	8'458
TonerCartridge	-	-	-	-	-	-	-	-	-	-	-

POM year / Material/component	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Product mass	19.10	19.60	20.10	20.60	21.00	21.50	22.00	22.40	22.90	22.90	22.00	21.74
AgAlloyUnspecified	2	2	2	2	2	2	2	2	2	2	2	2
AlloyTungstenUnspecified	1'347	1'347	1'347	1'348	1'348	1'348	1'348	1'349	1'349	1'349	1'348	1'348
AlloyZincUnspecified	4'800	4'801	4'802	4'803	4'804	4'805	4'806	4'806	4'807	4'807	4'806	4'805
AluminiumAlloyUnspecified	56'550	56'562	56'573	56'584	56'593	56'603	56'612	56'619	56'628	56'628	56'612	56'607
Brass	5'831	5'832	5'833	5'834	5'835	5'836	5'837	5'838	5'839	5'839	5'837	5'837
Bronze	13'295	13'298	13'300	13'303	13'305	13'307	13'309	13'311	13'313	13'313	13'309	13'308
cardboard	225	225	225	225	225	225	225	225	225	225	225	225
castIronUnspecified	-	-	-	-	-	-	-	-	-	-	-	-
ceramicUnspecified	156	156	156	156	156	157	157	157	157	157	157	157
CoAlloyUnspecified	1	1	1	1	1	1	1	1	1	1	1	1
concreteCementUnspecified	-	-	-	-	-	-	-	-	-	-	-	-
CopperAlloyUnspecified	34'533	34'540	34'547	34'553	34'559	34'565	34'570	34'575	34'580	34'580	34'570	34'567
dust	-	-	-	-	-	-	-	-	-	-	-	-
glass	60'129	60'142	60'154	60'165	60'174	60'185	60'195	60'203	60'212	60'212	60'195	60'190
glassWool	385	385	385	385	385	385	386	386	386	386	386	385
HfAlloyUnspecified	10	10	10	10	10	10	10	10	10	10	10	10
MineralicMaterial	2'203	2'203	2'204	2'204	2'204	2'205	2'205	2'205	2'206	2'206	2'205	2'205
NiAlloyUnspecified	507	507	507	507	507	507	507	507	507	507	507	507
oil	139	139	139	139	139	140	140	140	140	140	140	140
otherMaterial	2'509	2'510	2'510	2'511	2'511	2'512	2'512	2'513	2'513	2'513	2'512	2'512
paper	17	17	17	17	17	17	17	17	17	17	17	17
PbAlloyUnspecified	185	185	185	185	185	185	185	185	185	185	185	185
polymerABS	23'127	23'132	23'137	23'142	23'145	23'149	23'153	23'156	23'159	23'159	23'153	23'151
polymerAPVC	3	3	3	3	3	3	3	3	3	3	3	3
polymerBrominated	7'244	7'245	7'247	7'248	7'249	7'250	7'252	7'253	7'254	7'254	7'252	7'251
polymerOther	-	-	-	-	-	-	-	-	-	-	-	-
polymerPA	41	41	41	41	41	41	41	41	41	41	41	41
polymerPA12	1'127	1'127	1'128	1'128	1'128	1'128	1'128	1'128	1'129	1'129	1'128	1'128
polymerPA6X	6'468	6'469	6'470	6'472	6'473	6'474	6'475	6'476	6'477	6'477	6'475	6'474
polymerPBT	1'832	1'833	1'833	1'833	1'834	1'834	1'834	1'834	1'835	1'835	1'834	1'834
polymerPC	6'672	6'673	6'675	6'676	6'677	6'678	6'679	6'680	6'681	6'681	6'679	6'679
polymerPCA	1'882	1'882	1'882	1'883	1'883	1'883	1'884	1'884	1'884	1'884	1'884	1'883
polymerPCPT	376	376	376	376	377	377	377	377	377	377	377	377
polymerPE	317	317	317	317	317	317	318	318	318	318	318	317
polymerPET	867	868	868	868	868	868	868	869	869	869	868	868
polymerPMMA	2'664	2'665	2'665	2'666	2'666	2'667	2'667	2'668	2'668	2'668	2'667	2'667
polymerPOM	5'706	5'707	5'708	5'709	5'710	5'711	5'712	5'713	5'714	5'714	5'712	5'712
polymerPP	16'871	16'875	16'878	16'882	16'884	16'887	16'890	16'892	16'895	16'895	16'890	16'888
polymerPPE	1'144	1'144	1'144	1'144	1'144	1'145	1'145	1'145	1'145	1'145	1'145	1'145
polymerPPO	200	200	200	200	200	200	200	200	200	200	200	200
polymerPPS	156	156	156	156	156	156	156	156	156	156	156	156
polymerPS	1'551	1'551	1'552	1'552	1'552	1'552	1'553	1'553	1'553	1'553	1'553	1'553
polymerPTFETeflon	232	232	233	233	233	233	233	233	233	233	233	233
polymerPUR	275	275	275	276	276	276	276	276	276	276	276	276
polymerPVC	159	159	159	159	159	159	159	159	159	159	159	159
polymerSAN	236	236	236	236	236	236	236	236	236	236	236	236
polymerUnspecified	33	33	33	33	33	33	33	33	33	33	33	33
rubberUnspecified	1'487	1'488	1'488	1'488	1'489	1'489	1'489	1'489	1'490	1'490	1'489	1'489
StainlessSteelUnspecified	47'050	47'060	47'070	47'079	47'086	47'094	47'102	47'108	47'115	47'115	47'102	47'098
SteelAlloyUnspecified	643'162	643'298	643'428	643'552	643'647	643'760	643'869	643'952	644'052	644'052	643'869	643'813
TitaniumAlloyUnspecified	3	3	3	3	3	3	3	3	3	3	3	3
WoodOther	2'089	2'089	2'090	2'090	2'090	2'091	2'091	2'091	2'092	2'092	2'091	2'091
BatteryCell	10	10	10	10	10	10	10	10	10	10	10	10
Cables	15'169	15'172	15'175	15'178	15'180	15'183	15'186	15'188	15'190	15'190	15'186	15'184
CapUnspecified	-	-	-	-	-	-	-	-	-	-	-	-
CathodeRayTubes	-	-	-	-	-	-	-	-	-	-	-	-
DisplayCRT	-	-	-	-	-	-	-	-	-	-	-	-
DisplayLcd	90	90	90	90	90	90	90	90	90	90	90	90
DisplayModuleOther	-	-	-	-	-	-	-	-	-	-	-	-
DisplayPlasma	-	-	-	-	-	-	-	-	-	-	-	-
DisplayTFT	-	-	-	-	-	-	-	-	-	-	-	-
Diverter	-	-	-	-	-	-	-	-	-	-	-	-
DriveCDDInt	-	-	-	-	-	-	-	-	-	-	-	-
DriveFDD	-	-	-	-	-	-	-	-	-	-	-	-
DriveHDD	-	-	-	-	-	-	-	-	-	-	-	-
ElectronGun	-	-	-	-	-	-	-	-	-	-	-	-
Lamp	1'130	1'131	1'131	1'131	1'131	1'131	1'132	1'132	1'132	1'132	1'132	1'131
LED	84	84	84	84	84	84	84	84	84	84	84	84
Magnet	19'408	19'412	19'416	19'420	19'423	19'426	19'429	19'432	19'435	19'435	19'429	19'428
Magnetron	-	-	-	-	-	-	-	-	-	-	-	-
MotorMagneticApp	-	-	-	-	-	-	-	-	-	-	-	-
otherComponent	44	44	44	44	44	44	44	44	44	44	44	44
PCBUnspecified	8'270	8'059	7'859	7'668	7'522	7'347	7'180	7'052	6'898	6'898	7'180	7'267
TonerCartridge	-	-	-	-	-	-	-	-	-	-	-	-

Figure 41 Screenshot from consolidation template, sheet “m-p, c-p (t)” Data are filled in for mass fractions of materials and components in the product as a function of time.

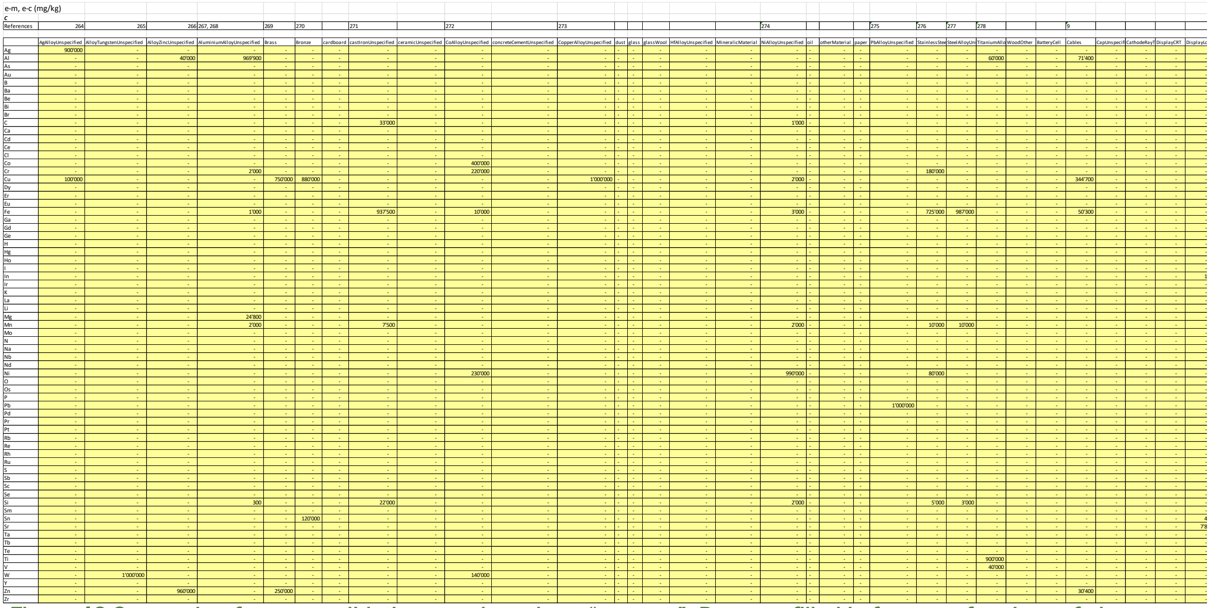


Figure 42 Screenshot from consolidation template sheet “e-m, e-c”. Data are filled in for mass fractions of elements n materials and components specific for this product.

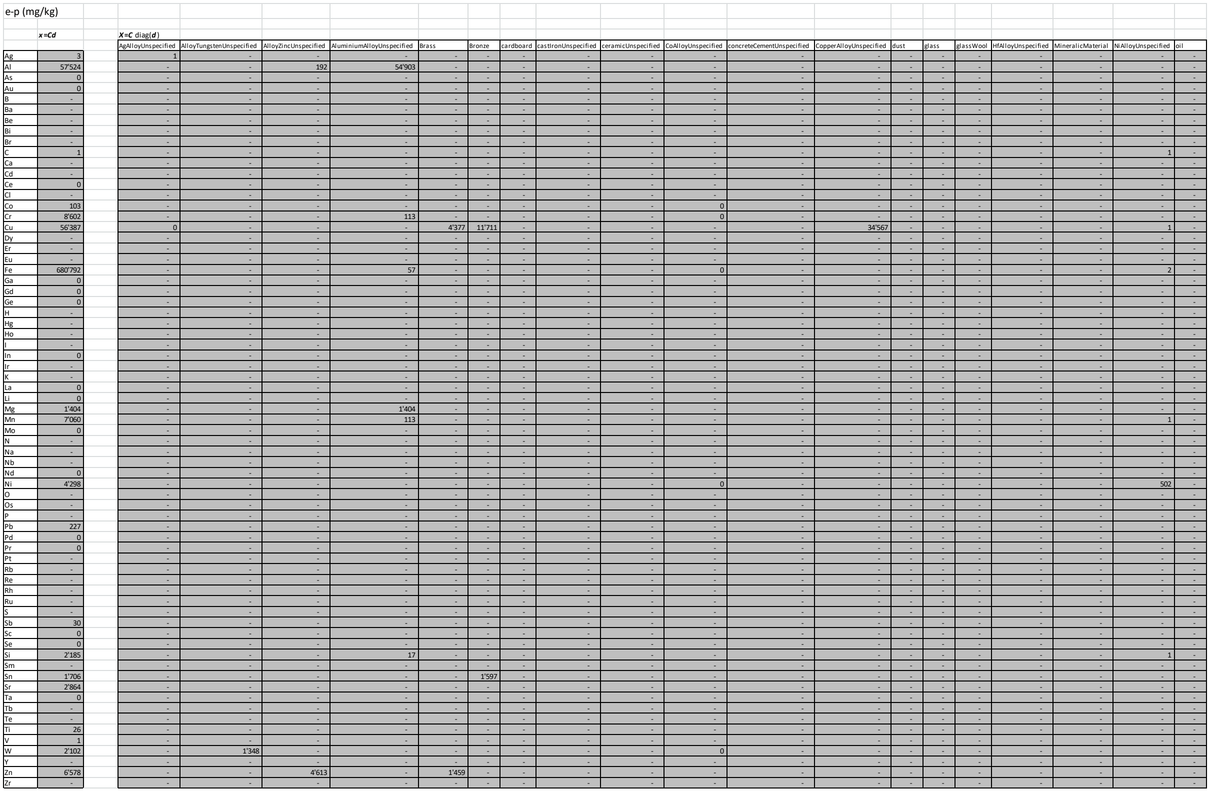


Figure 43 Screenshot from consolidation template, sheet “e-p”. Mass fractions of elements in the product, including contribution from different materials and components, are calculated automatically.

Annex 3 – Template for harvesting data (portrayal)

The template for harvesting data (portrayal) is provided as a separate file, "D2.5_Annex3_harvest_template.xlsx".