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Product flow analysis using trade statistics and consumer survey data: a case study of mobile phones in Australia

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ABSTRACT

This study describes an integrative approach to product flow analysis of (waste) electrical and electronic equipment using trade statistics and consumer survey data. We demonstrate this approach with a case study of mobile phones. Using statistical and empirical data for Australia over 1997–2014, we have shown how different sources of information can be collated and cross-checked to estimate the product in-use stocks and flows, product lifespan and lifespan structure, as well as to detail the product age structure in stock and at the end of life.

From our results, the total number of mobile phones in in-use stocks in Australia has been estimated at 46 million at the end of 2014, or about 2 phones per capita. The proportion of phones kept in storage (not being in use) has been constantly rising, reaching 50% in 2012–2014. The average expected lifespan for a mobile phone sold in Australia decreased from about six years in the late 1990s to about five years in the early 2000s, and then stabilised at around four years (±0.5 years). The average time of active use for mobile phones was estimated in the range of 2.0–2.6 years (which includes first use and reuse). The estimated lifespan profile for mobile phones in Australia has been confirmed to be relatively similar to that reported in Japan.

While this methodology presented here provided meaningful results, the accuracy and relevance would be improved by better quality of original data. Therefore, in conclusion, we also highlight potential improvements in consumer surveys that would help to enhance the analysis.

1. Introduction

Electronic products such as mobile phones, laptops, TVs and tablets utilise the physical properties of highly specialised and geochemically scarce metals to function. These metals (e.g. Ag, Au, In and many others) must be mined and refined, sometimes at significant environmental and social cost, to be integrated into these products. Yet many electronic products are wasted at the end of their useful lives, appearing in landfill or in some cases illegally exported to developing nations, fostering further economic, environmental and social problems for these countries (Balde et al., 2015). The recovery of valuable components in electronic products has attracted significant interest in recent years as a means to reducing these risks (e.g. Li et al., 2015; Pickren, 2014), particularly amidst growing environmental impacts and regulations facing the mining industry (e.g. Mudd, 2010). However, the economic recovery of metals from e-waste requires some understanding of the location, composition and volume of products available for future extraction, so that investments into recovery operations can be properly informed. Approximations and modelling are necessary to obtain such information in the absence of direct measurement and reporting.

The materials in electronic products, and indeed all metals in society, whether active in use or dormant and not yet disposed of, are known as ‘in-use stocks’. In-use stocks have been indirectly or directly estimated through various approaches and methodologies, each with different emphases, for example in input–output accounts, national capital accounts, life-cycle assessments (LCA) and material flow analyses (MFA) (Pauliuk et al., 2015). Within the MFA studies, there are two primary approaches by which in-use stocks

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of products or their contained materials have historically been estimated: top-down and bottom-up. The top-down approach essentially entails the collection and analysis of data on material inputs and outputs for a specified system. The difference between inflows and outflows (e.g. imports plus domestic production minus exports) over a specified time period can indicate in-use stocks via mass balance. The bottom-up approach entails the collection of data on the number of products/commodities within a given area and summing these to estimate the total in-use stocks.

Both the top-down and bottom-up approaches have advantages and disadvantages. For example, while bottom-up studies permit the spatial distribution of in-use stocks to be estimated, they are often temporally restricted to one year. Here, top-down studies can shed more light as they permit multi-year analyses and hence trends in stock accumulation, although they often rely on highly aggregated data that do not relate to specific products, and are further problematic to disaggregate spatially. These and other methodological uncertainties are described in numerous previous studies, e.g. (Chen and Graedel, 2015a; Gerst and Graedel, 2008; UNEP, 2010).

The multi-year analyses under the top-down approach are referred to as Dynamic MFA (DMFA) and have been applied to describe historical material flows and stocks of various metal resources. Several DMFA studies have projected possible future developments and related resource flows at both national and global levels based on scenarios. Muller et al. (2006) and Wang et al. (2007) focused on the anthropogenic iron and steel cycle, Daigo et al. (2007) estimated both the in-use and the total steel stock, which includes hibernating stock in Japan, and Reck et al. (2008) analysed the nickel stock and flows at the national and global scale. While the above studies have focussed on specific metals, other MFA studies have emerged which focus on the flows of specific products. Oguchi et al. (2008) analysed the circulation of major consumer durables in Japan, Harper (2008) analysed global flows of tungsten-containing products, and Chen and Graedel (2015b) estimated in-use stocks of 91 products in the United States.

Studies in MFA have additionally used monetary Input Output (IO) tables even for relatively small flows; an example is found in the work of Nakamura et al. (2007). IO analysis is one of the most widely used tools for describing economy-wide activities and their environmental implications (Suh, 2009). IO based MFA models, for example Waste IO-MFA, analyse the compositions of the materials or substances in products and scrap. Nakamura and colleagues provided several studies on IO based MFA (Nakamura et al., 2008, 2009; Ohno et al., 2014). Nakamura et al. (2014) also provided a worthy methodological framework, MaTrace model to enable visual tracking of the fate of materials whether accumulated in in-use stocks or dissipated in waste streams. In addition, Wang et al. (2013) provided a detailed overview of different IO models used for product flow analyses and e-waste estimation.

If elements of multiple MFA methodologies are applied to the same commodity under the same system boundaries, more can be revealed about the nature of that commodity. For example, both the spatial distribution of the commodity and potential trends over time in stock accumulation could be determined, and further the uncertainty associated with each method could be compared and interpreted. Very few studies have conducted multiple assessments, e.g. both top-down and bottom-up assessments of the same commodity or product, with Hirato et al. (2009) being a notable example. This is likely due to the time taken to conduct MFA studies, and given that regardless of the specific MFA method employed, almost all MFA studies must contend with a lack of up to date and spatially relevant data. Indeed, it is relatively accepted that the contribution offered by an MFA study is that it synthesises available data to characterise the flows of a new commodity, and/or to represent previously un-studied spatial/temporal aspects, but not necessarily that it employs raw data collection.

The limited data sources which are available for MFA studies can often be re-used through multiple generations of studies, which ultimately become less spatially and temporally relevant to the source data. For several electronic products including mobile phones, we have seen increases in value and utility, and considerable hoarding behaviour developed (ACMA, 2015; Read, 2015), which affects the in-use stocks and average lifespans of the products. There are therefore considerable uncertainties for future projections of e-waste volumes associated with using fixed product lifespan and distribution parameters (e.g. Weibull function) based on previous investigations. Furthermore, the limited number of studies currently used to inform in-use stock behaviour may provide source data that is spatially explicit (i.e. reflecting usage behaviour in a certain country), making them problematic to infer for other locations.

Empirically collected data, which reflects the system boundaries of the MFA study itself, can assist in reducing these uncertainties, and hence this study focuses on how such data can be integrated into multiple methods of product in-use stocks and flows estimation. In the following sections we describe this approach in detail and demonstrate its application with the case study of mobile phones in Australia.

2. Methodology description

Estimating (waste) electrical and electronic equipment ((W)EEE) circulation is a difficult task due to often low quality and incomplete data, meaning that multiple assumptions are required for input–output modelling (Wang et al., 2013). The annual sales of EEE (in monetary value and units) are usually well recorded through national and international systems and institutions (e.g. UN Comtrade database), while the information on in-use stocks and end-of-life (EoL) products is not directly documented. To uncover the latter, detailed consumer (and institutional) surveys, information from professional associations and authorities (e.g. telecommunication regulatory bodies), recycling and waste management companies data, as well as special investigations are needed (Fig. 1).

The top-down approach in this study uses aggregated information at the country level. The modelling of in-use stocks and flows in this approach can be solely based on trade statistics. Using estimations of products average lifespans from previous studies allows an approximation of the overall circulation of (W)EEE in the economy (Balde et al., 2015). However, for many EEE categories the lifespans significantly differ over time and/or between countries. The up-to-date (dynamic) country/region based information derived from bottom-up approaches can significantly improve and/or help validate the modelling.

The overall approach to estimating the circulation of mobile phones in this study is presented in Fig. 2. Most individual parts of this approach are generic and can be applied to any EEE, however the integration of top-down and bottom-up components is permitted by the available data, which is an uncommon feature in MFA. The system boundaries for this study are limited by EoL products generation, although the (historic) consumer surveys also indicate the likely pathways for mobile phones at the end of life.

Our methodology first requires the compilation of two major datasets: sales and in-use stocks, based on trade statistics and consumer surveys accordingly. The information on mobile services subscriptions can be used for comparative purposes to support the mobile phones in active use estimation. The number of EoL phones (outputs) can be estimated via mass balance between inputs (phone sales) and in-use stocks for every respective year.

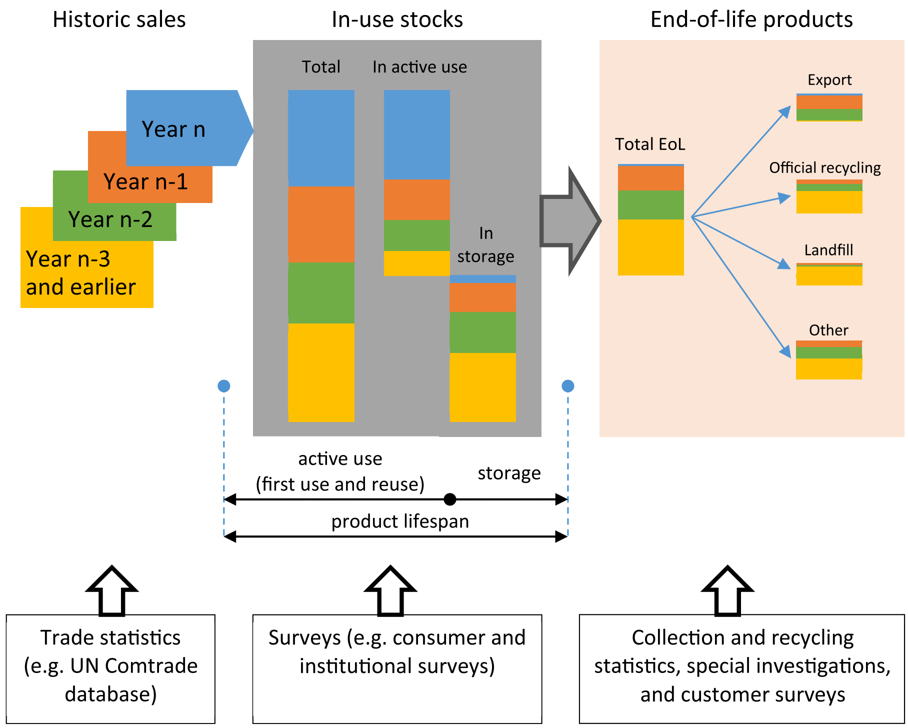

Fig. 1. Illustration of in-use stocks and flows estimation across different product age groups in product flow analysis for (W)EEE. Note: the size of individual bars is for illustrative purposes and may not match the balance in total.

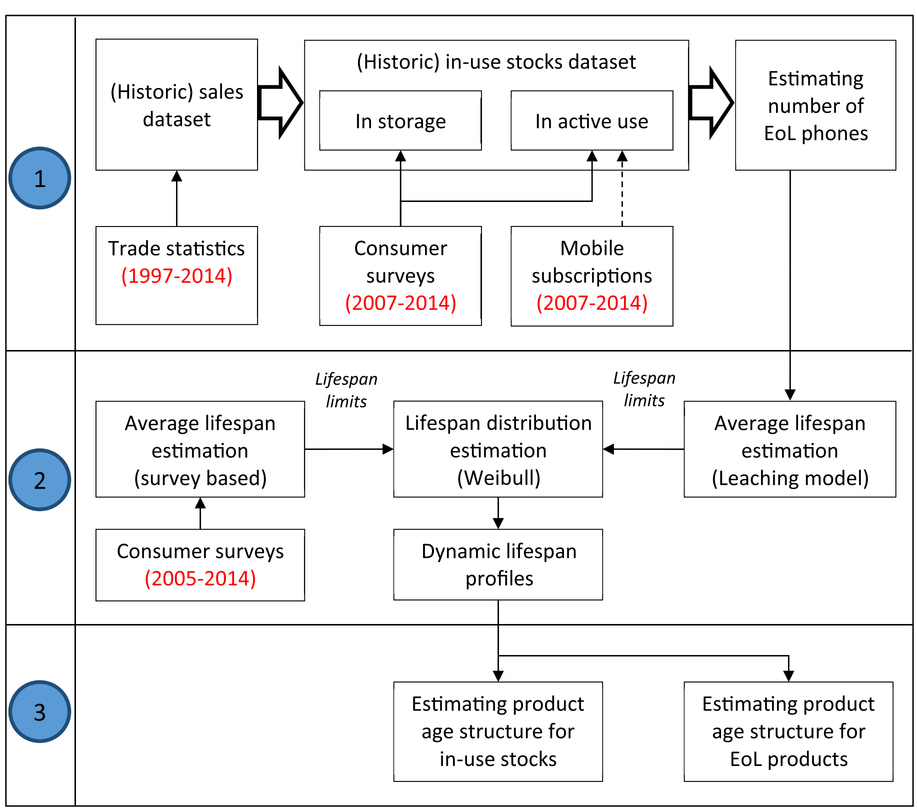

Fig. 2. Using empirical data to model in-use stocks and flows of mobile phones in this study.

Second, the product lifespan is estimated by different methods and cross-checked. Different scopes of a product or commodity circulation within the economic system can be used to define the lifespan. Murakami et al. (2010) and Oguchi et al. (2010) provided a detailed overview of lifespan scopes and classified different methodologies for estimating the lifespan distribution. The product lifespan which we use in this study can be referred to total lifespan for consumer durables in the classification by Murakami et al. (2010), and is measured by the following techniques:

- **Average lifespan estimation based on the Leaching model**. The input–output data from the previous step allows the use of the Leaching model (assuming that the product has reached the market saturation level). The average lifespan can be estimated as the total stock divided by the EoL products generation (Wang et al., 2013).
- **Average lifespan estimation based on consumer surveys**. The consumer survey data, namely information regarding expected time of use for a new mobile phone (and/or time of use for the previous phone) and expected destiny for this phone after use (and/or destiny for the previous phone), are used to reconstruct the average lifespan of a phone.
- **Lifespan distribution estimation based on the use of the Weibull function**. The models above provide estimation of average lifespan only, while statistical functions such as the Weibull function also determine the lifespan distribution. The use of lifespan range (limits) allows for optimizing the search for suitable distribution function parameters.

Finally, the Weibull distribution parameters can be used to reconstruct the product age structure for the in-use stocks and EoL flows.

The use of a Weibull function provides better results for modelling stocks and flows of EEE products than other statistical functions (Wang et al., 2013). In general, the estimation of distribution parameters requires detailed information, not only on the number of devices coming into and being in stock, but also on the age structure of products (in stock and/or at the end of life). Without the latter, there is still a possibility to find suitable parameters, however there may be multiple solutions satisfying the requirement of matching the inflows and stocks (and/or inflows and outflows). As shown in Fig. 2, we suggest a possible way to resolve this issue by limiting the lifespan range, based on findings from other methods for product lifespan estimation, while searching for the best-fit Weibull function parameters. This drastically decreases not only the number of required iterations but also the number of satisfactory solutions. The non-linear regression analysis along with the solver function in MS Excel can help to define the best-fit parameters for Weibull distribution (Wang et al., 2013). However, there is still a possibility that the solution does not exist or does not provide an adequate result; in this case the original data needs to be checked for possible errors and/or alternative statistical distributions considered.

3. Case study – mobile phones in Australia

In this section, we demonstrate the application of the developed methodology to mobile phones in Australia. First, the existing trade statistics and consumer survey data are compiled to estimate the number of mobile phones in stock and at the end of life. Second, the average lifespan for a mobile phone is estimated by different methods, including the Leaching model, survey based approach, and Weibull distribution fitting. Third, the Weibull distribution parameters are used to reconstruct the in-use stocks and EoL product flows age structure. Finally, the adequacy of the data and the reliability of results are discussed, including suggestions for improvement. Most data in this investigation are represented on a one-year basis, approximated to the end of the year where applicable (also see Supplementary document for details).

3.1. Estimating in-use stocks and end-of-life products

The export–import statistics for every country can be obtained from the UN Comtrade database. The mobile phones are represented by the code 851712, Harmonised System, "Telephones for cellular networks/for other wireless networks, other than line telephone sets with cordless handsets". There is no known production or assembly of mobile phones in Australia, and the domestic EEE sector is relatively small overall (IBISWorld, 2015). Therefore, in this study we assume imports being equal to sales of mobile phones. There is an uncertainty on how to interpret the export data, which forms up to 10% of imports of mobile phones (by the number of units). By comparing average prices between imported and exported devices, it can be concluded that a significant part of mobile phone exports may be represented by old devices for resale and reuse overseas (Fig. 3); this issue was also highlighted by Wang et al. (2012) for EEE in general.

In Australia, the consumer surveys on mobile phone possession and use have been regularly performed by Mobile Muster, the Australian mobile phone industry's official product stewardship program (Read, 2015). The Mobile Muster's reports also provide data to similarly estimate the number of phones in active use (see Supplementary materials to this article for details), which can be further compared with mobile phone subscriptions statistics from the Australian Communication and Media Authority (ACMA). Since 2009, there has been a growing disparity between the estimated, based on surveys, number of phones in active use versus the number of mobile subscriptions, which has reached about 8% (or two million units) in the last three years (Fig. 4). This could be explained by the presence of mobile phones supporting two SIM cards at the same time. However, there is also a growing number of children owning mobile phones, which is not covered by current consumer surveys focussing primarily on adults (at least 15+ years old). For example, the recent investigation initiated by Telstra in Australia highlighted that the average age to receive the first mobile phone was 12 in 2014 (SMH, 2015).

The numbers of phones in active use and in storage equate to the total number of phones in in-use stocks; comparing the latter with annual sales allows us to estimate the number of EoL phones (Fig. 5). The mobile phone annual sales in Australia were in the range from 10 to 13 million units in 2008–2014, peaking at 13.1 million in 2010 (Fig. 5). The total number of mobile phones in in-use stocks had been increasing until 2012, and stabilised at around 46 million units or about 2 phones per capita (or 5.1 per household). The mobile phones not in use (kept in storage) form a significant part of the total in-use stocks, in the last three years they accounted for about 50% of all phones hold by Australian households (Fig. 4). The generation of EoL phones has reached parity with new phone sales, and estimated at 12 million units in 2014 (Fig. 5).

3.2. Estimating product lifespan

3.2.1. Leaching model

The Leaching model provides an adequate estimate of lifespan if the product has reached the market saturation level (Wang et al., 2013). The mobile phones have been widely introduced to the market in the second half of 1990s. By the mid-2000s the product penetration level, based on mobile subscriptions, has reached 100% in Australia, on average covering every person aged 15+ (ACMA, 2006).

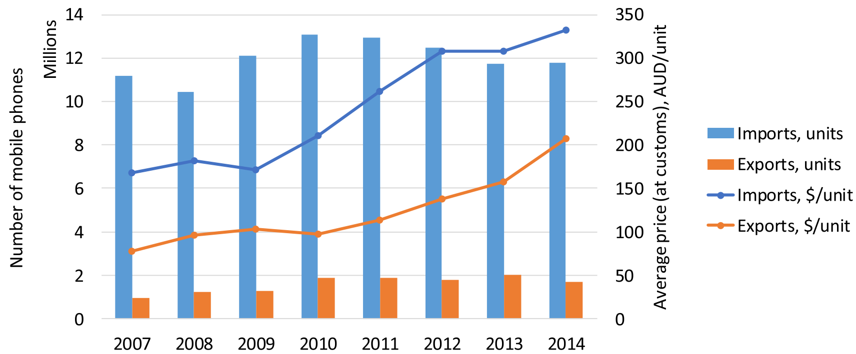

Fig. 3. Import and export statistics for mobile phones in Australia. Data source: (UN Comtrade, 2015).

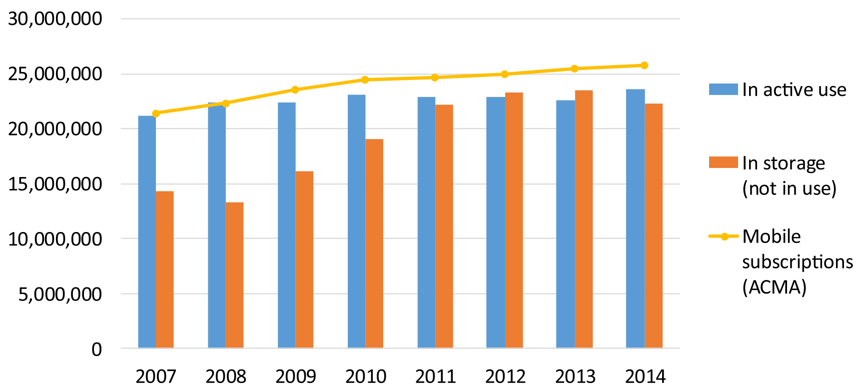

Fig. 4. Number of mobile phones in Australia. Data sources: (ACMA, 2015; Read, 2015).

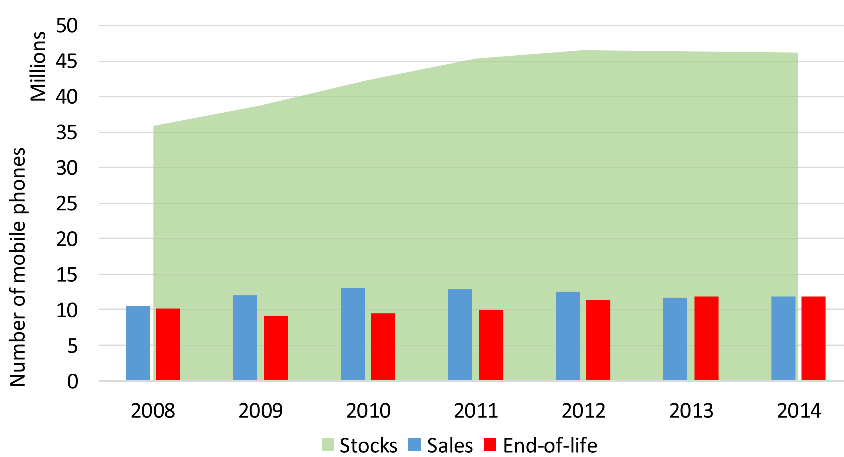

Fig. 5. Stocks and flows of mobile phones in Australia.

Using the number of mobile phones in stock and at the end-of-life from the previous section, the average lifespan has been estimated and presented in Fig. 6. In 2008–2014, it was fluctuating around 4 years with plus or minus of a half-year difference.

3.2.2. *Consumer surveys based approach*

The consumer surveys can provide invaluable insights into estimating the life of electronic devices in the society. These include patterns of ownership and use, hoarding behaviours, awareness and attitudes of recycling, and ways of disposing. The data from such surveys can be used to estimate product in-use stocks and lifespan. When performed regularly, the survey data also allow the temporal analysis of patterns. In this study, Mobile Muster's consumer survey data from 2006 to 2015 (Read, 2015) were used to estimate mobile phone lifespan and its changes over time.

Mobile Muster has conducted consumer surveys on mobile phone use and recycling every year since 2006. The survey respondents were selected randomly from an online panel, who were 15 years old or older and owned a mobile phone (Read, 2015). The sample size for each survey ranged from 600 to 1100 people. The survey questions include those about the current phone ownership and use patterns, the length of the actual and expected time period consumers use their phones, when and why they get a new phone, what they are doing with old phones, and how they recycle their

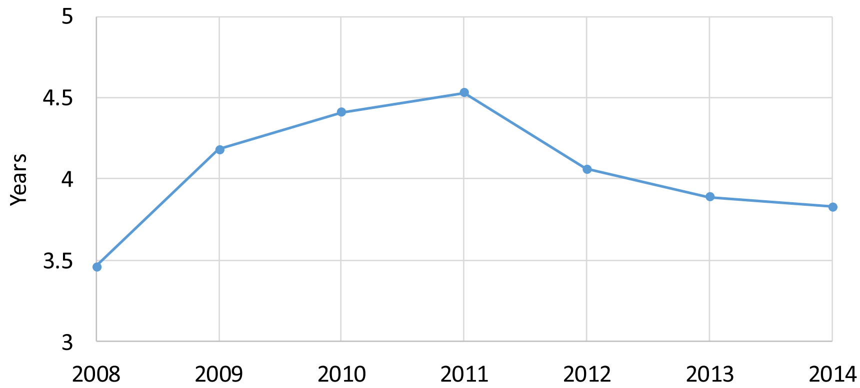

Fig. 6. Average lifespan of a mobile phone in Australia (Leaching model).

phones. Read (2015) provided a detailed description of the survey methods. The data on the destiny of consumers' previous mobile phones, and their expected period of use for new phones from the surveys were used to reconstruct the structure of mobile phone lifespan.

The expected lifespan of mobile phones (L) can be calculated as the sum of three components: time of the first use (T_F), time of reuse (T_R), and storage time (T_S).

$$L = T_F + T_R + T_S$$

Mobile Muster's surveys divided the length of the use of new mobile phones into 6 groups (or time intervals): <6 months, 6–11 months, 12–18 months, 19–24 months, 2+ years and "don't know". The time of the first use and time of storage after the first use can be estimated by multiplying percentages of respondents and average values of time intervals for the first use/storage, based on the survey data. The average value of a time interval is defined as its middle point. For example, if a time interval is from 12 to 18 months, the average value of the time interval would be equal to 15 months (or 1.25 years). For the time interval of 2+ years, the middle point is set as 2.5 years. The percentage of people who answered "don't know" is added to the answers for the "2+ years" group.

There is no available information for estimating a phone's reuse time and storage time after reuse. Therefore, we applied the estimates of first use (storage) with additional 0.8 ratio, assuming that second hand phones are of less value for consumers, and thus the average time of reuse and following storage is likely to be shorter compared to a new phone.

The estimated results are presented in Fig. 7. It is interesting to note that the estimated average expected lifespan for a mobile phone did not fluctuate much in the period 2005–2014, namely from 3.6 to 3.8 years. This could be partly explained by mobile phones reaching the saturation level and maturity in the market, but may also be due to some inaccurate or unreliable answers from the surveys. In this investigation, while assuming that available data are reliable, we also cross-checked the results using different approaches to the lifespan estimation. The results from the previous section (Fig. 6), while being slightly higher, generally align closely with the estimation presented in Fig. 7.

As it can be seen in Fig. 7, the period of active use of mobile phones (first use plus reuse) typically comprises about two thirds of the life of a mobile phone. This should result in a similar ratio between mobile phones in active use and in storage (i.e. two to one). However, the consumer surveys have showed that this proportion is about one to one (Fig. 4). A possible explanation to this could be that people tend to underestimate the expected time of mobile phone storage after use (and the number of phones stored after use), and/or overestimate the expected time of new phone use (i.e. replacing phones more often than originally expected).

According to the consumer survey results, every second phone in Australia is expected to be stored after the first use, every fourth gets a second life with relatives/friends or resold for reuse, every 10th goes to recycling, and one out of 20 is lost or disposed (Read, 2015). Some important questions arise from a more detailed analysis of the survey data. These include the lack of information regarding the destiny of older phones in storage, e.g. while most respondents admitted that they would prefer to store their last phone, the same may or may not be valid for older phones in storage, which in turn affects the average storage time and overall product lifespan. An additional question regarding how long the consumers were actually using their previous phone (apart from

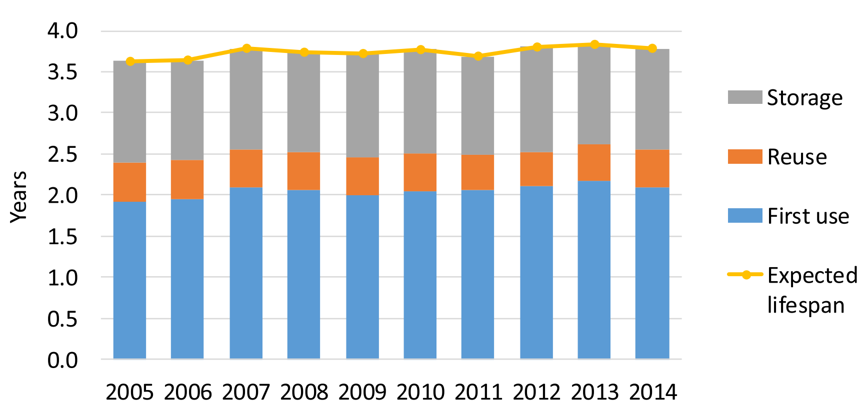

Fig. 7. Expected lifespan for a mobile phone in Australia (based on consumer surveys).

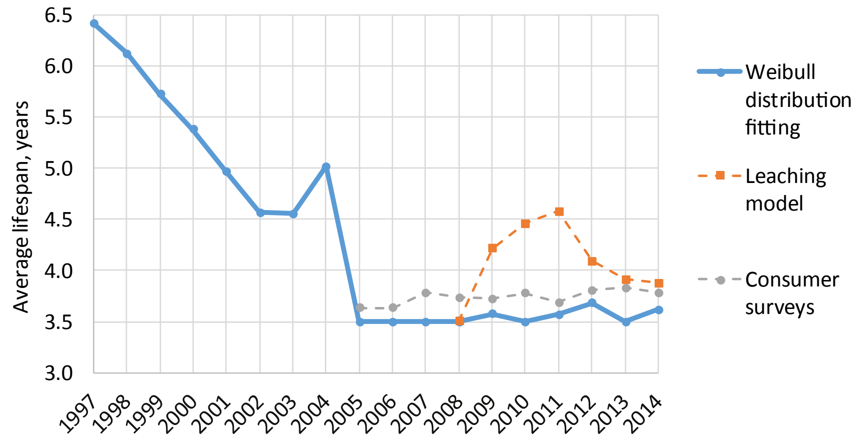

Fig. 8. Comparison of estimated average lifespans for mobile phone by different methods.

what happened to it) would also be helpful to verify the lifespan of a mobile phone. There is also a lack of details about the behaviour of consumers who prefer replacing their mobile phones more often (e.g. every year). A critical question is: does this show a different pattern, e.g. would a mobile phone be more likely to be reused/resold rather than stored if replaced more often?

3.2.3. *The use of Weibull function distribution*

The Weibull distribution has been demonstrated as the most suitable function to describe the obsolescence of consumer durables, including mobile phones. The generation of EoL products can be estimated with the use of a cumulative function, while product's average lifespan is represented by the mean value of Weibull distribution (Oguchi et al., 2008; Polák and Drápalová, 2012).

The lifespan estimates from previous sections can be used as limits in non-linear regression analysis to define the best-fit parameters for Weibull distribution, with the use of solver function in MS Excel (Wang et al., 2013). The following limits have been applied to average lifespan (mean value): 3.5–4.5 year range over 2005–2014, and extended to 3.5–7 years over 1997–2004 (no survey data are available for this period). Additionally, parameter α (shape) of a Weibull function has been limited to values from 0.7 to 3.1 based on the range of values for this parameter defined in previous studies for different EEE (Oguchi et al., 2008; Wang et al., 2013); we believe that this can representatively cover different potential rates of ageing for mobile phones.

For the computation of stocks and flows with the use of a Weibull function, we applied the midpoint values for every year (e.g. 0.5 for year #1, 1.5 for year #2 etc.), similar to the approach used by Wang et al. (2013). We also believe that this is more relevant for products with shorter lifespan, i.e. a certain part of product sales is accounted for the EoL flows starting with the first year. The results from estimating the best-fit parameters for Weibull distribution over 1997–2014 are presented in Table 1, and also compared with estimations by other methods in Fig. 8.

The estimated parameters for the Weibull distribution (Table 1) show a constant decrease in parameter β until stabilising at around 4.0 since 2005, while there is a significant fluctuation in parameter α – from 1.03 to 3.10 (within the applied limits of 0.7–3.1). This may be caused by potential inconsistencies in the original data. It can also be explained by the fitting process itself, i.e. there may be several solutions (combinations of Weibull parameters values) that meet the requirements within the applied limits. For comparability with other studies, we suggest to average the parameters in Table 1 over the 5-year period. The lifespan distribution curves for mobile phones in Australia, averaged for 2001–05 and 2010–14, are compared with the results from studies in other countries in Fig. 9 (a) and (b).

The proportion of mobile phones reaching the EoL status earlier has increased in Australia over time: in 2001–05 about 37% of mobile phones were expected to reach the end of life within 3.5-year time versus about 50% in 2010–14 (Fig. 9b). Based on the shape of curves, the lifespan distribution in Australia is relatively close to that from the Japanese study for 2003, while the results for the Netherlands in 2005 and Czech Republic in 1996–2008 are standing apart (Fig. 9).

The Czech study was based on the analysis of the EoL mobile phones' age structure in 2008 derived from the official collection systems and special campaigns (Polák and Drápalová, 2012). This could result in a bias due to the fact that a significant number of EoL phones can be exported for reuse, end up in landfills, and/or go through unofficial collection and recycling systems (see also Fig. 1 for details on possible destinations for the EoL products). The use of only one source of information (i.e. official collection systems) and only one selected year in reconstructing the age structure of EoL products would not provide an adequate result in the lifespan modelling for mobile phones, thus has to be avoided.

Table 1
The best-fit parameter values of Weibull distribution for mobile phones in Australia.

Year	Weibull parameters		Average lifespan (mean value), years
	α (shape)	β (scale)	
1997	3.10	7.17	6.41
1998	2.99	6.85	6.12
1999	2.97	6.41	5.72
2000	3.05	6.02	5.38
2001	3.06	5.55	4.96
2002	3.10	5.10	4.56
2003	2.03	5.14	4.56
2004	0.97	4.94	5.01
2005	2.38	3.95	3.50
2006	1.57	3.90	3.50
2007	1.28	3.78	3.50
2008	2.87	3.93	3.50
2009	1.65	4.00	3.58
2010	3.10	3.91	3.50
2011	1.82	4.01	3.57
2012	3.10	4.11	3.68
2013	2.66	3.94	3.50
2014	3.05	4.05	3.62

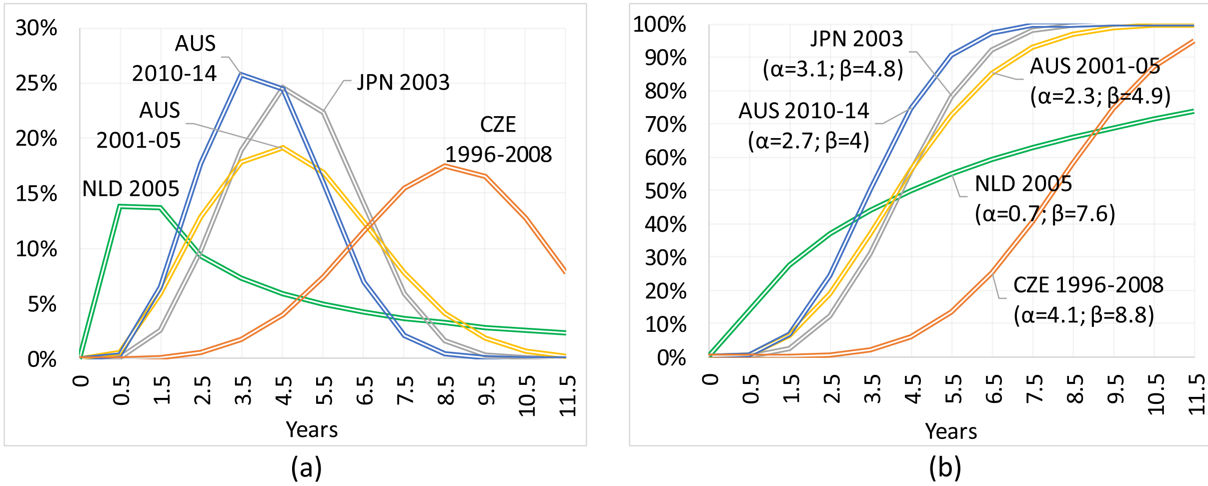

Fig. 9. Comparison of Weibull lifespan distribution curves for mobile phones from this study (average for Australia in 2001–05 and 2010–14) with previous estimations in Japan, Netherlands, and Czech Republic: a) annual EoL product rate; b) accumulated EoL product rate.

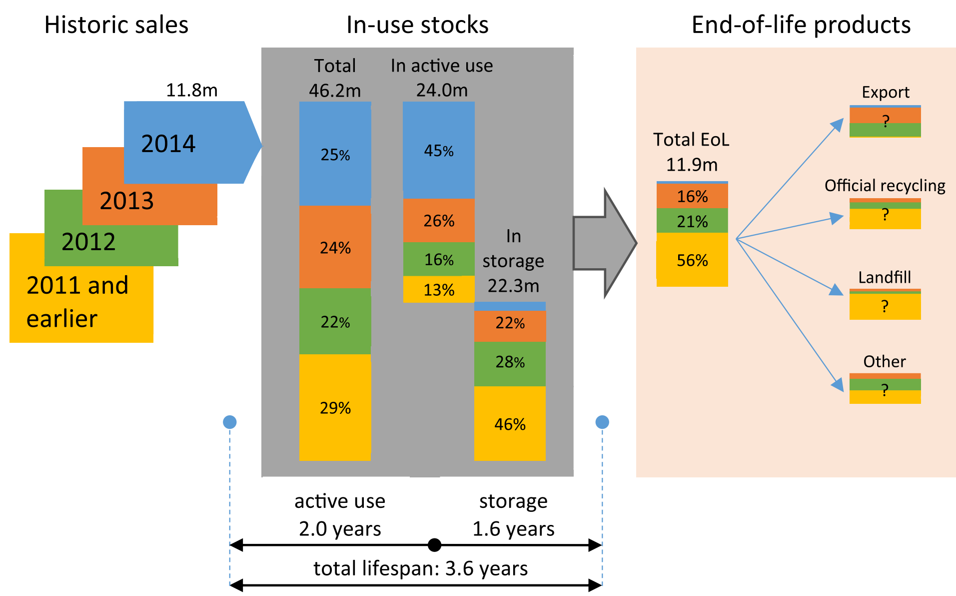

Fig. 10. Estimated in-use stocks and flows across different product age groups for mobile phones in Australia in 2014.

The lifespan estimate in the Dutch study (Wang et al., 2013) shows a relatively high EoL product rate in the first two years followed by a drastic decrease resulting in about 30% of mobile phones being in stock even 10 years later after purchase (Fig. 9b). One of possible explanations for this rather unusual result could be that it is based on the consumer surveys. These surveys often indicate the expected time of use for new bought phones, but usually detail only the first 2–3 years. Another important point for analysing the consumer survey results is that the first use of mobile phone is not equal to its total lifespan, which also includes the reuse and storage components.

3.3. Estimating product age structure for in-use stocks and end-of-life products

The lifespan distribution parameters allow the modelling of the product age structure for mobile phones in stock and at the end of life. Similar to Section 3.2.3, the Weibull distribution fitting can be applied to define the age structure of mobile phones in active use (see Supplementary document for details). Subtracting the latter from the total stocks would indicate the age structure of mobile phones kept in storage. The results are summarised and presented in Fig. 10.

About one quarter of all mobile phones in stock were brand new (less than a year old) at the end of 2014, but these phones form close to a half (45%) of mobile phones in active use (Fig. 10). Similarly, the mobile phones less than 2 years old cover about 50% of total in-use stocks, and more than 70% of phones in active use. At the same time, relatively old phones (dated 2011 and earlier), while representing 29% in stock, account for only 13% of mobile phones in active use, but 46% of phones in storage. About 56% of EoL mobile phones in 2014 were also represented by old phones.

The visual representation of product stocks and flows (Fig. 10) can help to better understand the circulation of different EEE in the economy, informing the development of appropriate policy measures to increase the collection rates and improving the accuracy for estimating the value associated with recycling of EoL products. If statistical and empirical data allow, the analysis can be extended further for specific brands and/or models of electronic devices.

4. Conclusion

The use of empirical data in modelling the product in-use stocks and flows can help overcome inconsistency and reduce uncertainties attributed to a lack of official information sources and statistics. The key novelty of the developed methodology in this article is the combination of top-down and bottom-up approaches, based on trade statistics and consumer survey data respectively, to assess the product lifespan, in-use stocks and flows, including reconstructing the product age structure if this information is not available from primary sources. It has been successfully demonstrated with the case study of mobile phones in Australia over 1997–2014.

The total number of mobile phones in in-use stocks in Australia has been estimated at 46 million, or about 2 phones per capita, being relatively stable since 2012. The proportion of phones not being in use (kept in storage) has been constantly rising, accounting for about 50% of all phones in Australian households in 2012–2014. The generation of EoL phones has reached 12 million units, being equal to new phone sales and indicating the saturation level in the market.

The average lifespan of a mobile phone in Australia in 2005–2014, estimated by different methods, is in the range between 3.5 and 4.5 years, with a consensus estimate of 3.8 years for the last five-year period from 2010 to 2014. The estimated Weibull distribution shows that the average lifespan has been shortening over time – from about six years in late 1990s to five years in early 2000s, and then stabilised at around 3.6 years which further supports the fact that mobile phones have reached the market saturation level. The comparison with previous studies in other countries revealed that the lifespan distribution profile for mobile phones in Australia is relatively close to results reported in Japan, while the available European studies are inconsistent with each other and standing apart from our results.

Based on existing customer surveys for 2005–2014, a mobile phone's average expected lifespan includes 2.1 years (55%) of first use, 0.5 years (12%) of reuse, and 1.2 years (35%) of being in storage. The use of the Weibull function for modelling the lifespan distribution indicated a slightly different result. The average time of active use for mobile phones was estimated at about two years (which includes first use and reuse) (56%), while the storage time was about 1.6 years (44%). The estimation of stocks and flows across different product age groups showed that the mobile phones less than 2 years old cover about 70% of all phones in active use, and 50% of total in-use stocks. At the same time, relatively old phones (4+ years old) account for only 13% in active use, but 46% of kept in storage and about 56% of EoL mobile phones in 2014.

The analysis of existing consumer survey data revealed a lack of details regarding potential differences in consumers' decisions towards previous mobile phones depending on how often phone is replaced. This would help to verify the Weibull function distribution, namely higher/lower EoL products generation in the first (and second) year due to higher/lower rates of phones resale, reuse, or temporal storage. An additional question regarding how long the consumers were actually using their previous phone (apart from what happened to it) would also be helpful to verify the lifespan of a mobile phone.

Mobile phones contain a significant recovery value compared to other electronic devices, thus the consumers' hoarding behaviour in Australia means an accumulation of significant potential resources for future (metal) recovery. A better collection and recycling system would help capture this value. On the other hand, the facilitation and wider enabling of mobile phone reuse can help mitigate the shortening of the lifespan of these devices, while minimising the overall environmental impacts over the product life cycle.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2016.05.117.

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