Waste Management 33 (2013) 2397–2407

Contents lists available at SciVerse ScienceDirect

Waste Management

journal homepage: www.elsevier.com/locate/wasman

Enhancing e-waste estimates: Improving data quality by multivariate Input–Output Analysis

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ARTICLE INFO

Article history:
Received 15 March 2013
Accepted 3 July 2013
Available online 28 July 2013

Keywords:
E-waste
WEEE
Input–Output Analysis
E-waste estimate
Waste management

ABSTRACT

Waste electrical and electronic equipment (or e-waste) is one of the fastest growing waste streams, which encompasses a wide and increasing spectrum of products. Accurate estimation of e-waste generation is difficult, mainly due to lack of high quality data referred to market and socio-economic dynamics. This paper addresses how to enhance e-waste estimates by providing techniques to increase data quality. An advanced, flexible and multivariate Input–Output Analysis (IOA) method is proposed. It links all three pillars in IOA (product sales, stock and lifespan profiles) to construct mathematical relationships between various data points. By applying this method, the data consolidation steps can generate more accurate time-series datasets from available data pool. This can consequently increase the reliability of e-waste estimates compared to the approach without data processing. A case study in the Netherlands is used to apply the advanced IOA model. As a result, for the first time ever, complete datasets of all three variables for estimating all types of e-waste have been obtained. The result of this study also demonstrates significant disparity between various estimation models, arising from the use of data under different conditions. It shows the importance of applying multivariate approach and multiple sources to improve data quality for modelling, specifically using appropriate time-varying lifespan parameters. Following the case study, a roadmap with a procedural guideline is provided to enhance e-waste estimation studies.

1. Introduction

Waste electrical and electronic equipment (WEEE or e-waste) is one of the fastest growing solid waste streams. Continuous technological innovations, combined with rapid growth in consumer demand lead to a rapid proliferation of electronic devices (Dwivedy and Mittal, 2010). As a result, large quantities of e-waste have been generated. This phenomenon is accelerated by decreasing lifespans and increasing range of new product types. For instance, there are more than 900 types of electrical and electronic equipment identified in developed world (Huisman et al., 2012). If handled improperly, the substantial amounts of valuable and hazardous materials in the e-waste stream may result in a loss of resources and substantial damage to the environment.

Current estimates predict close to 50 million tons of e-waste worldwide per year (StEP Initiative, 2010; Huisman, 2012). A more precise assessment of the current and future e-waste generation is needed to quantify its resource potential (as "urban mining") and toxic content. The results of such research provide a baseline to optimise planning of e-waste policies, management of take-back systems, and monitoring of legislative implementation (Beigl et al., 2008). In February 2012, the EU adopted an updated WEEE collection target to be achieved in 2019. The target is 65% of the average of electrical and electronic equipment (EEE) sold in the three preceding years or alternatively 85% of e-waste generated (European Commission, 2012). However, no uniform methodology has been formulated to estimate national e-waste quantities which will be critical for the implementation of these targets. As a consequence, there is a clear need for accurate quantification of e-waste streams.

A number of evaluation methods are available for quantifying e-waste generation (Walk, 2004; Yu et al., 2010; Chung, 2011; Araújo et al., 2012; Lau et al., 2012). Generally, they can be classified into four groups: disposal related analysis, time series analysis (projections), factor models (using determinant factors for correlation) (Huisman et al., 2008; Huisman, 2010) and Input–Output Analysis (Walk, 2004; Beigl et al., 2008; Chung, 2011). Disposal related analysis uses e-waste figures obtained from collection channels, treatment facilities and disposal sites. It usually requires empirical data from parallel disposal streams to estimate the overall generation. Projection models forecast the trend of e-waste

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http://dx.doi.org/10.1016/j.wasman.2013.07.005

generation by extrapolating historical data into the future. It can be also applied to fill in the gap of past unknown years from available datasets. Factor models are based on hypothesized causal relationships between exogenous factors like population size and income level versus e-waste generation (Beigl et al., 2003, 2008). It is the least explored method so far due to complex anthropological effects, high uncertainty in long-term patterns and considerable requirement for advanced modelling techniques. Input–Output Analysis is so far the most frequently used method with multiple model variations, which has been applied to estimate e-waste generation in many regional and country studies (He et al., 2006; Kang and Schoenung, 2006; Peralta and Fontanos, 2006; Yang et al., 2008; Robinson, 2009; TemaNord, 2009; Dwivedy and Mittal, 2010; Chung et al., 2011; Zhang et al., 2011; Araújo et al., 2012; Polák and Drápalová, 2012. This method quantitatively evaluates the sources, pathways and final sinks of material flows. The present paper further explores the application of IOA models with a specific focus on the data quality of model variables.

In current literature, the problem of low data quality is often underestimated or not fully understood yet. Data has often been considered as an external problem independent from the mathematical modelling. However, the accuracy of non-validated results can be limited due to low data quality, insufficient validation of model parameters, unrealistic assumptions and oversimplification of market conditions (Beigl et al., 2008; Murakami et al., 2010; Oguchi et al., 2010). Therefore, reporting results with little review on validity, completeness and reliability of data can lead to very inaccurate estimations.

Data qualities vary from diverse sources, and they are often inconsistent with each other. Product sales and stock data are usually sporadic and incomplete for all historical years (EEA, 2003). Product lifespan data are often roughly obtained without comprehensive consumer survey and further validation. In meantime, rapidly changing market conditions and the introduction of new product types demand dynamic modelling of actual flows. However, product weights and lifespan profiles are often considered to be constant over time in existing studies, and complete time series data are rarely available (Babbitt et al., 2009). Therefore, these issues regarding data quality have created considerable difficulties for accurate estimation.

This article will systematically address how to improve e-waste estimates and provide solutions to the challenges. These include: (a) to propose an advanced Input–Output Analysis under a multivariate approach; (b) to highlight data consolidation steps to improve the qualities of input data; and (c) to present a procedural guideline for advanced estimation.

2. Advanced Input–Output Analysis

In a socio-economic system, products flow into the society (sales), then accumulate in the built environment (stock); when reaching end of life after a certain period (lifespan), they flow out as e-waste (van der Voet et al., 2002; Bergbäck and Lohm, 2008). IOA models quantitatively describe the dynamics, magnitude and interconnection of product sales, stocks and lifespans (Brunner and Rechberger, 2004; Walk, 2004; Gregory et al., 2009; Lau et al., 2012). This section mainly explores the mathematical relations among these three variables for e-waste estimates.

2.1. Variations of existing Input–Output Analysis

Table 1 summarises the use of IOA variables on estimating e-waste generation in existing literature. It shows that commonly applied methods use two variables (from the three above-defined variables: sales, stock and lifespan) for computation.

2.1.1. Model A. Time Step model

In Time Step model, the change of stock within a period in a system equals the difference between the total inflows and outflows. The method is represented by:

$$W(n) = POM(n) - [S(n) - S(n-1)] \tag{1}$$

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

2.1.2. Model B. Market Supply models

Market Supply models estimate e-waste generation from product sales in all historical years with their respective obsolescence rates in evaluation year (Streicher-Porte et al., 2005; Jain and Sareen, 2006; Oguchi et al., 2008; Dwivedy and Mittal, 2010). The method is represented by:

$$W(n) = \sum_{t=t_0}^{n} POM(t) \cdot L^{(p)}(t, n) \tag{2}$$

where $POM(t)$ is the product sales in the historical year t; t_0 is the initial year that product has ever been put on the market; $L^{(p)}(t, n)$ is the discard-based lifespan profile for the batch of products sold in historical year t, which reflects its probabilistic obsolescence rate in evaluation year n (discarded equipment in percentage to total sales in year t) (Melo, 1999; Murakami et al., 2010; Oguchi et al., 2010).

Instead of using continuous lifespan distribution of a product, the Carnegie Mellon Method applies discrete average lifespan for different lifecycle stages (Walk, 2004; Peralta and Fontanos, 2006; Steubing et al., 2010). This method allocates product sales in phases such as reuse, household stock, recycling or landfill, and each phase has different time delays. For accurate estimate, it demands comprehensive analysis of material flows and their representative time delays in all product lifecycle stages.

A simplified version of the Market Supply model is the Simple Delay model, in which e-waste generation in the evaluation year is seen as a pure delay from the sales in one historical year:

$$W(n) = POM(n - L^{(av.)}) \tag{3}$$

In this formula, $L^{(av.)}$ is the average lifespan which represents the most possible time when the product becomes obsolete. It can be calculated from the mean value of the lifespan distribution function.

In a completely saturated market with stable population, the quantity of new products sales equals e-waste output at the same time, which is named as the "Complete Saturation Method" (Walk, 2004). However, the use of these two simplified methods can only be justified for saturated market (van der Voet et al., 2002; UNEP, 2007; Lau et al., 2012).

2.1.3. Model C. Stock and Lifespan model

In Stock and Lifespan model, combining time-series stock data with lifespan distributions of products can also estimate e-waste generation (Binder et al., 2001; Müller et al., 2009; Walk, 2009). It can be calculated according to Eq. (5) with Eq. (4) being the initial condition.

For the initial year t_0:

$$W(t_0) = POM(t_0) - S(t_0) = POM(t_0) \cdot L^{(p)}(t_0, t_0) \tag{4}$$

For the evaluation year n:

Table 1
Required variables and datasets for e-waste estimates in existing IOA models.

Estimation models	Variables and data requirement						Key references
	Sales cont.*	Dis.*	Stock cont.	Dis.	Lifespan age distribution	Average lifespan	
A. Time Step model		√	√				Oguchi et al. (2008), Yu et al. (2010), Araújo et al. (2012)
B-i. Market Supply model (Distribution Delay)	√				√		Melo (1999), Yang et al. (2008), TemaNord (2009)
B-ii. Market Supply model (Simple Delay)		√				√	van der Voet et al. (2002)
B-iii. Market Supply model (Carnegie Mellon method)	√					√	Kang and Schoenung (2006), Peralta and Fontanos (2006), Dwivedy and Mittal (2010), Steubing et al. (2010)
C. Stock and Lifespan model			√		√		Müller et al. (2009), Walk (2009), Zhang et al. (2011)
D. Leaching model			√			√	van der Voet et al. (2002), Robinson (2009), Chung et al. (2011), Araújo et al. (2012)

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

$$W(n) = POM(n) - S[(n) - S(n-1)] = \sum_{t=t_0}^{n} POM(t) \cdot L^{(p)}(t,n) \tag{5}$$

2.1.4. Model D. Leaching model

In a saturated market, sales of new products and the age distribution of appliances in stock are no longer changing dramatically (van der Voet et al., 2002). The "leaching model" calculates the e-waste generation as a fixed percentage of the total stock divided by the average product lifespan (van der Voet et al., 2002; Robinson, 2009; Chung et al., 2011; Araújo et al., 2012):

$$W(n) = S(n)/L^{(av.)} \tag{6}$$

This model requires little data input therefore is convenient when data is extremely scarce. However, the model is not suitable for all market types due to oversimplification and loss of dynamic elements compared to the actual situation. It can only be used for products with a relatively short lifespan in a saturated market (van der Voet et al., 2002; Walk, 2009).

2.2. Multivariate analysis: Sales-Stock-Lifespan model

In various e-waste country studies, the applications of these IOA models in e-waste estimates are rather straightforward (He et al., 2006; Yang et al., 2008; Robinson, 2009; Dwivedy and Mittal, 2010; Chung et al., 2011; Araújo et al., 2012; Polák and Drápalová, 2012). The common approach is to select a corresponding estimation method based on available data and the use of only two variables from the three pillars. As a consequence, the estimated result is potentially extremely sensitive towards their data qualities, especially in case of an assumed or non-validated lifespan profile (Jain and Sareen, 2006). Oversimplification of methods and potential data uncertainties in variables (such as lifespan distributions) can substantially decrease the reliability of the estimated results.

In reality, there are often available data from the unused variable or data points, which can provide additional information to support the calculation. When multiple data points are available or can be collected for all three IOA pillars, it is possible to apply a multivariate IOA called the "Sales-Stock-Lifespan model" (referred as Model E).

Fig. 1 illustrates the presence and relationship between these IOA variables and data points. The consuming mechanism of electronic products in societies can be explained as the inflows, stock and outflows of a funnel. Information can be extracted from each data point for any historical year: sales, stock size and stock age composition, lifespan profile, and disposal age composition of e-waste. Relationship between these data points complies with the conservation of mass, IOA rules and algorithms provided in the following. These mathematical and logical functions are instrumental to facilitate filling the data gaps and checking data quality.

For product sales in a specific year, it can be calculated by Eq. (1), when e-waste generation in the same year and stock data in two neighbouring years are known; or by Eq. (2), when the e-waste generations and lifespan profiles are known for all historical years.

For the stock age composition in the evaluation year n, it can be calculated from historical sales and lifespan profiles:

$$S(t,n) = POM(t) \cdot [1 - L^{(c)}(t,n)] \tag{7}$$

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

In addition, the total product stock size in any historical year t can be calculated by:

$$S(t) = \sum_{t'=t_0}^{t} POM(t) \cdot [1 - L^{(c)}(t',t)] \tag{8}$$

For the disposal age composition of e-waste in the evaluation year, it can be calculated from historical sales and lifespan profiles:

$$W(t,n) = POM(t) \cdot L^{(p)}(t,n) \tag{9}$$

Lifespan of a product differs between individual owners and it takes the form of a probability distribution for a given population (Murakami et al., 2010). Owing to social and technical development, lifespan of products is time-dependent, so parameters of lifespan distributions have to be modelled corresponding to each historical sales year. In the present paper, the Weibull distribution function is applied to model the lifespan profile. Compared to other statistical distributions (such as Normal, Lognormal, or Beta distributions), it has been verified that the Weibull function has the advantages of higher analytical tractability and produces the best fits of the lifespans for most products (Melo, 1999; Walk, 2009; TemaNord, 2009). The Weibull distribution is defined by a time-varying shape parameter $\alpha(t)$ and a scale parameter $\beta(t)$ (van Schaik and Reuter, 2004; Polák and Drápalová, 2012):

$$L^{(p)}(t,n) = \frac{\alpha(t)}{\beta(t)^{\alpha(t)}} (n-t)^{\alpha(t)-1} e^{-[(n-t)/\beta(t)]^{\alpha(t)}} \tag{10}$$

Simulation of lifespan distribution can apply non-linear regression analysis for curve fitting, in order to determine best-fit data for these two parameters. For lifespan distribution in each

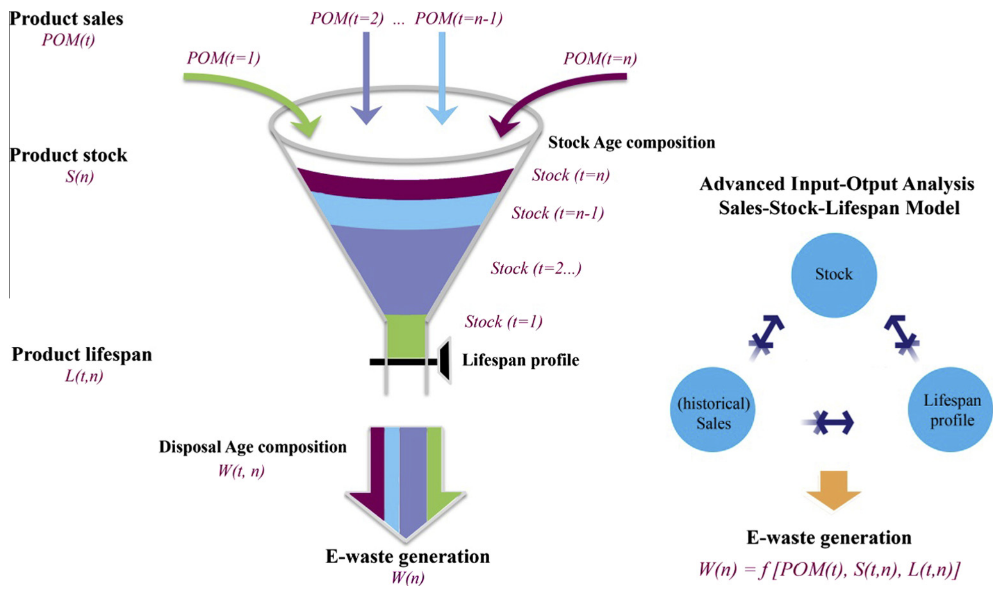

Fig. 1. Multiple variables and data points applied in the Sales-Stock-Lifespan model to enhance e-waste estimates.

historical year, at least two data points are required to calculate the parameters α and β. For instance, in order to determine $\alpha(1990)$ and $\beta(1990)$ for products sold in 1990, their probabilistic obsolescent rates in two years have to be obtained (such as $L^{(p)}(1990, 2011)$ and $L^{(p)}(1990, 2012)$). In addition, numeric and logical constraints can facilitate the process of curve fitting from known data. For instance, the accumulative obsolescence rates for one sales year cannot surpass 100%.

The probabilistic obsolescent rate $L^{(p)}(t,n)$ can be obtained from consumer surveys or calculated from Eq. (2) and Eq. (5), if corresponding sales, stock and e-waste generation data are available. Alternatively, the disposal age composition in e-waste sorting analysis can also be applied to retrieve it for specific year:

$$p(n-t) = \frac{W(t,n)}{W(n)} = \frac{POM(t) \cdot L^{(p)}(t,n)}{\sum_{t=t_0}^{n} POM(t) \cdot L^{(p)}(t,n)} \tag{11}$$

where $p(n-t)$ is the percentage of the e-waste with the age of $(n-t)$ years proportional to the total sampled e-waste; $W(t,n)$ is the amount of e-waste in evaluation year n generated by the sales of products in year t.

Sometimes, it is difficult to calculate the overall e-waste generation in evaluation year according to Eq. (11). Therefore, the ratio of disposal age compositions between two random years can also help to determine the lifespan parameters:

$$\frac{p(n-t)}{p(n-m)} = \frac{W(t,n)}{W(m,n)} = \frac{POM(t) \cdot L^{(p)}(t,n)}{POM(m) \cdot L^{(p)}(m,n)} \tag{12}$$

where t and m are any two historical years before the evaluation year n.

During consumer survey, it is also possible to obtain the age composition of products in stock. Therefore, this type of data can also provide extra information for the lifespan distribution in different historical years. It is presented in the following formula:

$$\frac{S(t,n)}{S(m,n)} = \frac{POM(t) \cdot [1 - L^{(c)}(t,n)]}{POM(m) \cdot [1 - L^{(c)}(m,n)]} \tag{13}$$

where $S(t,n)$ and $S(m,n)$ are the quantity or percentage of products in stock, which was originally sold in years t and m respectively.

To summarise the analysis so far, each data point (as presented in Fig. 1) not only carries information about its own representing variable, but also contains potential indication for other variables. By applying all the formulas presented in this section, additional or alternative data can be extracted from known data. This can enable the maximal capture of all available data to improve the estimation, without losing their potential implications. Therefore, the Sales-Stock-Lifespan model adopts multivariate analysis by involving all three variables in IOAs and multiple data points to estimate e-waste generation.

From the aspect of mathematics, these three variables are equally important or functional. However, when facing a collection of data from different sources in real life calculation, their qualities are usually not equal. Some data points like sales and stock size may have an advantage than other data points because they are easier to measure or have lower level of uncertainty. The following section will further explain the procedure to apply the Sales-Stock-Lifespan model by taking data quality into consideration.

3. Improvement of data quality

There is a variety of data sources for all three variables in IOA, and their qualities vary greatly. This section aims to provide the procedure of applying Sales-Stock-Lifespan model, by constructing a most plausible dataset for more precise estimates.

3.1. Data sources for variables

For product sales, data can be obtained from national statistics on domestic commodity production and import/export figures. Alternatively, sales stemming from marketing surveys and producer foundations can also be used. The latter is usually difficult to obtain due to confidentiality and is often known to be incomplete or too aggregated.

The stock size includes products both in use and in "hibernation" (or "dead storage"). Its quantity can be obtained from consumer and business surveys by requesting the number of products currently staying in the built environment. The conducted survey needs to be representative for demographic, geographic and social-economic factors. In some cases, the age composition of products in stock can be obtained from detailed surveys. According to Eq. (7), the stock age distribution can provide extra and very advantageous information for both sales and lifespan profile for specific historical year(s).

Product lifespan as used in this paper covers the interval between the shipment of new product and the end point when discarded out of the households/enterprises. It differs with the commonly used "service time" as it includes the periods of both use and hibernation (Müller, 2006; Murakami et al., 2010). The statistical distribution of lifespans can be derived from four sources: from consumer surveys describing the age of discarded products; also from surveys, the present age composition of products in stock; stock levels at the beginning and the end of a certain period; and from sorting and sampling of the waste streams (Murakami et al., 2010; Oguchi et al., 2010; Polák and Drápalová, 2012).

It is intrinsically challenging to accurately portray the actual distribution of lifespan in relatively simple statistical functions. Errors can be introduced if the statistical function is oversimplified, for instance when only mean value or time-invariant lifespan distribution is applied for all years. Compared to sales and stock, time-dependent lifespan distribution has a higher degree of freedom as shown in Eq. (10). As a result, multiple methods or data points need to be in place to improve the quality of curve fitting. In consumer surveys, it has been observed that the obtained lifespan data (from asking respondents about the age of their disposed products) is usually more uncertain than the obtained age distribution of the products in stock (Magalini et al., 2012). This is normally due to the sample size: there are more products in stock than being removed from a household. Therefore, stock age distribution (in a specific year) fulfils an important role to check the fitted parameters of the disposal lifespan curve (Eq. (7) and Eq. (13)).

In addition, the average weight of product is an important variable to link product quantities (units or pieces) to their weight (metric tons). The data can either stem from sorting analysis in recycling facilities or surveys from producers, processed by using standard deviation of a group of product weights. Time-series data for product weights over time, for instance via sampling of the return stream, is also essential to measure the dynamics in product design.

3.2. Data quality

Data obtained from different sources and stakeholders might have distinct scopes and qualities. Therefore, efforts need to be spent on understanding and cleansing unrealistic data and constructing continuous dataset by filling data gaps or mismatches. In many cases, the scope of EEE related data is not uniform or clear. For instance, unspecified data about computers can include both desktop computers and laptop computers. Sometimes, such data also include servers, work stations, netbooks, tablets and even peripherals. Sales figures from producer registers are frequently incomplete or based on assumed or outdated average product weights. Non-reported extrapolations within input data need to be understood.

For these reasons, data need to be acquired via statistically robust sampling method and pre-checked for errors. Errors need to be corrected for model input such as: using wrong units, unrealistic average product weights, and the mixing of components with products, of household and professional equipment, of new and second hand goods (Troschinetz and Mihelcic, 2009). As an important source for sales and lifespans, the use of market survey data should be checked regarding coverage, sampling size and demographic conditions in order to be representative for a larger region (Murakami et al., 2010). Also concerns about structural bias like the so-called telescope effect from respondents is relevant, and would potentially bring uncertainty to the disposal based lifespan distribution (Morwitz, 1997). For e-waste specifically, data obtained from sorting analysis requires careful examination. Due to the exclusion of data from other end-of-life streams such as informal recycling, illegal export or landfill, the sampled return streams frequently consist of the least valuable and oldest equipment and are thus not representative for the entire stream.

Data quality mainly reflects the completeness, representativeness, accuracy and uncertainty of the collected data. During modelling of e-waste generation, clear documentation of data quality is preferable. It can be evaluated qualitatively by above mentioned aspects such as data scope (consistent definition of referenced data, products type covered, target company/group/region), acquisition method (statistical measurement, assumptions or unqualified sources), and time coverage (availability of historical data). Furthermore, data quality can be also assessed in the following quantitative attributes: population sizes, confidence intervals, standard deviations, sample sizes, (the procedure for) removing erroneous data points. A checklist for evaluating data quality in e-waste estimation is provided in Table S1 of the Supplementary Data (Appendix 1). As an advanced analysis, a weighting scheme or indicator system can be established to evaluate the data quality. The overall score can be used to either compare alternative data sources for the same data point or between different variables.

3.3. Process data by applying Sales-Stock-Lifespan model

After the data quality has been understood and assessed for all variables, the Sales-Stock-Lifespan model can be used to carry out a multivariate analysis based on available data points. The main purpose is to construct reliable and continuous datasets for model calculation, by either filling the data gap or finding the most reliable data source. The approach is to apply the variable(s) with higher data quality to validate and consolidate the variable with lower data quality. For instance, in case data of both lifespan and stock are available for e-waste estimates. After evaluating the data qualities of both these two variables, if lifespan distributions are found out to unreliable than stock data, then available stock size and initial stock age composition can consolidate lifespan data. For calculation among variables, it can be operated by applying the mathematical functions from Eq. (1) to Eq. (13). Through this process, structural or data errors of less reliable variable become visible by cross-checking with other variables and data points.

In addition to the provided formulas, empirical and logical constraints are also functional to further consolidate data. An example constraint is market saturation levels, such as a maximum of one washing machine per household. It can also include external reference points like the number of cell phones in stock (use) versus the number of subscriptions. Another important source of constraint comes from monitoring the waste and export streams. For example, the identified quantity of products in the total waste streams cannot exceed the model outcomes; for typical replacement products like washing machines, it is not likely that there is more discarding of old products than sales of new products in a given year. Therefore, by setting a dedicated data quality weighting scheme and initial values from available data, the Sales-Stock-Lifespan model can generate a more continuous dataset by closing the data gaps and prioritization of data with higher quality when there are multiple sources present.

After this step, the Time Step Model can be applied directly to calculate e-waste generation, if reliable sales and stock data are obtained. The Market Supply model (distribution delay) can be applied, if reliable sales and lifespan distribution are retrieved from the analysis. There is a fundamental difference between the direct application of these two-variable models and the advanced model, despite using the same formula to calculate e-waste generation eventually. The advanced IOA model improves the quality of input data through data consolidation procedure by multivariate analysis; while the preparation of data has not been considered by Models A–D.

Through these steps of data consolidation and multivariate analysis, the accuracy of the model output is significantly improved, compared with other straightforward approaches. The following section will practice the Sales-Stock-Lifespan model through an empirical study from the Netherlands.

4. Case study for Dutch e-waste flows

In 2011, a national study was conducted to determine the generation, collection, treatment and export of all types of e-waste in the Netherlands (Huisman et al., 2012). For most product categories, multiple data sources were obtained for EEE sales, stock, lifespan and average weights. These include national statistics, consumer surveys, compliance schemes, producers, industrial associations, recyclers and exporters. These data are applied to calculate the e-waste generation in the Netherlands. The quality of data compared to many other studies is regarded to be very high. In this empirical study, all IOA models presented in Section 2 have been examined under the same dataset, in order to compare the results between models.

4.1. Data

In order to capture all the EEE present in the Dutch society, a comprehensive classification of EEE has been developed to divide all possible EEE into 55 product categories (Wang et al., 2012). It was established under three essential criteria: product type, waste management and legislative relevancy. An important source facilitating the categorisation was the international coding system of goods. Information from the European Prodcom (Production Statistics Database for the domestic statistics on the production of manufactured goods) and CN (Combined Nomenclature Database for the external trade statistics of goods) codes was compiled to categorise all the EEE. The EEE related codes were collected for the period 1993–2011 from the Eurostat Ramon database (Eurostat, 2011).

Historical product sales were obtained from three data sources. The commodity registrations from Statistics Netherlands have been compiled covering all 55 EEE categories between 1995 and 2010. Sales of product were calculated from the annual quantity of domestic production (from Prodcom) plus the import (from CN) and minus the export (from CN) at the national level. For each product category, detailed scrutiny of the micro-data was conducted, and error-resolving was applied to remove highly unlikely records of domestic sales, import and export. The approach was to check the consistency among the quantity, weight and value per product shipment, and then the identified abnormal record was corrected. Sales data for recent years were also obtained from the Wecycle producer registers and from Agency Netherlands for individually notifying companies. In addition, complementary data from retail panel and branch organizations were used.

Lifespan distribution and stock levels of various EEE in the Netherlands were primarily derived from extensive market surveys. Lifespan profiles were calculated from two data sources: the stock data including stock size and age distribution; and the age composition of products discarded from households. To obtain these data, a national survey was conducted towards 5200 representative Dutch households for the purchasing, possession and disposal of domestic appliances (63 types), consumer electronics (18 types) and IT products (5 types) during 2006 and 2007 (Hendriksen, 2007). In 2008, 3000 representative Dutch households were interviewed for discharge lamps (Hendriksen, 2009). Also the stock levels of EEE in small and medium sized enterprises were surveyed (Hendriksen, 2010). In these surveys, face to face visits were conducted to validate and correct online responses. Additional data from complementary end-of-life streams and sorting analysis in the Dutch e-waste recycling facilities in 2011 were applied to validate the survey results. Based on the Weibull distribution function, first year failure rates were incorporated when abrupt discarding behaviours were observed for the first year of product purchase (e.g. guarantee claims and consumer dislike of products). Therefore, a compound lifespan distribution has been applied for better capturing the actual disposal behaviours: increased defects risk for the first year after purchase, described by a constant parameter added to the first year obsolescence rate of the Weibull distribution; other years still with the original Weibull distribution (TemaNord, 2009). In meantime, except for lamps, it is assumed that lifespan profile for business use is similar for consumers in this case study.

Average weight per EEE category was acquired through the sorting analysis and the Wecycle producer register, while literature data has been included for comparisons as well. The obtained raw data have been processed by analysing their standard deviations and confidence intervals to reflect the weight distribution over time.

4.2. Modelling process and results

Based on Section 2.2 and fed with the data described in 4.1, the Sales-Stock-Lifespan model has been developed. The model was constructed in MS Excel to allow for flexible application of Microsoft Excel Solver (Frontline System Inc., 2012) for non-linear regression analysis per product category. Data quality was qualitatively evaluated based on data availability for the respective years for all three pillars, together with the accuracy of fit (R-squared values) for the lifespan profiles. Dependent on the data quality of each pillar, the solver was applied to determine the parameters for variables, correct data errors and complete the missing data for model input. The variables with higher data quality were used to validate and consolidate the variable with lower data quality consecutively.

Regarding the data quality in the Dutch study, the sales of products had the most complete and reliable time-series dataset. Then the total quantity and age composition of products in stock were also very reliable for year 2006. In addition, the age composition of the discarded e-waste in 2006 was also available but required further verification. In consideration of the data quality hierarchy in this case study, as a starting point, the Weibull parameters were obtained by curve fitting from the disposal age composition $W(t, n)$ for the investigated years in consumer surveys; then stock age composition $S(t, n)$ was used as a supplementary and a more reliable source to determine dynamic lifespan parameters for all historical years, by applying Eq. (13). The detailed process of modelling the time-varying lifespan parameters are provided as a tutorial in Supplementary Data (Appendix 2). After acquiring the lifespan distributions, data gaps of historical stock were then filled in by combining sales and lifespan profiles under Eq. (9), with the minimal deviation of the results compared to all original data points.

After continuous and reliable dataset were obtained and consolidated for all historical sales and lifespan profiles, e-waste generation was calculated by Eq. (2). Resulting data of sales, stock, lifespan, average weight, e-waste generation are provided in Table 2 for selected years.

5. Significance of model selection and data quality

In order to understand the influence of lower data quality in traditional IOA models, a selection of representative EEE is used from

Table 2
Classification of EEE with their sales, stock, average weights, lifespan distributions and e-waste generation in the Netherlands (in selected years).

Primary EEE category	Sub-category		Primary WEEE collection category	Average weight (kg/piece)		Lifespan distribution (Weibull)				EEE sales 2010 (kg/inh.)	Model output	
	Sub-key	Description		1995	2005	1995		2005			EEE in stock 2010 (kg/inh)	WEEE Generated 2010 (kg/inh)
						α shape	β scale	α shape	β scale			
Large household appliances (LHA)	1-01	Prof. Heating and ventilation	F. PROF	83.7	83.7	1.8	16.2	1.8	15.8	0.44	5.24	0.37
	1-02	Dishwashers	A. LHA	49.4	45.5	1.7	13.5	1.6	13.1	1.05	11.26	0.99
	1-03	Kitchen (furnaces, ovens)	A. LHA	41.5	45.6	2.7	19.4	2.5	18.0	0.66	8.68	0.47
	1-04	Washing machines	A. LHA	69.1	71.4	2.3	14.6	2.2	13.9	2.93	32.88	2.68
	1-05	Washing dryers and centrifuges	A. LHA	37.7	43.2	2.7	16.9	2.6	16.5	0.89	11.36	0.69
	1-06	Room heating and ventilation	A. LHA	9.6	9.9	2.0	13.5	2.0	13.5	0.35	3.68	0.30
	1-07	Sun beds and tanning	A. LHA	69.1	71.4	1.5	11.4	1.5	11.2	0.02	1.06	0.14
	1-08	Fridges (for food, wine etc.)	B. C&F	33.1	38.2	2.3	16.9	2.2	16.5	1.39	16.28	1.01
	1-09	Freezers (for food, ice, etc.)	B. C&F	43.6	43.9	2.7	24.0	2.6	23.2	0.67	12.94	0.62
	1-10	Combined fridges and freezers	B. C&F	54.3	64.4	2.3	16.9	2.2	16.5	1.11	12.81	0.78
	1-11	Air conditioners	B. C&F	50.0	35.0	2.8	12.6	2.8	12.3	0.04	1.24	0.13
	1-12	C&F Other (Cooling and Freezing)	B. C&F	9.8	9.8	2.5	14.0	2.4	13.6	0.08	0.85	0.08
	1-13	Prof. C&F	F. PROF	120.0	137.9	2.5	21.0	2.5	20.6	0.82	10.88	0.40
	1-14	Microwaves	C. SHA	15.9	17.5	1.0	17.8	0.8	14.7	0.63	5.56	0.48
Small household appliances (SHA)	2-01	SHA (iron, scale etc.)	C. SHA	1.3	1.2	1.4	9.8	1.3	9.4	0.63	5.01	0.65
	2-02	Food processing	C. SHA	2.9	3.1	1.6	14.7	1.3	12.3	1.33	11.63	1.10
	2-03	Hot water (coffee, tea etc.)	C. SHA	1.9	1.9	2.0	9.1	1.8	7.9	0.53	2.91	0.45
	2-04	Vacuum cleaners	C. SHA	4.8	5.5	1.5	10.5	1.5	10.3	0.54	3.98	0.44
	2-05	Personal care	C. SHA	0.6	0.6	1.4	11.6	1.3	10.8	0.13	1.15	0.13
IT and telecom equipment (IT)	3-01	Small IT and accessories	D. IT	0.6	0.5	1.3	6.1	1.3	5.9	0.47	2.46	0.51
	3-02	Desktop PC (excl. monitor)	D. IT	10.4	9.3	2.2	10.1	2.1	9.6	0.64	6.33	0.83
	3-03	Laptop PC (incl. netbook, tablet)	D. IT	4.6	3.7	1.6	5.6	1.5	5.2	0.43	1.36	0.31
	3-04	Printing and imaging	D. IT	7.9	7.3	2.0	11.8	1.7	10.1	0.86	5.86	0.67
	3-05	Telephones and equipment	D. IT	0.8	0.6	2.3	7.4	2.1	6.5	0.06	0.31	0.07
	3-06	Mobile phones	D. IT	0.12	0.10	0.8	7.9	0.7	7.6	0.02	0.13	0.02
	3-07	Prof. IT (server, router etc.)	G. PROF/D. IT	36.0	36.0	1.5	8.0	1.5	7.8	0.76	4.17	0.63
	3-08	CRT monitors (cathode ray tube)	E1. CRT	14.6	19.4	2.4	9.5	2.2	8.5	-	4.32	1.28
	3-09	FPD monitors (flat panel display)	E2. FPD	5.0	6.5	2.7	8.0	2.5	7.5	0.76	4.75	0.57
Consumer equipment (CE)	4-01	Small CE and accessories	C. SHA	0.4	0.4	1.8	13.5	1.4	10.2	0.15	0.93	0.11
	4-02	Portable audio and video	C. SHA	0.4	0.3	0.8	8.2	0.8	8.0	0.07	0.57	0.07
	4-03	Radio and Hifi components	C. SHA	3.6	2.6	2.1	15.8	2.1	15.6	0.63	7.21	0.51
	4-04	Video and projection	C. SHA	4.1	3.3	1.7	10.7	1.7	10.5	0.33	4.37	0.56
	4-05	Speakers	C. SHA	3.1	2.4	1.5	11.0	1.5	10.8	0.31	3.04	0.33
	4-06	Camera	C. SHA/D. IT	1.1	0.5	1.5	8.6	1.4	8.2	0.06	0.49	0.07
	4-07	CRT TVs (cathode ray tube)	E1. CRT	24.2	31.8	2.2	14.5	2.0	12.6	-	13.68	1.76
	4-08	FPD TVs (flat panel display)	E2. FPD	7.8	12.6	2.1	12.0	2.1	12.0	1.71	7.13	0.28
Lighting equipment	5-01	Lamps (others, Christmas light etc., excl. incandescent lamps)	F. Lamps/C. SHA	0.09	0.09	2.0	12.3	2.0	11.6	0.27	2.33	0.23
	5-02	Compact fluorescent lamps	F. Lamps	0.08	0.08	2.1	9.0	2.1	9.1	0.08	0.44	0.04

(continued on next page)

Table 2 (*continued*)

Primary EEE category	Sub-key	Description	Primary WEEE collection category	Average weight (kg/piece) 1995	Average weight (kg/piece) 2005	Lifespan distribution (Weibull) 1995 α shape	1995 β scale	2005 α shape	2005 β scale	EEE sales 2010 (kg/inh.)	Model output: EEE in stock 2010 (kg/inh)	Model output: WEEE Generated 2010 (kg/inh)
	5-03a	Straight tube fluorescent lamps (business to business)	F. Lamps	0.11	0.11	1.3	6.6	1.4	7.2	0.11	0.59	0.12
	5-03b	Straight tube fluorescent lamps (household)	F. Lamps	0.11	0.11	1.9	17.8	1.9	17.8	0.02	0.25	0.01
	5-04	Prof. special lamps	F. Lamps	0.08	0.08	1.5	8.0	1.2	5.5	0.01	0.03	0.01
	5-05	LED lamps	F. Lamps	0.08	0.08	N.A.	N.A.	2.0	10.9	0.02	0.02	N.A.
	5-06	Household luminaries	F. Lamps	0.5	0.5	2.3	13.5	2.1	13.0	0.60	7.71	0.53
	5-07	Prof. luminaries	F. Lamps	2.7	2.7	2.2	17.0	2.1	16.6	0.40	1.93	0.31
Electrical and electronic tools	6-01	Prof. tools (excl. dual use)	C. SHA	23.2	23.2	2.0	12.0	1.9	11.6	0.16	1.25	0.11
	6-02	Small tools (household)	C. SHA	2.6	2.5	3.0	18.0	2.6	15.7	0.73	8.91	0.58
Toys, leisure and sports equipment	7-01	Small toys	C. SHA	0.25	0.22	1.5	4.9	1.5	4.7	0.05	0.18	0.05
	7-02	Game Consoles	D. IT	0.5	0.5	1.2	5.8	1.2	5.6	0.11	0.49	0.10
	7-03	Large Music and Exercise	G. PROF	14.5	14.5	2.5	12.0	2.4	11.6	0.06	0.44	0.03
Medical devices	8-01	Small medical (household)	C. SHA	0.18	0.18	1.5	8.0	1.4	7.6	0.01	0.03	0.00
	8-02	Prof. medical	G. PROF	67.0	67.0	2.8	20.0	2.6	19.2	0.32	3.11	0.13
Monitoring and control instruments	9-01	Small monitoring	C. SHA	0.24	0.24	1.8	10.0	1.7	9.6	0.14	0.85	0.09
	9-02	Prof. monitoring	G. PROF	5.5	5.5	2.0	12.0	1.9	11.6	0.11	0.89	0.08
Automatic dispensers	10-1	Prof. dispenser (non-cooled)	F. PROF	78.5	78.5	2.1	10.5	2.0	10.1	0.33	2.46	0.27
	10-2	Prof. dispenser (cooled)	F. PROF	92.2	92.2	2.1	10.5	2.0	10.1	0.18	1.28	0.13
Total										25.18	259.7	23.33

the Dutch study. Four products are selected to illustrate different market types and discarding patterns: washing machine (saturated replacement market), laptop computer (steadily increasing market), Cathode Ray Tubes (CRT) TV (declining/phase-out market) and flat panel TV (new market).

The modelling results of e-waste generations from Model A to E are presented in Fig. 2. It generally demonstrates that these models lead to distinct results for all four appliances. In order to examine the discrepancies between models, results from Model E (Sales-Stock-Lifespan Model) are referred as the baseline to enable comparison in the present case study (red lines in Fig. 2). Model E is intrinsically more accurate as it links and validates existing data from multiple sources for all three independent variables based on their data quality and respective model algorithms.

The Time Step model (Model A, black lines) simply applies mass balances and the result contains "noises" from the sales and stock fluctuations (washing machines in first chart). Confined by availability in the Dutch case study for historical stock data, the results of other three appliances do not contain serrated "noises" due to the use of modelled stock data. In this case, Model E generated a smooth curve through these dynamic points, and the fluctuating noises have been evened out by applying fitting of dynamic lifespan profiles. The accuracy of model A highly relies on the quality of the sales and stock data.

The Market Supply model (Model B) applies dynamic time-varying lifespan distributions (B-1, orange lines) generates the closest results to the baseline. If fixed lifespan distribution from a reference year is used instead (B-2, pink lines; B-3, yellow lines), it leads to deviation from the baseline for certain years. In the case of CRT TVs, applying fixed lifespan distribution from 1990 generates a very similar result with the baseline during 1990–2001, but it starts to deviate significantly from 2002 onwards with average relative difference of −6% compared to the baseline. It indicates that applying a fixed lifespan distribution is not the right modelling choice for phase-out market conditions.

For Stock and Lifespan model (Model C), the accuracy of the calculation primarily relies on the representativeness of the lifespan distributions applied. The two scenarios selecting marginal lifespan distributions from 1990 (C-1, light green lines) and 2011 (C-2, deep green lines) have shown significant deviation from the baseline in four product cases. For laptop computers, the scenario applying fixed lifespan distribution from 1990 has a large difference compared to the baseline for 2001–2011; while applying the 2011 lifespan distribution results in a similarly large deviation. The potential reason of such difference is decreasing sales prices per unit, desktop replacement and subsequent shortening of lifespans over time.

Leaching model (Model D) generates the most discrepancy among all models, by comparing the deviations from the baseline. For instance, the model (D, blue lines) generates comparable results with the baseline for washing machine (2003–2011), laptop computer (1998–2011), CRT TV (1990–2002). In contrast, for

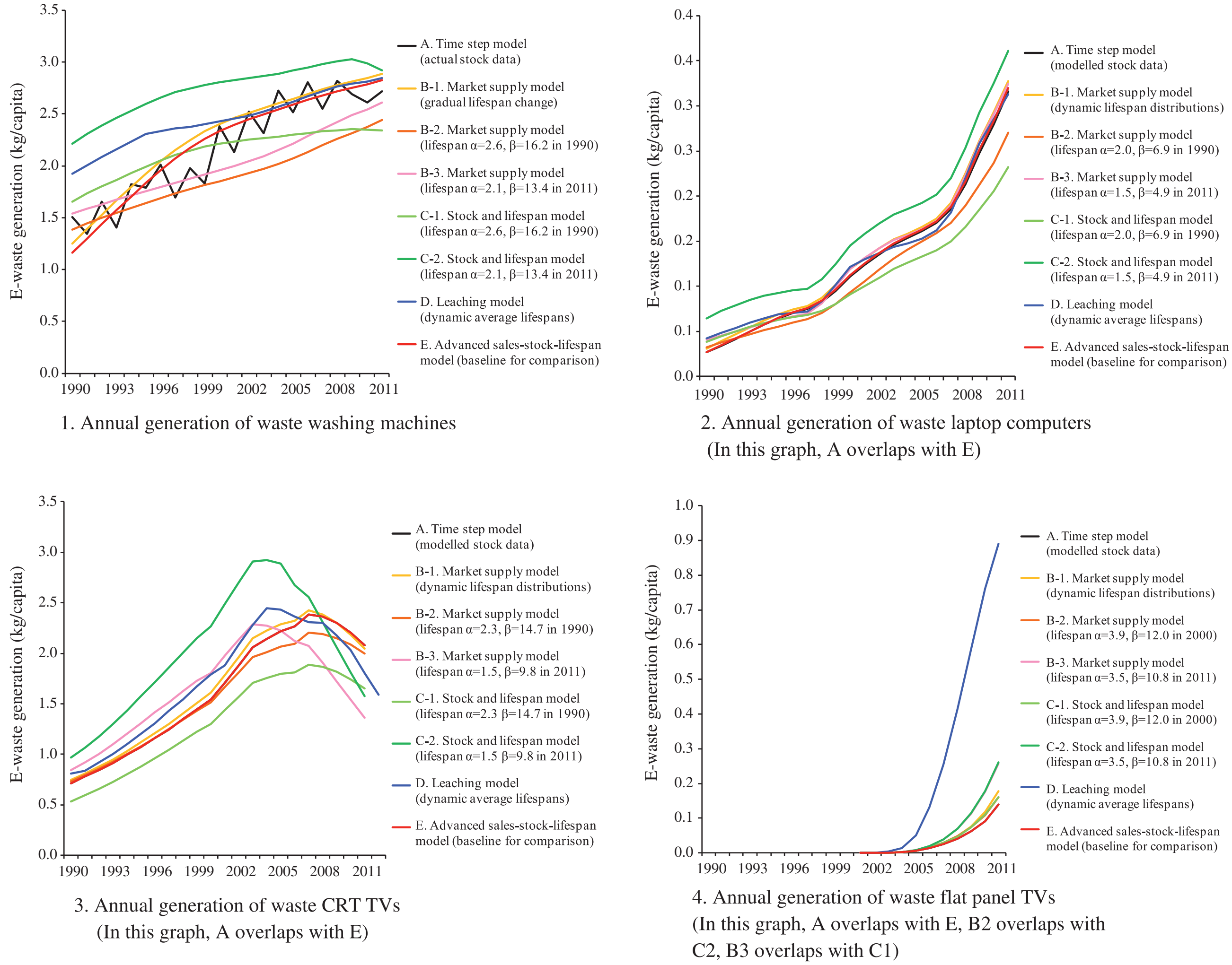

Fig. 2. Estimated annual waste generation of four representative electrical and electronic equipment in the Netherlands (1990–2011), under ten appraisal scenarios with different Input–Output Analysis models and lifespan parameters

unsaturated markets (Flat panel TV), this model shows significant disparity with the baseline, resulting in a faster growth rate. For declining markets (CRT TV), the peak of obsolete TVs in three leaching models appears earlier than the baseline. Therefore, leaching model is only valid by applying recent average lifespan data in saturated markets (van der Voet et al., 2002).

The examples demonstrate that different IOA models can lead to distinct results under different lifespan parameters. The "Time Step model" can be the most accurate and has a low degree of freedom compared to other methods; but it demands reliable sales and historic stock data. The "Market Supply model" can generate representative results if historical sales and time-varying lifespan distributions are available. The "Stock and Lifespan model" can be applied when continuous historical stocks and lifespan profiles are available. Improper selection of representative lifespan distribution can introduce significant errors. The "Leaching Model" is only suitable for products with short lifespan in saturated markets. The result is again sensitive towards the selected average lifespan.

In conclusion, simple models without processing the data to improve quality can substantially introduce errors for e-waste estimates. Reliability of the sales and stock data, together with the selection of lifespan profile greatly determines the accuracy of the estimated e-waste generation. In contrast to sales and stock size, measurement of lifespan is more complicated, entailing both extensive surveys and mathematical fitting of the curve parameters. It has been observed in the Dutch study that most products, except energy saving lamps, have declining average lifespans. Therefore, this key variable should be monitored for dynamic changes, especially for non-saturated markets or for new technology and subsequent replacements. The accuracy of time series modelling for lifespan profile can be improved collectively by: better modelling techniques (more sophisticated mathematical functions and complementary estimation methods) or more abundant data with higher quality (representative sampling and alternative data sources).

6. Discussion and roadmap for constructing estimation scheme

To summarise, a procedural guideline for estimating e-waste generation under various conditions is presented in Fig. 3. By checking the data availability of (continuous or discrete) sales, stock and lifespan profile, the most applicable modelling method can be selected. Prior to model computation, extra effort should be spent on improving the data quality and reliability, in order to reduce the influence from inferior data. Consistency needs to be checked between different data sources to ensure that no contradiction is present. Data quality can be improved by comparing

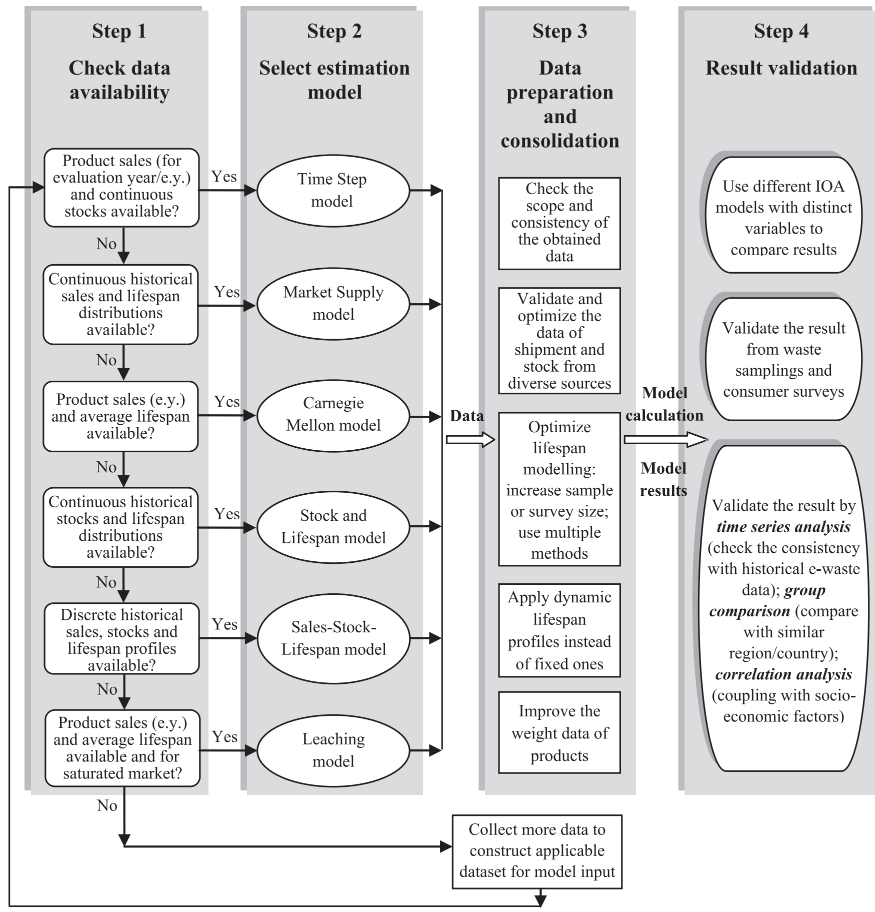

Fig. 3. Procedural guideline for estimating e-waste generation.

and validating through multiple sources and data analysis methods. Additional data gathering for missing IOA pillars or increasing sampling size can enable the preferred use of time-varying lifespan profiles over fixed ones. In addition, results can also be validated: (1) by using different IOA methods in parallel; (2) through cross-checking from external and independent data of sorting analysis in end-of-life channels and questionnaire surveys in dwellings; and (3) by non-IOA methods.

From previous lessons it can be concluded that the IOA model itself does not entail complicated algorithms or formulas. However, data uncertainty in the three IOA variables can lead to great deviation of the estimation outcomes with actual flows. It is inherently difficult to obtain comprehensive and reliable data on EEE and e-waste. Given aforementioned data quality issues, data analysis techniques are needed to check errors and consolidate data. Variables with higher reliability shall be used first for model input.

At the same time, IOA models provide detailed physical information of material flows for a system. Its result can be compared with other models such as time series analysis (check the consistency with historical e-waste data); group comparison (compare with similar region, country and market); correlation and regression analysis (coupling with socio-economic factors). IOA models have a good capability to estimate past and current e-waste generation, due to the use of actual system flow data. However, its application in predicting future quantities will be confined by the quality of available data for future sales, stock and lifespan. To achieve optimum planning of future flows, models with stronger forecasting function shall provide additional support. Due to the presence of different appraisal objectives and requirements for accuracy, combining the multivariate IOA model with non-IOA models can further explore the fundamental influences and even correlation between demographic and economic factors and e-waste quantities.

7. Conclusions

Data used in e-waste related research is usually a compilation of information from a variety of sources. Hence, difference in data quality needs to be considered for rigorous modelling of e-waste generation. This study has proposed an advanced IOA method involving all three variables (sales, stock and lifespan) and best available data points to prepare better datasets for modelling. The result from the Dutch case study demonstrates significant disparity between different estimation models, arising from the use of data under distinct qualities. To enhance e-waste estimates, it is suggested how additional data gathering and multivariate analysis can be conducted to improve data quality for more precise estimation.

Acknowledgments

The authors would like to thank the Dutch e-waste compliance schemes Wecycle and ICT~Milieu for providing funding, extensive datasets, contacts and guidance for the Future Flows project. We are thankful to Statistics Netherlands for their support in compiling statistical nomenclatures and Dutch micro-level figures, all relevant EERA and MRF members in the WEEE market survey, the Dutch Ministry of Infrastructure and Environment and the VROM Inspectorate for their feedback and access to key information.

Many thanks to David Peck (from TU Delft) for proof-reading this paper.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.wasman.2013.07.005.

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