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Assessment of e-waste flows: a probabilistic approach to quantify e-waste based on world ICT and development indicators

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Abstract

The rapid pace of technological change, the highly diffused implementation of electronics in everyday life and a decrease in prices has made appliances for home and office equipment both affordable and widely used. The high growth rates combined with increasing obsolescence rates result in large quantities of end-of-life electrical and electronic equipment to be disposed of. In many countries flows of electric and electronic waste have never been quantified due to the lack of data and missing take-back schemes. Furthermore, studies to collect the data and to assess the e-waste quantity are often expensive and very complex. In this study a model was developed and applied to derive e-waste flows from existing indicators which are published periodically by international organizations (e.g. International Telecommunication Union, World Bank) and which are often cheaply accessible. The method allows estimating e-waste quantities in a certain region or country as well as on a global scale. A probabilistic model approach accounts for the fact that for many countries calibration data is not available. Results are shown for personal computers which show one of the highest growth rates. Further electronic appliances as well as whole e-waste categories are planned to be introduced in the model in the future.

Keywords: e-waste, personal computers, ICT, obsolescence rate distribution, probabilistic model

1 Introduction

Waste electric and electronic equipment (WEEE or e-waste for short) is one of the fastest growing waste flows worldwide. Rapid product innovations and upgrades, especially in information and telecommunication technologies (ICT) and office equipment, and decreases in prices contribute to an exponential growth of the market for electronic products. This increasing quantity of electric and electronic equipment in use will eventually end up as e-waste.

Existing studies targeting the quantification of e-waste volumes often consider specific countries, mainly from the developed world with already existing e-waste recycling systems, e.g. (EPA 2007; SWICO 2008). A regional study exists for the European Union (UNU 2008). Studies from developing countries are rare due to the lack of national statistics and missing take-back schemes. Most of the data in developing countries origins from international partnerships in e-waste management, such as SECO's Swiss e-waste programme[1] e.g.(Steubing 2007; Espinoza, Villar et al. 2008; Finlay and Liechti 2008; Ott 2008) and the

[1] Swiss State Secretariat of Economies Affairs (SECO) – www.ewasteguide.info

HP/DSF/Empa project “e-Waste Management in Africa” (Laissaoui and Rochat 2008; Waema and Muriethi 2008; Wone and Rochat 2008) Only a few national initiatives exists, e.g. (EEI 2007). This makes it difficult to get estimations on a regional or global level.

To close this knowledge gap, Empa has developed a model to derive e-waste quantities from free or cheaply available indicators provided by the International Telecommunication Union (ITU) and the World Bank. Existing ITU data includes time series of stock data, i.e. of equipment in use, for 210 countries. Sales or e-waste data are not available. This shortcoming of data required customisations of already existing approaches to quantify e-waste (Walk 2004). In a first step, the model was applied to personal computers (PCs) which show one of the highest growth rates.

2 Model development

2.1 Basic model structure

The basic structure of the system is given by the flow diagram in figure 1. It considers the life cycle of electronic equipment reflecting the three processes "Production", "Consumption" which is equivalent to building up a stock, and "Disposal" (figure1). The system is considered time-invariant.

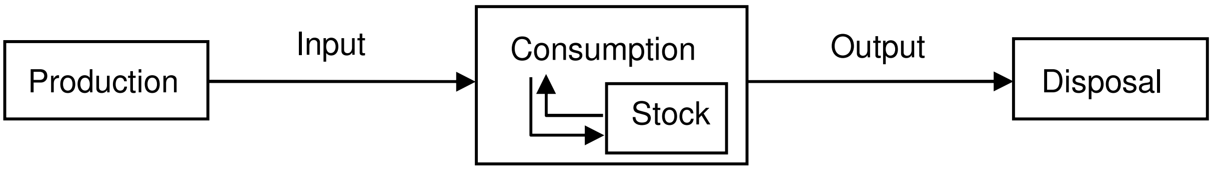

Figure 1: *Flow diagram of basic model.*

The flows in the basic structure can be described as:

$$Input(n) = [Stock(n) - Stock(n-1)] + Output(n) \qquad (1)$$

with

$$Input(n) = 0\big|_{n<1} \qquad (2)$$

Input: Sales of new and 2nd-hand equipment
Stock: Equipment in use
Output: Potential e-waste (incl. stored unused equipment)
n = 1…N: Year of calculation

2.2 Obsolescence rate

As already mentioned above, free or cheaply available data of electronic equipment are often limited to time series of stocks. This information alone is not sufficient to solve equation (1) and to calculate time series of input or output flows. The output of the process “Consumption” does, in a first approximation, not depend on stock but on input flows and a characteristic obsolescence behaviour of the respective equipment. This behaviour is often described as a time dependant obsolescence rate represented as a probability density function.

In most approaches that have been applied so far to estimate quantities of e-waste, obsolescence has been modelled as a constant product life time, which corresponds to a Delta distribution of the obsolescence rate. (Walk 2004). After testing several distributions in our model, we selected a Gaussian or normal obsolescence rate distribution with mean μ (average life time) and standard deviation σ.

The calculation of output flows from stock data and a obsolescence rate distribution corresponds to a convolution (3). Since it is not possible to solve this convolution analytically, it is discretised (4) and integrated numerically in MS Excel.

$$Output(t) = (f_1 * f_2)(t) = \int_{-\infty}^{\infty} f_1(u) f_2(t-u) du \quad (3)$$

$$Output(n) = (f_1 * f_2)(n) = \sum_{m=1}^{M} f_1(n-m) \cdot f_2(m) \quad (4)$$

$f_1(t)$, $f_1(n)$: Input, continuous and time discrete, respectively
$f_2(t)$, $f_2(m)$: Gaussian obsolescence rate distribution, continuous and time discrete, respectively
n = 1…N: Year of output calculation
m = 1…M: Year of product life time
Output(1) = 0: Initial value, results from condition (2) and equation (4)

Equation (4) is introduced in iteration (1) which results in time series for both, input and output flows.

2.3 Model Calibration

Available sales data of personal computers from China, the European Union (EU25), India and Switzerland were used to calibrate the model, i.e. to fit the parameters of the Gaussian obsolescence rate distribution (Robert Weiss Consulting 2007; Cobbing 2008; MAIT 2008; UNU 2008). The time period of the calculation of input and output flows (N) was set according to available years of stock data, the maximum life time (M) of a computer was set to 15 years. The parameters were fitted using the Generalized Reduced Gradient method (GRG2, MS Excel Solver). The Gaussian parameters fitted to the data of the four different countries are listed in table 1.

Equipment	**Data of**	**Gaussian parameters** average life time μ	standard deviation σ
PC	China	4.91	1.20
PC	EU (25)	6.40	1.10
PC	India	6.12	1.89
PC	Switzerland	5.44	1.85

Table 1: *Parameter of the Gaussian distribution fitted to available sales data.*

2.4 Probabilistic approach

The Gaussian distributions based upon the fitted parameters (table 1) obviously vary for the four different countries. Thus, there seems to be no single Gaussian distribution that fits all countries or regions of the world. Since we wanted to calculate also output quantities for regions, where no sales data for calibration is available, the so far deterministic approach was extended to a probabilistic model.

For that purpose, the means of the parameters μ and σ in table 1 are calculated and used as the parameters for a new Gaussian obsolescence rate distribution (μ_A, σ_A in figure 2). Also this new distribution is discretised to get constant annual obsolescence rates. In the probabilistic model, the annual obsolescence rates are no longer certain and given by a single value each, but probable and given by 100’000 normally distributed values each (e.g. μ_B, σ_B in figure 2), derived from Monte Carlo (MC) simulations performed in “R” (R Development Core Team 2008). The robustness of this number of iterations is discussed and verified in (Gottschalk, Scholz et al. 2009) where MC simulation is used for probabilistic material flow analysis (PMFA).

Each mean value of these distributions, e.g. μ_B in figure 2, equals the corresponding constant annual obsolescence rate. The standard deviations, e.g. σ_B in figure 2, are computed in the way that the resulting distributions remain valid probability density functions, i.e. in each of the 100’000 MC iterations all annual obsolescence rates must be positive and their sum must equal 1.

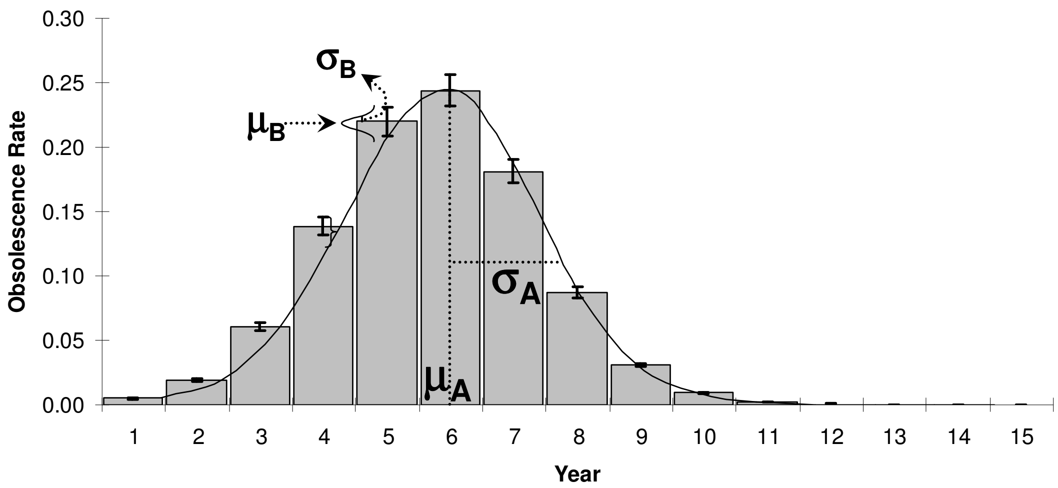

Figure 2: *Probabilistic approach of modeling the obsolescence rate distribution.*

The probabilistic model produces density distributions for input and output flows out of deterministic time series of stock data. Hence input and output flows for a given year can now be specified as a range, e.g. the 95% confidence interval.

3 Model implementation

3.1 Data acquisition and preparation

The data used for the model implementation was derived from two sources. ICT indicators were provided by the ITU (ITU 2008) and basic development indicators were available from the World Bank (The World Bank 2007). To calculate e-waste quantities from PCs, the ICT indicators “personal computers per 100 inhabitants” and “personal computers” were used, which correspond to the stock of PCs per 100 inhabitants and the total stock of PCs in a given country, respectively. Since data from ITU is not available for every country, and time series are often very short especially for developing countries, synthetic data had to be introduced or existing data extrapolated. Data analysis showed that the ICT indicator "personal computers per 100 inhabitants" correlates with the basic indicator "GDP per capita, PPP (current international $)" (correlation coefficient 0.84 in year 2001, 0.82 in year 2005). Thus, for missing "PCs per capita" data, a data series of a country with similar "GDP per capita" were scaled to the respective country according to their population. Missing "GDP per capita" and "population" data was provided by the CIA World Factbook (CIA 2009) and various national statistics (CNMI Department of Commerce 2000; Secretariat of the Pacific Community and Nauru Bureau of Statistics 2002; Palau Office of Planning and Statistics 2005; Principauté de Monaco 2007; Amt für Volkswirtschaft/Abteilung Statistik 2008; MONSTAT 2008; Barrientos 2009) Short time series were extrapolated according to the growth behaviour of the time series. Since most data was available for the year 2005, time series were completed up to that year.

The completed time series of stock data were classified into eight regions, summed up to regional stock data and implemented in the model. In addition to regional stock data, data of some specific countries were also prepared for implementation (for regions and countries, see table 3).

The indicator "personal computers" is specified in number of units. To calculate e-waste flows in tonnes for a specific year, the ratio of end of life desktop and laptop computers in a given country and their respective weight had to be assumed. Therefore, all countries were classified in high income, upper middle income, lower middle income and low income economies, according to the World Bank list of economies (The World Bank 2008). For every class, a ratio of end of life desktop and laptop computers in 2005 was defined according to available data (table 2). A desktop computer was estimated a weight of 25 kg (including monitor), a laptop 4 kg. Thus, average weights per country and region could be calculated.

Income Class	Desktop (ratio in %)	Laptop (ratio in %)	Average Weight / Equipment (kg)
High Income	85	15	22
Upper Middle Income	90	10	23
Lower middel Income	95	5	24
Low Income	100	0	25

Table 2: *Ratio of desktop and laptop computer and resulting weight per equipment assumed for e-waste flows in 2005.*

3.2 Results and Discussion

Potential e-waste flows from PCs, calculated according to the procedures described above are presented in table 3. North America produced the most e-waste from PCs, followed by East Asia and the European Union. The Middle East, Africa and Central Asia contributed the smallest amount to the total e-waste flows from PCs.

Converted to tonnes, total e-waste from PCs in 2005 amounted up to ca. 2'200'000 tonnes. This equaled 0.3 kg/capita·year as a worldwide average. Africa on average, produced the smallest amount of e-waste with 0.04 kg/capita·year, in North America it added up to 2.5 kg/capita·year. Considering some specific countries, the calculated values differed between 0.01 kg/capita·year in Uganda and 2.7 kg/capita·year in Switzerland. Compared to data from existing e-waste assessments (see chapter 1), the calculated values differ from a few percents up to a factor three. The results of some assessment methods are, however, based on rough estimations and thus not precise. In general, the model seems to underestimate e-waste flows from PCs.

Region	Mean [Pieces]	Standard dev. [Pieces]	Quantile [Pieces] 0.025	0.975	Mean [Tonnes]
North America	36'667'500	351'500	35'985'900	37'365'000	806'700
Latin America & Caribbean	5'922'000	82'600	5'761'100	6'085'400	136'800
European Union	20'788'100	169'900	20'463'800	21'130'800	457'300
Western Europe	1'402'300	8'900	1'385'100	1'419'800	30'900
Eastern Europe	2'637'300	43'700	2'551'500	2'722'400	60'900
Middle East	1'951'800	28'600	1'895'600	2'008'000	45'300
Africa	1'609'100	19'900	1'570'400	1'648'200	38'600
Central Asia	935'800	8'400	919'600	952'400	22'000
East Asia	25'740'800	360'200	25'042'400	26'453'000	594'600
Total Pieces	***97'654'700***		***95'575'400***	***99'784'900***	***2'193'100***
Country					
Colombia	272'500	2'900	266'800	278'300	6'500
Peru	242'000	4'100	233'700	250'000	5'800
Switzerland	933'100	5'000	923'400	942'900	20'500
Kenya	35'700	600	34'600	36'800	900
South Africa	585'100	5'300	574'700	595'700	13'500
Uganda	14'000	200	13'600	14'300	300
China	6'297'700	147'500	6'011'600	6'590'200	151'100
India	1'124'300	13'900	1'097'200	1'151'600	27'000

Table 3: *Estimated number of obsolete PCs in specific regions and countries in 2005.*

The standard deviation and therefore the range between the quantiles of the output density functions appears to be very small. This is attributed to two reasons: first, the constraints for the variation of the standard deviation σ_B (figure 2) render the influence of the dispersion almost insignificant. Second, we have introduced deterministic stock data into a probabilistic model where the dispersion of the output flows is only determined by the annual obsolescence rate distributions. Since we do not know and therefore not account for the error of the stock data, this induces a false impression of the reliability of the model results.

4 Conclusion and Outlook

The simple time invariant model using stock data and normally distributed obsolescence rates can be convoluted and iterated in a simple spreadsheet calculation to produce time series for input and output streams. If stock data is extrapolated, also future e-waste flows (output) can be computed.

A probabilistic expansion of the model, restricted by a normally distributed variation of the annual obsolescence rate is possible but has little effect on the input/output flows. Further adjustments to the presented model are suggested. As a first step, the deterministic stock data could be replaced by a probabilistic, e.g. by merging countries with similar share of PCs per 100 inhabitants and assign them time series of density distributions instead of constant values. Another possibility would be to include an error analysis in the model to determine to what extent errors of the stock data are transferred to the input and output flows.

As a second step a more flexible random obsolescence rate distribution could be synthesized. This, however, requires improved life time data of specific equipment, which is currently difficult to obtain.

After the further adjustments, the presented model shall be utilized for and extended to other electrical and electronic equipment. e-Waste quantities from single devices can then be extrapolated to whole e-waste categories (e.g. PCs to ICT).

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