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Dynamic estimation of future obsolete laptop flows and embedded critical raw materials: The case study of Greece

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ABSTRACT

The coronavirus pandemic has turned school and university learning system from classroom-based to exclusively online all over the world. As this change is accompanied by a spike in demand of laptops, an excessive amount of obsolete devices will be witnessed in the near future. Laptops are the most valuable e-waste category containing a high content of numerous critical raw materials, thus their waste management is crucial. Considering the impact of the coronavirus pandemic on the laptop lifespan, the future quantities and pieces of obsolete laptops in Greece are estimated (2016–2040), as well as the critical raw materials (CRMs) and precious metals (PMs) embedded in them, to illustrate the potential of recovering useful resources, thus contributing to a circular economy. To this end, dynamic material flow analysis is adopted, lifespan distribution is evaluated and future sales are predicted by the logistic model utilizing a bounding analysis. Then the future End-of-Life (EoL) laptop quantities are estimated taking time-varying parameters into consideration such as penetration rate, population, laptop weight and lifespan. This study is a dynamic estimation that avoids using average values adopted from literature that are not country specific. The provided information is useful for implementing national plans, improving the management of the most valuable category, EoL laptops, enhancing resources efficiency and contributing to a circular economy. The coronavirus pandemic has a similar impact on laptop sales in other countries, affecting their future laptop waste as well.

1. Introduction

We are living in an era affected by the coronavirus pandemic which rapidly transformed the educational system from classroom-based into a virtual learning environment. In Greece, the majority of university lectures and school lessons are currently still held online. This change in the education mode has driven all students but also all kinds of workers to go online. Globally, this technology demand is accompanied by a rise in computer sales especially laptops, notebooks and tablets. The estimated impact on notebook computer shipments worldwide due to the coronavirus (COVID-19) outbreak in February and the whole of 2020 is 5.7 and 150.1 million units, respectively, indicating an increase in sales (Statista, 2020a). In Italy, in the first week of May 2020, the sell-out value of laptops increased by 154% compared to the same period of the previous year. Similarly, tablets sales in Italy grew by 61% (Statista, 2020b). In Greece, 8,400 laptops and tablets were distributed in 2020 to schools to cover the emerging needs. As this spike in demand for laptops, notebooks and tablets has left stores with empty selves, an excessive amount of obsolete devices will be witnessed in the near future. This study focuses on Greece, but the impact of the pandemic on laptop sales will affect the generated laptop waste in other countries as well.

In Europe, the Waste Electrical and Electronic Equipment (WEEE) Directive states that, from the year 2019, 65% of the average weight of EEE placed on the market in three preceding years or 85% of WEEE generated should be the minimum annual country collection rate. The Directive subdivides the e-waste into six categories and poses separate recycling targets for each category on a mass basis. In order to accomplish the targets, the recyclers, are mostly interested in materials present in great amounts in the waste flow, such as ferrous metals or plastics. In this way, materials existent in small amounts are often neglected (Bigum et al., 2012; Sun et al., 2016). Especially small WEEE, like laptops, tablets or mobile phones represent a perpetually growing waste stream that contains both treasured and hazardous materials. Considering the large amount of these waste categories, the CRMs and PMs present in them, although in tiny amounts, are substantial.

The European Commission started in 2008 the Raw Materials Initiative in order to encounter the expanding concern of assuring valuable raw materials for the EU economy. CRMs are those materials...
that combine a high economic significance to the EU with a great risk of supply disruptions. Many of these materials are, at present, only derived from a few countries. Among these, China is the leading provider and consumer of various important raw materials e.g. rare earth metals (REEs), antimony, bismuth, magnesium, etc. Thus, this grows the risk of supply scarcity and susceptibility along the value chain. Moreover, in December 2019 the EU adopted the Green Deal Communication that acknowledges access to resources as a vital security issue to accomplish its aspiration towards 2050 climate neutrality (EU Final Report, 2020).

CRMs are extensively used in electrical and electronic equipment (EEE), particularly in high-tech devices. The renewed 2020 CRMs list includes 30 metals among which are Cobalt, Palladium, Platinum, Neodymium, Praseodymium, Dysprosium Antimony, Yttrium, Indium and Tantalum, all embedded in laptops. Laptops, notebooks and tablets, (together with desktops and servers), are the most valuable WEEE because of their extremely high content of numerous key metals in some of their main sub-systems. Indeed the number of CRMs and PMs embedded in them surpasses other e-waste categories (Cucchiella et al., 2015). Especially the Nd and Ta concentration in notebooks/laptops units is the highest among all EEE. Interest for CRMs will unavoidably rise with the broad penetration of consumer goods. Thus, laptop wastes are a valuable resource for CRMs and PMs and the estimation of their future EoL quantities is vital for their efficient management to ensure that resources will not be lost. Endorsement of the circular economy is a solution to materials criticality challenge, in which products and their CRMs, are kept within the economy over numerous product life cycles via reuse and effective recycling. In this way the economic productivity of CRMs is maximized and global demand is reduced (Krystofik et al., 2018; Charles et al., 2020).

Estimation of e-waste generation can be accomplished by many methods. These have been summarized by Wang et al. (2013), Guo and Yan (2017), Islam and Huda (2019a) and involve Material Flow Analysis (MFA) that estimate the Input-Output of materials within the system boundaries. MFA can be static or dynamic when it involves average values or time- varying parameters, respectively. Briefly the methods are: (1) the Time Step Model that requires sales and stock data, (2) the Market Supply Model requiring sales and average lifespan data, (3) the Market Supply A, involving sales data and a lifespan following a Weibull distribution, (4) the Carnegie Mellon model that applies discrete average lifespan for reuse, household stock, recycling or landfill, (5) the Simple Delay Model using sales and average lifespan data, (6) the Leaching Model for saturated markets and products with short lifespan. All these methods can be applied to estimate e-waste amounts that have been generated in past years.

However, as the amount of e-waste is increasing, the estimation of future quantities and the key metals contained in them is of primary importance to policy makers, producers and manufacturers to promote actions and legislations at local and national level related to their sustainable management. Specifically, this study focuses on laptops as these are consumer goods with rising adoption rate in Greece, especially nowadays due to coronavirus pandemic and they are the most valuable e-waste in terms of CRMs content, and last, their EoL management engages diverse stakeholders. The generation of obsolete amounts of laptops, notebooks and tablets (referred to as “laptops” hereafter) in Greece until 2040 (2016–2040) is presented. Both precious and hazardous compounds are present in waste laptops that require proper management in order to recover most of the valuable materials, while minimizing the amount of hazardous and toxic substances to toxic subchronic and toxic chronic health impacts (s). Thus, the objectives of this paper are: (i) to precisely determine time-varying lifespan values (1983–2015) by numerically solving the corresponding mathematical equations as suggested in E-Waste Statistics (Forti et al., 2018) given that high quality data are available instead of adopting a survey method. The latter is impossible to apply over an extended time period (32 years) and may introduce bias if not appropriately conducted. To the best of our knowledge, this is the first time this approach is applied. Such a long period can reveal the lifetime dynamics and the economic and social changes reflected in the laptop lifespan. Furthermore, in order to check the validity of calculated lifespan profiles, since no specific data were available for Greece, the same analysis was performed for laptops in the Netherlands, where lifespan data existed in the literature and consistency check could be applied. Also the same evaluation was performed for Sweden for comparison reasons. Next, (ii) to reliably estimate by dynamic material flow analysis (dMFA) the future generation of EoL laptops in Greece, which is absent in the scientific literature, (iii) to consider dynamic changes in all parameters that are country specific like penetration rate, population, laptop weight and product lifespan. Furthermore, to assess the impact of the coronavirus pandemic on the lifespan of laptops and the estimated amounts of EoL laptops. Most reported studies apply simplifications of either the average product weight or the average lifespan (Polak and Drapalova, 2012; Zhang et al., 2012; Duygan and Meylan, 2015) and very few consider dynamic changes in more parameters (Wang et al., 2013). Further, (iv) to clarify how population, product lifespan and laptop weight affect the estimated future quantities and to what extent, (v) to estimate the CRMs and PMs content of future obsolete laptops and (¡) and therefore illustrate the potential of recovering valuable resources that exist in EoL laptops in Greece, which is missing in the literature.

The outcome of this work will be valuable for Greek authorities, policy makers and electronic goods dealers and may contribute to improved management of EoL laptops in Greece, benefiting society and the environment.

2. Literature review

In order to forecast the WEEE generation, several time-series analysis methods are employed like exponential smoothing, linear regression and moving averages autoregressive models. These models must consider data variations due to trends like seasonality (Rodrigues and Werner, 2019). However they exhibit low accuracy in long term predictions (Mentzer and Cox, 1984).

On the other hand, estimation of product adoption is accomplished by the S-shaped growth models such as the logistic model. It has been illustrated that new technology diffusion, market adoption of durable products and users of subscription services have a sigmoidal growth (Meyer et al., 1999; Sokele, 2008; Yang and Williams, 2009). The logistic model is an extensively used growth model with many useful properties for technological and market penetration forecasting. It has been employed to predict the future sales, possession or waste generation of electronic goods (Yang and Williams, 2009; Dwivedy and Mittal, 2010; Guo and Yan, 2017). Contrary to S-shaped cumulative adoption, adoption per period (sales) is a bell-shaped curve and is proportional to the first derivative of cumulative adoption. Thus, the possession is successfully modelled by the logistic curve while sales should be modelled by a bell shaped curve incorporating the phases of growth-saturation-decline (Sokele, 2008).

Moreover, the Norton-Bass model, describes both adoption and substitution, thus the decline phase is also included (Norton and Bass, 1987). The model was used to forecast adoption of electronic goods such as LCD TV’s and desktop display screens (Tsai, 2013; Lu et al., 2015). However, this model best fits when modelling direct replacement by consecutive technology generations is the case, which does not always apply on consumer electronics (Tseng et al., 2009).

As the penetration of laptops in Greece is currently at the growth phase, the logistic model was chosen as most suitable to describe the laptop possession.

Furthermore, the lifespan of electronic goods is fundamental for MFA calculations. There are two approaches referring to its estimation. First, it can be considered static, not following any statistical distribution. However, this consideration is imprecise as it doesn’t reflect the dynamic patterns of product lifetime (Babbitt et al., 2009). The second approach considers that lifespan follows a statistical distribution such as
the exponential, Rayleigh, lognormal, normal distribution or Weibull. Nevertheless, all the aforementioned distributions are approximated by the Weibull for different values of the shape parameter (Almalki and Nadarajah, 2014). Therefore the Weibull distribution is suitable to describe commodities lifespan, as it achieves the best fit for most products (Walk, 2009). In most studies the lifespan is adopted from literature data for a specific year and the time variance is neglected (Yu et al., 2010; Tran et al., 2018; Islam and Huda, 2019a). Nonetheless, this is inaccurate because the product lifecycle for electronic goods is decreasing. In other studies the survey method is used to reveal the lifetime of household electronic appliances either neglecting time variance or considering a limited one (Abbondanza and Souza, 2019; Kosai et al., 2020). However, the survey method has some disadvantages as it depends on consumer behaviour (Kang and Schoenung, 2006) and is difficult to estimate lifespan for an extended period of successive years. For a lifespan survey to be reliable it should be conducted on a yearly basis on an extensive national-level and on waste-disposal points. In this way the uncertainty associated with the lifespan can be mitigated (Islam and Huda, 2019b). Nevertheless, it is impractical to apply this approach to estimate the variation in lifespan over an extended period. As suggested in E-Waste Statistics (Forti et al., 2018) it is more precise if lifespan is numerically solved by the corresponding equations (Wang et al., 2013) given that high quality data (Put on Market (POM) and stock (SI)) are available to produce realistic outcomes. In our study, detailed time-varying lifespan data are calculated by numerically solving the appropriate equations over a period of 32 years. Device lifespan is shaped by consumer behavior, socio-economic factors and technology change and it fluctuates both geographically and temporally (Babbitt et al., 2009; Sabbagh et al., 2015; Wang et al., 2013). The detailed estimation of lifespan over a long period considers the socio-economic and consumer behavioral changes. In our study, the impact of coronavirus pandemic on the laptops lifespan has been taken into account and the influence on the generated EoL amounts of laptops has been estimated.

3. Methodology

3.1. Calculation of EoL laptop amounts in historical years (1983–2015)

The EoL products output at time $t$ is expressed as a function of product inputs and the change in product stock. This is expressed by the equation (Time Step model):

$$O_t = S_t - (S_{t-1} - S_{t})$$

(1)

where $O_t$: obsolete product in year $t$, $S_t$: Sales of product in year $t$ and $S_{t-1}$: stock of product in year $t$.

Also, the EoL products output can be given as a function of product inputs and the lifespan probability distribution (Market Supply A):

$$O_t = \sum_{i=1}^{n} (S_{t-i} \times f_i)$$

(2)

where $f_i$: lifespan probability distribution function and $n$: maximum possible lifespan.

The lifespan distribution is depicted by the Weibull distribution function. The Weibull probability distribution function is given by:

$$f(t, \alpha, \beta) = \frac{\alpha}{\beta} \left(\frac{t}{\beta}\right)^{\alpha-1} \exp(-\left(\frac{t}{\beta}\right)^\alpha)$$

(3)

where $\alpha$: the shape parameter that describes the gradual ageing of the product and $\beta$: the scale parameter describing the characteristic life of the product that is, it defines the years (age) when 63.2% of the products are expected to have failed.

The Mean Time to failure (MTTF), or else average lifespan is estimated by:

$$MTTF = \beta \times \Gamma(1 + 1/\alpha)$$

(4)

where $\Gamma$: gamma function.

The product lifespan in this work represents the total time the product stays in the possession of a person, including stock time after the product ceases to be used or donation to another person. After the product lifetime has elapsed the product is discarded in appropriate collecting centers.

3.2. Estimation of future possession of laptops

In order to predict future possession of laptops the three parameter logistic model was employed. For a non mature market like laptops in Greece, the logistic curve includes the phases of growth and saturation. Possible decline phase can be expected in the very distant future, especially if this technology is substituted by a new one, however, this is quite difficult to foresee. The general logistic equation for laptop procession modeled as penetration rate (items per inhabitant), is expressed by (Yang and Williams, 2009):

$$\frac{dN}{dt} = rN(1 - \frac{N}{K})$$

(5)

where $N$: penetration rate, number of laptops owned per inhabitant, $r$: growth rate, $K$: maximum penetration value. Solving this equation gives the penetration rate:

$$N_t = \frac{K}{e^{r \cdot t} + 1}$$

(6)

where

$$C = \ln\left(\frac{N_t}{N_0}\right)$$

(7)

and $N_0$ the penetration rate at time $0$. The penetration rate for year $t$ is calculated by:

$$N_t = \frac{St}{Q_t}$$

(8)

where $Q_t$: population at time $t$.

Using the simplification demonstrated (Meyer et al., 1999), the growth rate, $r$, was substituted by $\ln(81)/\Delta t$, where $\Delta t$ is the time required to grow from 10% to 90% of $K$, and $-C/r$ was substituted by $t_m$, the time needed to reach $K/2$ (Althaf et al., 2019). Thus, the logistic curve becomes:

$$N_t = \frac{K}{e^{\ln(81)/\Delta t} + 1}$$

(9)

The most critical parameter for the logistic curve is the maximum penetration rate $K$. The solution to this equation is given by non linear regression by minimizing the Objective Function (OF):

$$OF = \sum_{0}^{z} \left(\frac{K}{e^{\ln(81)/\Delta t} + 1} - \frac{St}{Q_t}\right)^2$$

(10)

Using the bounding approach the lowest and highest value for $K$ were estimated, and then the problem was solved for $\Delta t$ and $t_m$.

Furthermore, the fit of the calculated curve to the historic data curve, at the optimal set of parameters, was determined by:

$$\text{Deviation}^% = 100 \frac{\sqrt{OF(z - N)}}{\max(N_i)}$$

(11)

where $z$: number of data points, $N_i$: number of parameters engaged in the model, $N_t$: historic penetration data.

The procedure followed is described hereafter. Initially, obsolete amounts of laptops were calculated by Eq. (2) using sales and stock data.
for Greece from Statistics Netherlands (Van Straalen et al., 2016) which are retrieved from Eurostat website. The categorization applied follows the European Prodcom (Production Statistics database) and Eurostat Ramon Database. Sales were calculated as imports minus exports, since there is no laptop production in Greece. Once the obsolete amounts were calculated, non linear regression was applied to estimate α, β for various years by minimizing the Objective Function (OF1):

$$OF1 = \sum_{t=1}^{T} \left( \left( S_i - \left( f(t_i, \alpha, \beta) \right) \right) - \left( S_i - \left( S_{t-1} - S_{t-1} \right) \right) \right)^2$$  \hspace{1cm} (12)

The deviation for the curve fitting was calculated by (10) using $O_0$ as found by (1), instead of $N_t$ in the denominator. Several constraints were applied in order to solve the problem as $\alpha, \beta > 0$ and $\alpha < 4.5$. The shape parameter $\alpha$ was taken as $\alpha < 4.5$, because $\alpha > 4.5$ is unlikely as this denotes rapid wear-out of products associated with severe problems in manufacturing process (Zhu, 1991).

In addition, another constraint applied was that the total obsolete amount calculated in each year, as a sum of products that were sold several years before multiplied by the probability $f(t, \alpha, \beta)$ that the product is discarded in a particular year, was forced to be 100 ± 5% of the amount calculated by

$$\sum_{t=1}^{T} \left( S_i - \left( S_{t-1} - S_{t-1} \right) \right)$$  \hspace{1cm} (13)

for the same years.

Once the Weibull parameters ($\alpha, \beta$) were calculated for several years (1983–2015), their trends were extrapolated in the future considering two cases, (i) there is or (ii) there is no impact of coronavirus pandemic on laptop lifespan and impact. The future possession of laptops was calculated till 2040 by the logistic curve and the future obsolete laptops amounts of (2016–2040) were calculated by iteratively solving Eq. (2) and (1) (Liu et al., 2006).

3.3. Substance flow analysis of EoL laptops

The main components of interest in laptops are printed circuit boards (PCBs), Hard Disk Drives (HDDs) or Solid State Disks (SSDs) - which are continuously gaining ground substituting HDDs- LCD or LED screens and last lithium-ion batteries. PCBs contain PMs, base metals (i.e copper) and toxic metals (antimony, lead etc.) as well as ceramic compounds and plastics (Cucchiella et al., 2015). HDDs contain magnets with high amounts of REEs. The material composition of laptops/notebooks and tablets is presented in Table 1 (Cucchiella et al., 2015; Van Eygen et al., 2016; Gaustad et al., 2020). In this Table the percentage of EU dependence on imports and the input recycling rate for EoL devices targeting CRMs are also presented (EU Final Report, 2020; Talens Peiro et al., 2018). Gold and silver are not considered CRMs for the EU economy as they present an insignificant supply risk. As can be observed, significant differences exist in CRMs and PMs concentration between laptops/notebooks and tablets. For this reason the percentage of tablets in the total calculated pieces is clarified (in Appendix) and their content is calculated separately for EoL laptops and tablets. As far as notebooks and laptops are concerned an average value of key metals is used, as these were quite similar for these devices.

Then the quantity of metal i in year t was calculated by (Guo and Yan, 2017):

$$m_{(i)} = C_i \times O_i$$  \hspace{1cm} (14)

where $C_i$: quantity of metal i in year t per device, $O_i$: obsolete pieces in year t.

3.4. Data sources and collection

Data on past sales and stock were acquired from Statistics Netherlands (Van Straalen et al., 2016). Data on population were obtained from ELLSTAT, CIA-World Factbook and IndexMundi and data on employment in Greece from Eurostat and ELLSTAT.

The average laptop weight was estimated in each year (1995–2015) based on historic stock and population data. This was extrapolated to predict the future trend. Data showed that there was a decreasing trend, as anticipated. Since weight was continuously decreasing at an almost stable rate, 2 cases were considered: case 1, weight continuously decreasing till 2023 (0.44 kg) and then stable afterwards, or case 2, weight continuously decreasing till 2025 (0.14 kg) and then stable afterwards. The weight data calculated (reported in the Appendix) agree reasonably well with the weight data of Wang et al. (2013) and average EU-28 data report (Magalini et al., 2014). However, as most studies estimate the generated waste using an average weight value, this approach was also employed for comparison reasons. Thus, the average value calculated for the years 2006–2016, 2.23 kg, was used as the fixed average weight from 2016 onwards. The obsolete laptop weight was calculated by the same approach to ensure realistic calculations as items that become obsolete in one year do not have the same weight as the new ones purchased in the same year, but a little higher as these were bought a few years before.

Furthermore, the growth/decline rate of population in Greece was

Table 1
CRMs and PMs in LCD/LED notebooks, laptops and tablets and EU indices. (Sources: Cucchiella et al., 2015; Van Eygen et al., 2016; Gaustad et al., 2020; EU Final Report, 2020; Talens Peiro et al., 2018).

| Metal           | LCD/LED notebooks (g/unit) | Laptops (g/unit) | Average (notebooks/laptops) (g/unit) | Tablets (g/unit) | % EU Import reliance | % EU EoL recycling input* | EU Supply Risk (SR) | EU Economic Importance (EI) |
|----------------|-----------------------------|----------------|--------------------------------------|----------------|----------------------|--------------------------|----------------------|-----------------------------|
| Antimony-Sb    | 0.77                        | 1.95           | 1.36                                 | 0.154          | 100*                 | 28                       | 2                    | 4.8                         |
| Neodymium-Nd   | 2.10                        | 2.23           | 2.16                                 | 0.427          | 100                  | 3**                      | 6.1                  | 4.8                         |
| Praseodymium-Pr| 0.274                       | 0.13           | 0.20                                 | 0.055          | 100                  | 3**                      | 5.5                  | 4.3                         |
| Dysprosium-Dy  | 0.05                        | 0.05           | 0.05                                 | 100            | 8***                 | 6.2                      | 7.2                  |                             |
| Yttrium-Yt     | 0.002                       | 0.002          | 0.002                                | 0.0009         | 100                  | 8***                     | 4.2                  | 3.5                         |
| Indium-In      | 0.04                        | 0.04           | 0.04                                 | 0.008          | 100                  | 8***                     | 1.8                  | 3.3                         |
| Tantalum-Ta    | 1.70                        | 1.70           | 1.70                                 | 0.013          | 100*                 | 1                        | 1.4                  | 4                           |
| Cobalt-Co      | 0.065                       | 0.065          | 0.065                                | 0.013          | 32*                  | 22                       | 2.5                  | 5.9                         |
| Palladium-Pd   | 0.04                        | 0.03           | 0.035                                | 0.008          | 93                   | 14                       | 1.3                  | 7                           |
| Platinum-Pt    | 0.004                       | 0.004          | 0.004                                | 0.008          | 93                   | 14                       | 1.8                  | 5.9                         |
| Gold-Au        | 0.22                        | 0.22           | 0.22                                 | 0.044          | 98                   | 20                       | 0.2                  | 2.1                         |
| Silver-Ag      | 0.25                        | 0.57           | 0.41                                 | 0.05           | 55                   | 5                        | 0.7                  | 4.1                         |

EU data refer to 2020. EU data marked * refer to 2017. ** refers to LREEs group, *** refers HREEs to group.
SR on a scale of 0–6.2. EI on a scale of 0–8.1. The thresholds for the criticality assessment are set at 1 for SR and 2.8 for EI index.
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estimated till 2015 and this rate was extrapolated to give an approximation of future population. It is estimated for Greece that the population decreases from 11,123,000 inhabitants in 2011 to approximately 10,351,937 inhabitants in 2040.

All calculations in this work were performed by Excel software and Solver add-in program.

4. Analysis and discussion

4.1. Bounding analysis for maximum penetration rate

Since laptop sales are continuously increasing in Greece, indicating that the saturation phase has not been reached (Fig. 1, historical data till 2015), the estimation of $K$ was performed by the bounding approach of Yang and Williams (2009). This approach finds parameter values which serve as the lowest and highest conceivable values and calculates a range of results based on the two bounds. The upper bound is the maximum reasonably expected value for $K$ and the lower bound is the minimum. Thus, the future possession of laptops will be within this range.

The upper bound for $K$ is defined by assuming that due to coronavirus pandemic that changed the traditional education system to online, every pupil (from the age of 10) and university student owns a laptop. Also, all persons aged till 80 years old own a laptop for their personal needs and last, all employed persons own a laptop either at work or at home for remote working. According to ELLSTAT the population of Greece in 2011 aged between 10–80 years old was 9,183,113 people. In addition, as reported by Eurostat Employment Database, the number of employed persons in Greece was 4,083,030 (2016). Additionally, the total population of Greece in 2011 was 10,816,286 while in 2016, it was 10,835,000 people. Thus, the upper bound of $K$ is estimated to be about 1.23. Yang and Williams (2009) estimated the upper bound of 1.3 personal computers per capita in USA according to 2007 data sets.

The lower bound is estimated assuming that only university students, professors, companies, information and telecommunications workers (ITC) and only the financially sound share of the population own a laptop. The number of Greek companies in 2016 (ELLSTAT) was 233,151 while the university students and professors were 461,613. The people working on ITC sector were 83,970 (Eurostat, 2016), while the university students and professors were 461,613. The number of Greece companies in 2016 (ELLSTAT) was 233,151 while the university students and professors were 461,613. Additionally, the number of employed persons in Greece was 4,083,030 (2016). The total population of Greece in 2011 was 10,816,286 while in 2016, it was 10,835,000 people. Thus, the upper bound of $K$ is estimated to be about 0.62.

In 2018 the laptop penetration level reported in Denmark was 0.64 laptops/capita (Zhilyaev et al., 2021), while that predicted by the logistic curve for Greece, is 0.577 to 0.78 pieces/capita for the lower and upper bound scenario, respectively. Moreover, considering the effect of coronavirus pandemic on the laptop sales (2020), it is more likely that the penetration level in Greece will move closer to the upper bound scenario.

4.2. Estimating future penetration rate by logistic model

Fig. 1 depicts the estimated future laptop penetration rate for the upper bound ($K = 1.23$), the lower bound ($K = 0.62$) as well as the existing data (till 2015). As can be seen the penetration of laptops is at a growth phase as it continuously increases and has not passed through an inflection point yet. This indicates that from the perspective of technological life cycle, diffusion of laptops is still in its early stage.

It is observed that the penetration rate of 0.62 laptops per inhabitant will be reached in 2027 that is in 6 years time, while that of 1.23 laptops per inhabitant, in 2040, in approximately 19 years time. Comparing the deviation value as calculated by Eq. (10), the upper bound curve gives a better fitting than the lower bound, (2.62% compared to 3.25%). However, as deviation is calculated by comparing historic penetration data till 2015, both values are within acceptable limits. It is calculated that in 2023 1 and 0.62 laptop will be owned per inhabitant in Greece in the upper and lower bound scenario, respectively. The calculated values of $\Delta t$ and $t_m$ are 19.46 and 35.57 for the upper bound scenario and 13.19 and 30.22 years for the lower bound scenario.

4.3. Estimation of the Weibull parameters and the laptops lifespan

Following the procedure depicted in 2.1, the Weibull parameters are estimated for the years 1983–2015, as explained in Appendix. Lifespan is a dynamic parameter that depends on the socio-economic situation in each country, the diffusion of new technology, as well as the habits and awareness of the people (Islam and Huda, 2019a). This is depicted by MTTF values estimated for Greece, which are portrayed in Fig. 2. As can be seen, the lifespan of laptops in Greece is higher than in the Netherlands and Sweden, which shows that laptops are being replaced at a slower rate in Greece than in the other two countries. This indicates that the purchasing power is lower in Greece, laptops are probably stored for a longer period at home, the take-back system may work less efficiently and public awareness on e-waste recycling is lower. In Fig. 2 the lifespan of laptops increases around 2008, probably due to the economic crisis in Greece, indicating that people did not buy new products to substitute their old ones. However, as this financial crisis also influenced other Eurozone countries to some extent, a similar increase in lifespan is also observed for the Netherlands in 2009, although less intrusive. On the other hand, the lifespan of laptops is continuously decreasing in Sweden from 2002 to 2015 implying that Sweden was not affected by the European debt crisis, perhaps because it does not employ the Euro currency.

The values calculated for the Netherlands agree with the shape and scale parameters calculated by Wang et al. (2013) for years 1995 and 2005. Specifically, a, b are reported as 1.6 and 5.6 for 1995 which reasonably agrees with 1.14 and 5.47 estimated for years 1991–2003. Also, a, b are declared as 1.5 and 5.2 for 2005 which complies well with

![Fig. 1. Estimation of laptops penetration rate.](image1.png)

![Fig. 2. Dynamic profile of laptop Average Lifespan (MTTF) in Greece, the Netherlands and Sweden.](image2.png)
The variation in the laptop lifespan in Greece is also illustrated in Fig. S1 (in Appendix). It is obvious that the probability of laptops becoming obsolete has shifted to 5.74 years (2015) from 8 years in the past (1995), meaning that more laptop waste is currently generated. Forti et al. (2018) reported the average laptop lifespan for the Netherlands, France and Belgium was 5.9 years in 2016.

Further, the estimation of lifespan distribution parameters for 2016–2040 was accomplished by extrapolating the existing trend (1983–2015) as explained in the Appendix. Two cases were considered: the lifespan distribution follows a curve-pattern reflecting the effect of coronavirus pandemic or a continuously decreasing pattern not affected by the coronavirus pandemic.

### 4.4. Sensitivity and uncertainty analysis

The future generation of laptop waste was calculated according to the scenarios presented in Table 2. The examined parameters were: laptop penetration rate (0.6 or 1.23 pieces/inhabitant), laptop weight (either average value of 2.23 kg/piece or decreasing till 0.44 or 0.14 kg/piece), Weibull parameters (either changing according to curve or decreasing pattern, as referred in Section 4.3) and population change (either decreasing as described in 3.4 or stable from 2020 and on). In this way the effect of the examined parameters on the estimated obsolete laptop amounts is clarified and light is shed on the most influential parameters of the analysis.

First, regarding the lower bound penetration capacity (K = 0.62), the results depicted in Fig. 3(a), show that scenario A1 (0.44 kg) and A2 (0.14 Kg) yield almost identical results (deviation <1%), which means that for a reducing future laptop weight, there is insignificant effect after 2025. However, the A3 scenario, (average weight 2.23 kg) yields different results as there is a significant deviation from 2027 (0.5%) that gradually increases to 27% by 2040. Thus, the simplification of considering an average weight leads to overestimation of obsolete amounts of laptops. The detailed estimations are reported in the Appendix.

Also, there is a considerable difference regarding the calculated units in A3 scenario compared to A1, as can be seen in Fig. 4(a) and (b). In the case of average weight (A3), the unit curve follows the pattern of the weight curve, while on the contrary, when reducing weight is considered, the shape of the two curves is different. For the reducing weight, a peak in the number of pieces will occur in 2025, corresponding to 2,866,241 pieces, while for the average weight case, the peak occurs in 2020, corresponding to 740,883 pieces. Also, the accumulated pieces in 2016–2040 will be 47,844,127 and 15,011,523 in scenario A1 and A3 accordingly. The accumulated pieces by 2015 are only 7.6% and 25% of the accumulated pieces in 2016–2040 in A1 and A3 scenario accordingly, revealing that enormous amounts of laptop waste are anticipated in the future. In A2 scenario, the maximum number of pieces is 9,641,969 items in 2025 and the accumulated pieces in 2016–2040 are 138,006,988 (data not shown). Thus the scenario A1 seems more plausible than A2 or A3, or the reducing weight till 0.44 kg, is more realistic.

The comparison of A4 to A1 scenario reveals a deviation of 7–15% (effect of the Weibull parameters, Fig. S3) while the comparison of the other scenarios A3 to A6, A3 to A31 and A1 to A11 reveal insignificant fluctuations and are all reported in the appendix.

As far as the upper bound penetration capacity is concerned (K = 1.23), Fig. 3(b) presents the results from scenarios B1, B2 and B3. In the upper case capacity, significantly more amounts of obsolete laptops are accumulated in 2016–2040, which are 42,228, 41,350 and 62,122 tonnes for B1, B2 and B3 scenario respectively. Also, considerable and increasing amounts of obsolete laptops will be generated till 2030 and then the amounts will gradually decrease. Analyzing the data in Fig. 3(b), it is concluded again (as in lower bound scenario) that, B1 and B2 yield almost similar results (dev. 1.23–3.89% in 2028–2040), while the deviation in calculated results in B3 (compared to B1) is 1.4–39% in 2017–2040. According to B1 scenario the generated EoL laptops in 2010 are 762 tonnes, while the increase in the next 10 years (2010–2020) is estimated at 160%. The 10-year change rate is ~6.6% (2020–2030) while the annual rate in the same period ranges between ~3.9 to 1%. The annual rate is constantly declining after 2030. In B3 scenario the 10-year growth rate is 206% (2010–2020) and then 35% (2020–2030).

In B1 scenario (0.44 kg), the generated amount of obsolete laptops is described both in pieces and weight (Fig. 4(c)). It is observed that the maximum number of obsolete pieces will be 4,223,002 in 2028. Also, the accumulated pieces in 2016–2040 will be 71,617,824, while the accumulated pieces by 2015 are only 5.1% of the accumulated pieces in 2016–2040. This shows that huge amounts of laptop waste are expected in the future. In B2 and B3 scenario the peak in estimated pieces will be in 2025 (13,890,446 pieces) and 2030 (1,412,551 pieces), respectively and the total accumulated pieces in 2016–2040 will be 204,967,672 and 31,649,463 accordingly, (Fig. S4 and S5 in Appendix). While scenario B3 underestimates the number of EoL pieces, B2 seems to overestimate, thus the more realistic scenario is B1.

Furthermore, regarding the effect of the Weibull parameters pattern, Fig. S6 compares scenario B1 to B4. In B4 the accumulated amounts of obsolete laptops are 47,102 tonnes (2016–2040), substantially higher than 42,228 tonnes in B1. Thus, the effect of the Weibull parameters on the estimation of laptop waste is significant. Scenario B1 takes into account the effect of coronavirus pandemic on the laptop lifespan, while B4 does not. The deviation in years 2016–2040 in curves B1 and B4 is between 0.24–17%. The generated waste amounts according to B5 and B6 scenario are reported in the Appendix, as well as the comparison of

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Table 2

| Parameter                        | Scenario A1 | Scenario A2 | Scenario A3 | Scenario A4 | Scenario A5 | Scenario A6 | Scenario A7 | Scenario A8 | Scenario A9 | Scenario A10 | Scenario A11 | Scenario A12 | Scenario A13 | Scenario A14 | Scenario A15 | Scenario A16 | Scenario A17 | Scenario A18 | Scenario A19 | Scenario A20 | Scenario A21 | Scenario A22 | Scenario A23 |
|---------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| max penetration rate (pieces/inhabitant) | 0.62 1.23 0.62 1.23 0.62 1.23 0.62 1.23 | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing | decreasing |
| laptop/tablets weight           | 0.62 1.23 0.62 1.23 0.62 1.23 0.62 1.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 | average 2.23 |
| Weibull parameters              |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |
| according to scenario 1         |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |
| (curve pattern)*                |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |
| Population                      |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |
| Decreasing from 2010 and on     |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |             |

*Curve pattern reflects the impact of the coronavirus pandemic, ** Decreasing pattern is not affected by the coronavirus pandemic.
the B4 to B5 and B6 scenario (Fig. S7).

In addition, comparison of B11 to B1 scenario reflects the population fluctuations (stable after 2020 or decreasing) in the estimated amounts of obsolete laptops. This is insignificant as deviation is less than 1% till 2036, and then less than 2.5% till 2040. Thus, the population change regarded does not affect the waste amounts considerably.

In conclusion, the most important parameter affecting the calculated obsolete laptop quantities is the weight of the devices, which should be considered a dynamic changing parameter instead of an average one. Following, the Weibull parameters are significant as their pattern (affected by the coronavirus pandemic or not) substantially influences the estimated waste amounts. As for the population variation and the final considered weight (0.14 or 0.44 kg), these had a minimum effect.

A comparison of quantities of laptop waste with other EU countries reveals that the generated quantities in recent years in Greece are lower than in Belgium and the Netherlands. Van Eygen et al. (2016) calculated 2,449 tonnes laptop wastes were generated in Belgium in 2013 contrary to 1,090 tonnes in Greece. Wang et al., 2013 estimated 5,137 tonnes EoL laptops in the Netherlands in 2010 contrary to 762 tonnes in Greece. Also Cacchiella et al., 2015 estimated that there will be an increase in EoL notebooks and tablets in the EU of 42% in 2014–2020, while the calculated increase in Greece will be 33% in A1 and 41% in A3 scenario, 68% in B1 and 92% in B3 scenario. This information is important for waste management systems to be able to tackle forthcoming obsolete amounts and prepare suitable collection and treatment schemes.

4.5. Estimation of CRMs and PMs in the EoL laptops

An estimation of CRMs and PMs content in the generated EoL laptops is presented, to illustrate the potential of key metals recovery in EoL laptops. Table 1 presents CRMs and PMs content in LCD/LED notebooks, laptops and tablets. As observed, laptops and notebooks include many valuable metals in high concentrations, while the concentrations in tablets are lower. Although future changes in the products design may slightly affect the CRMs and PMs content, the results are indicative of the valuable materials embedded in these electronic devices. These changes may not be dramatic, i.e. Charles et al., 2017, estimated that the trend in random-access memory (RAM) modules in PCBs is that gold and silver content remains roughly stable while palladium content decreases (1988–2010). However, technological innovations in the field of
displays like flexible Organic Light Emitting Diodes (OLED) screens or rechargeable batteries like lanthanum-nickel-hydride (La-Ni-H) may change the average composition (Zhang et al., 2017), but predicting the future changes is challenging. Also, composition modifications may occur due to the substitution of scarce or expensive elements by more abundant or cheaper ones, like replacement of Pr and Nd by La and Ce (Zhang et al., 2017; Lixandru et al., 2017).

A possible future technology change in laptops will lead to new waste products of slightly different composition. The recycling industry must invest in research and development to adapt to new waste devices to

Fig. 4. Estimation of obsolete laptops by units and weight (tonnes) according to scenario (a) A1 (0.62/0.44 kg/Curve), (b) A3 (0.62/2.23 kg/Curve) and (c) B1 (1.23/0.44 kg/Curve).
ensure better resource management. An example of a technological shift in the past was the evolution of CRTs to LCDs TV screens. Ecological design, creation of devices that can be easily processed to recover embedded materials and cooperation between producers and recyclers are prerequisites for the success of future recycling (Kalmykova et al., 2015; Shittu et al., 2021).

Table 1 also includes various indices that illustrate the significance of these metals in the EU economy, as most of them are 100% imported, while they are recycled at a low level (<10%). The Supply Risk (SR) index is especially high for RREs while the Economic Importance (EI) index is very high for RREs and platinum group metals. This information points to the fact that EoL laptops are ‘treasured’ materials that must be collected, treated, effectively recycled to ensure that their valuable metals stay within the EU, contributing to a circular economy. Emphasis must be placed on improving recycling, as increasing the recycling rate, reduces the supply risk of materials. For instance, the EoL recycling rate of antimony is 28% in 2020 (while <5% in 2011) thus the SR decreased from 2.6 in 2011 to 2 in 2020, as recycled Sb can enter the supply chain, relieving the import reliance stress (100% imported in EU in 2017). At the same time the EI has fallen from 5.8 in 2011 to 4.8 in 2020, as substitute materials are partly used, mitigating the risk of supply disruptions. Substitute materials can help reduce both EI and SR indices. For instance, compounds of Sn, Ti, Cr, Zn and Zr can replace Sb in the manufacture of pigments and glass. However, in its principal application as flame retardant, substitution of antimony is much harder (EU Final Report, 2020; EU factsheets on CRMs, 2020). With the increasing amounts of e-waste, (laptop waste in particular), developing non-polluting, efficient and economical recycling technologies is crucial to recovering their valuable metals (Kiddee et al., 2013; Kaya, 2016). In order to facilitate recycling, it is necessary to design devices for recycling, promoting disassembly and recovery (Shittu et al., 2021).

Regarding EoL laptops, the estimations of key metals (from 2000 to 2040) are illustrated in Fig. 5 for B1 scenario and in Fig. S7 (in the Appendix) for B3 scenario. In B1 scenario the number of generated pieces is far greater because the weight of the devices is considered reducing instead of stable as in B3. In B1 scenario the 10 year growth rate (2010–2020) of the key metals in EoL laptops is about 170%, while it is predicted that the same growth rate will be achieved in only 5 years time in the future (2020–2025). From 2025–2040 the annual growth rate declines to almost below 1%. The generated amounts in 2020 are 1055 kg Sb, 1675 kg Nd, 155.2 kg Pr, 38.8 kg Dy, 1.6 kg Y, 31 kg In, 1319 kg Ta, 50.4 kg Co and the precious metals 27.2 kg Pd, 3.1 kg Pt, 171 kg Au and 318 kg Ag, while in 2025 they are predicted 2.7 times more. The total accumulated amount in waste laptops in 2020–2040 will be 46 t Sb, 73 t Nd, 6.7 t Dy, 1.7 t Y, 1.35 t In, 57.3 t Ta, 2.2 t Co and 1.18 t Pd, 0.13 t Pt, 7.4 t Au and 13.8 t Ag. The accumulated amounts till 2019 are only 16% of the accumulated amounts in 2020–2040, showing the great potential for urban mining in the near future, which should not be lost.

Concerning the key metals in EoL tablets the estimations for B1
scenario are depicted in Fig. 6 and for B3 scenario in Fig. S9 (in the Appendix). The annual growth rate in key metals in 2015–2020 is estimated between 14–59%, while it will range between 14–35% in 2020–2025. The estimated amounts in 2020 are 119.5 kg Sb, 331 kg Nd, 0.7 kg Y, 6.2 kg In, 10 kg Co, 6.2 kg Pd, 34 kg Au and 39 kg Ag. In 2025 the predicted amounts are almost three times more. The total accumulated amounts in waste tablets in 2020–2040 will be 5.19 t Sb, 14.4 t Nd, 0.03 t Y, 0.27 t In, 0.44 t Co, 0.27 t Pd, 1.48 t Au and 1.69 t Ag. The accumulated amounts of key metals in the past (till 2019) are only 7% of the future accumulated amounts (2020–2040), revealing that we must invest on collecting and recycling to maintain the secondary resources within the economy.

The calculated metal contents depict the potential that exists in the obsolete waste, while there is still a long way till efficient recycling can be accomplished for most of these metals. Indeed, the EoL recycling input for Pd and Pt is currently at 14%, while it is 0–8% for CRMs. The only exceptions are Sb with a recycling input ratio of 28% and the precious metals Ag and Au with 55% and 20% respectively. It is evident that urban mining is an attractive option in order to meet future resource needs within the circular economy concept (Zeng et al., 2020), but new efficient recycling methods must be applied.

5. Policy implications

This study has significant implications for developing appropriate e-waste policies in Greece, especially for category 3 (ICT devices). The estimation of future EoL laptops (particularly in the long run) is a prerequisite to better organize collection and treatment processes and ensure the appropriate infrastructure. Our study shows that significant waste laptop quantities are anticipated in the near future, far greater than the laptop waste generated in the past. This opportunity of urban mining should not be lost, as great amounts of key metals are contained in this waste.

Moreover, the 2015 National Waste Management Plan (NWMP) states that in 2011 about 73 thousand tonnes of WEEE were generated and 15 thousand were promoted to other countries for further treatment. Also the prediction of e-waste increase in 2011–2020 is 9.1%, while according to our calculations, only EoL laptops will present an increase of about 123–163% according to B1 and B3 scenario and 71–86% in A1 and A3 scenario for the same years. The calculated laptop waste shows that great amounts will be generated in the future. The 2020 NWMP states that there is no reliable method to estimate WEEE and that the EEE POM quantities are used to estimate future quantities, however our study shows that future quantities of e-waste can be reasonably calculated.

The next important step in e-waste management is waste collection. As far as the collection, recovery and recycling targets in Greece are concerned, these were not met for category 3 in 2018 (collection 44.6%, recovery 83.8% and recycling 73.8%) and it is very unlikely that they will be fulfilled in 2020 since collection target rises from 45 to 65% (based on POM quantities). As illustrated in our work, EoL laptops are among the most important e-wastes from a CRMs and PMs recovering perspective, thus their inefficient collection plan is not promoting circular economy in Greece, as valuable resources are lost. In order to enhance the collection several actions can be adopted to motivate people to participate in WEEE collection instead of storing non functional
electronic devices at home. Financial incentives may include vouchers for individuals when they hand in their old devices, discounts for a new buy or reduction in waste fees for residents or communities willing to separate more e-waste at source. For the latter legal regulation at local level is a key factor for the implementation. Also, all municipalities in a prefecture can organize e-waste collection campaigns with prizes for the citizens (Dri et al., 2018). All these actions are important as Greece includes many islands that hinder efficient collection, thus establishing multiple collection points and increasing public awareness is vital.

6. Conclusions

Future EoL laptops amounts in Greece are estimated considering time-varying parameters of penetration rate, population, laptop weight and lifespan. The impact of the coronavirus pandemic on the lifespan of laptops is also assessed. It is concluded, the most important parameter affecting the calculated obsolete laptops amounts is the weight of the devices, followed by the Weibull parameters (lifespan). The estimated CRMs and PMs amounts in these wastes reveal a great potential of key metals recovery. The results point out that significant amounts of EoL laptops will be generated in the future in Greece and existing compila-
tion schemes should be improved to enhance collection as much as possible. In this way valuable resources, like key metals will not be lost and the EU economy can become more material sufficient in accordance with the circular economy concept.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2021.07.017.

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