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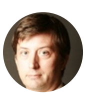
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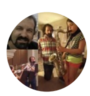
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Evolution of Product Lifespan and Implications for Environmental Assessment and Management: A Case Study of Personal Computers in Higher Education

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Product lifespan is a fundamental variable in understanding the environmental impacts associated with the life cycle of products. Existing life cycle and materials flow studies of products, almost without exception, consider lifespan to be constant over time. To determine the validity of this assumption, this study provides an empirical documentation of the long-term evolution of personal computer lifespan, using a major U.S. university as a case study. Results indicate that over the period 1985–2000, computer lifespan (purchase to "disposal") decreased steadily from a mean of 10.7 years in 1985 to 5.5 years in 2000. The distribution of lifespan also evolved, becoming narrower over time. Overall, however, lifespan distribution was broader than normally considered in life cycle assessments or materials flow forecasts of electronic waste management for policy. We argue that these results suggest that, at least for computers, the assumption of constant lifespan is problematic and that it is important to work toward understanding the dynamics of use patterns. We modify an age-structured model of population dynamics from biology as a modeling approach to describe product life cycles. Lastly, the purchase share and generation of obsolete computers from the higher education sector is estimated using different scenarios for the dynamics of product lifespan.

1. Introduction

The environmental management of computers and other electronic goods is undergoing significant and increasing attention from the public and from policy makers around the world. Of particular concern is the management of electronic waste ("e-waste"), which, when managed properly, can contribute to growing economies (*1*) and narrowing the digital divide (*2, 3*), but when recycled informally in developing countries, it can potentially create significant human health and environmental impacts (e.g., refs *4–7*). Although receiving less public and media scrutiny, environmental impacts associated with electronic product manufacturing and use phases are also major components of these products' life cycle environmental impacts. Due to the combination of relatively short lifespans and energy intensive manufacturing, electronic products such as computers are distinct from many "products with a plug" in that much of the environmental burden over the product life cycle is driven by manufacturing (*8, 9*).

When assessing environmental impacts associated with both the upstream and downstream processes in electronic product life cycles, product lifespan is obviously a fundamental variable of interest. Not only does lifespan dictate the manufacturing energy and impacts created due to product replacement, but also the quality and operational characteristics of obsolete equipment requiring end-of-life (EOL) management. Furthermore, technological progress and the evolution of product lifespan are expected to induce changes in the environmental characteristics of manufacturing processes, the performance characteristics of products, and in how consumers purchase, use, and dispose of products.

Considering electronic products in use today, the challenges of understanding and managing impacts of rapid technological innovations and change in product lifespan are perhaps most clearly exemplified through personal computers, which have been undergoing rapid changes in technology, lifespan, adoption, and use. Computer ownership in the United States is increasing at a rapid rate. The U.S. Census Bureau estimated in 2005 that 62% of all households had at least one personal computer (PC) in 2003, up from 23% in 1993 and 8% in 1984 (*10*). Similar trends are shown in the commercial sector, as the number of computers in commercial buildings increased from 30 million in 1992, to 43 million in 1995, and to 58 million in 1999 (*11*). However, there has not been a clear empirical documentation of the changes in computer lifespan over these same time periods.

Nevertheless, existing studies, policy forecasts, and life cycle assessments (LCAs) of computers and related products, almost without exception, consider lifespan or lifespan distribution to be constant over time (e.g., refs *8, 12–17*). Although this oversimplifying assumption is often required by the scarcity of publicly available and temporally variable data, the inability to account for technological progress, lifespan evolution, or temporal dynamics in product adoption and use represents a fundamental methodological challenge inherent to LCAs (*18–21*) and a significant limitation on the ability of such studies to inform environmental management and policy decisions.

Therefore, it was our goal to study the evolution of personal computer lifespan and to identify methods by which this aspect of technological progress could be quantified and integrated into LCAs and other environmental assessment studies. This approach was operationalized through a case study of computer adoption and life cycle parameters in a major U.S. university, Arizona State University (ASU), in Tempe, Arizona. The primary objectives of this study were to provide empirical data demonstrating personal computer lifespan evolution over the last 20 years and to present an age-structured model that can be adapted to integrate lifespan evolution in future e-waste and computer LCA

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studies. A secondary objective was to use the case study approach to provide the first characterization of trends in life cycle parameters for personal computers in higher education, including purchase, stocks, ownership, lifetimes, and obsolete equipment generation. One motivation for studying the education sector was to scope its importance in e-waste generation and management at a national level. The second motivation was that universities often collect decades of data on computer purchase and disposal and have an open perspective regarding public access to these data, as compared to the private sector.

2. Case Study

This work was initiated as a case study of personal computers (PCs) and related equipment purchased and used in U.S. higher education. Colleges and universities were expected to be major contributors to computer purchasing, use, and disposal in the U.S., an assumption supported by recent commercial computer usage surveys, which estimated that the education sector (K-12 and postsecondary) accounted for 21% of the approximately 58 million PCs in commercial buildings in 1999 and that the overall education sector had an ownership rate of 1335 PCs per thousand employees, as compared to an average of 707 computers per thousand employees for all commercial sectors in 1999 (*11*). Furthermore, colleges and universities are often viewed as hubs of technological research innovation where students are increasingly adept with computer and Internet applications and instructors are more commonly using computer-based instruction platforms. However, even with the intuitive perception that higher education must be a significant contributor to the life cycle of PCs, no work (to our knowledge) has tried to quantify how colleges and universities align with national trends or may possibly influence future impacts of PC use, reuse or recycling, and disposal.

The case study focused on ownership and life cycle parameters of institutionally owned computers at Arizona State University (ASU). This institution was selected because it is one of the largest universities in the U.S. (a projected enrollment of 66 000 students in 2008 and over 12 000 employees), and therefore, expected to be representative of other large institutions, which may be likely to contribute most to overall computer ownership in U.S. higher education sector by the magnitude of their sizes. Furthermore, ASU maintains an extensive database of all inventory purchased, including computers and computer equipment, which enabled a thorough investigation into computer life cycle trends.

The case study was conducted by examining all data available from the property control database related to institutional computer purchase and use, including the numbers of computers purchased each year, the purchase price of each unit, the number of computers retired, or discontinued from use at the university, each year, and the age at which the unit was retired. No individual/student PC ownership was included in this assessment. Data were extracted from this database between June and October, 2008. Calculations of annual PC stock at the university were normalized on a per employee basis, where an employee was defined to include any individual employed at the university at a half-time rate or greater, which included graduate students because they are expected to often be employed in teaching and research positions, but at less than full time employee status. Annual employment and graduate student enrollment data were provided by the ASU Office of Institutional Analysis.

The system boundary included all desktop and laptop computers purchased by the university between 1985 and 2000, a 15-year window that allowed for examination of historic and recent trends. Furthermore, interviews with ASU property control staff indicated that data up until 2000 would be the most complete, as all computers purchased during that time would be known. However, after 2000, the university only mandated inclusion in the database of computers with a purchase price greater than $2000 (this threshold increased to $5000 in 2004). Although many individuals and departments continued to self-report all computers purchased, there was no way of ensuring the completeness of data after 2000. A limited number of extrapolations were performed on existing data to create projections to the present or future, where needed.

There were two identified data quality issues inherent to data collected from the university property control database. First, the change in reporting requirements discussed above limited the use of more recent data. Second, during data analyses, it was observed that there were a small number of computers purchased each year (from 1985 onward) that were never shown as having been retired from use, even though their ages (e.g., 15−20 years old) indicated they would likely no longer be in use. To address these limitations, subsampling was conducted for specific units. It was known from interviewing university staff that the Ira A. Fulton School of Engineering had continued reporting all computers purchased, even after the university created the price threshold. Therefore, data specific to this department were extracted from the database and analyzed in the same manner as the university-wide data, to determine the similarity in historic (1985−2000) and recent (2000−2005) trends and to obtain a second estimate of the number of residual or missing computers, those expected to have been retired because of their age but still shown as being in active use.

3. Definition of Lifespan

Though perhaps seen as trivial, definition of lifespan, particularly for computers, deserves special care and attention. Product lifespan can have different definitions, including (1) the length of time a product is possessed by its first user, (2) the length of time between first purchase of a product from a manufacturer and its processing in the waste management sector, and (3) the length of time between purchase of a new product by a consumer and the product's obsolescence (i.e., lifespan of the "primary product" in use).

The distinction between these definitions is often ignored, and using them interchangeably can skew results. For example, in a recent LCA study of computers commissioned by the European Commission for the developing Energy using Products (EuP) Directive, lifespan of a desktop computer was assumed to be 6.6 years based on the first definition (*14*). However, computers are often stored or put into secondary use for significant periods. A 2004 survey showed that Japanese residential computer users on average purchase new computers every three years and that computers spend three years in storage before next stage disposition (e.g., resell, disposal, recycle) (*22*). For this data set, lifespan using the first definition is 6 years, while for the third definition, lifespan is three years. The EuP study uses the 6.6 year figure based on the first definition to estimate total life cycle impacts of a computer. This skews the results in two ways. First, the life cycle impacts of operating the computer in question are overestimated by a factor of around two since for around half of the period the machine is probably in storage. Second, the manufacturing impacts needed to provide computing services are undercounted since the fact that the consumer purchased a second computer halfway through the period is ignored. This conceptual error in defining using lifespan contributes to the conclusion drawn in the EuP study that computer manufacturing does not significantly affect life cycle impacts.

The reason we go into such detail in the above example is to illustrate that it is crucial to clearly define and interpret lifespan appropriately. In our study, constraints on the data set limit us to only studying the first definition where the "user" is considered to be the organization: ASU. At this point, we do not and cannot describe the period a computer is used by individuals in the organization or how long it will take end-of-life equipment sold to the secondary market to reach final disposition in waste management.

4. Statistical Data Analysis

Lifespan data obtained from the case study could potentially be fit to a number of statistical models to describe the distributions and calculate mean and variance parameters. The fit of annual lifespan data to four distributional models (normal, log-normal, gamma, and Weibull) were compared by calculating negative log likelihoods and the Akaike Information Criteria (AIC) (*23*). This method allows competing models to be ranked according to their AIC score, for each data set, with the lowest AIC corresponding to the best fitting model. Subsequently, best-fitting parameters were obtained by maximizing the log-likelihood function for each model (see the Supporting Information (SI) for the probability density functions used). The maximization was performed using the conjugate gradient method within unconstrained solve blocks in the program MathCAD by Mathsoft (2001).

5. Age-Structured Forecasting

The extent of long-term data available for this study enabled an empirical assessment of how dynamic PC lifetime distributions could potentially affect the future generation and characteristics of obsolete computer equipment. This assessment was conducted by creating a dynamic age-structured forecast of PC lifespans that would predict the likelihood that computers purchased over time would be retired at any given age. Age-structured or age-specific life tables and models are used commonly in demography and population ecology to investigate the effect of age on birth and death rates or other demographic parameters of individuals in a population (*24*). In economics, "vintage capital models" have been applied to predict the economic effect of technological diffusion (*25*), derive optimum ICT lifespan for replacement (*26*), and assess emissions and environmental impact of industrial processes (*27*). Therefore, we sought to extend these methods to the study of computer lifespan and e-waste generation.

In this approach, we defined a population cohort as all of the PCs purchased in a given year. Annual inputs and outputs were defined as the annual purchase rate and annual generation rate of obsolete equipment, respectively. The PC lifespan was defined as the time between the institutional purchase of a new computer and the ultimate sale and removal of the computer from the university. It is expected that this lifetime in some cases may include a storage phase of unknown duration between discontinuation of use by the first owner and transport to the surplus property division for disposition. No secondary storage phase in the surplus property operation was expected, as that unit sells all computer inventory on a monthly basis.

Age-structured obsolescence rates were determined for each cohort from 1985 through 2000, by quantifying the number of computers from a cohort being retired in a specific age class. An age class i was defined as all PCs between the age of i and $i+1$ (e.g., PCs retired in age class 2 were between 2 and 3 years old). These distributions were used to construct "mortality," or obsolescence, curves that demonstrated the cumulative percentage of PCs in a cohort retired over time. To assess how the age structure changed over time, the obsolescence curves and the corresponding distributions of computer age at retirement were created for four-year averages between 1985 and 2000.

To forecast the effect of the age-structured obsolescence curve on future generation of obsolescent equipment, a distribution of expected lifespans was obtained using the best fitting model, as determined in Section 4, with inputs of the predicted future PC cohort sizes and lifespans. Future PC purchase rates were forecast from 1985 to 2000 trends, following the method of Tasaki et al. (*28*), assuming a maximum penetration of 1.3 computers per person, consistent with commercial computer use surveys (*11*) and an estimated upper bound to ownership (*29*). Linear increases in employee numbers were assumed to forecast the total annual stock. To determine how future changes of PC lifespan would affect projected obsolescence curves, three scenarios were considered: (1) average computer lifespan would decrease linearly, based on most recent data (1995−2000) (most conservative estimate); (2) average lifespan would follow an exponential decrease, with lifespans from 2000 onward below the point of inflection in the curve; and (3) average lifespan would decrease linearly, based on trends from 1985 to 2000 (most speculative estimate). Although Scenario 3 is extremely unlikely, it is included to provide an lower bound of expected lifespans. 2010 was selected as the year for comparison among these three forecasts. MathCAD (2001) was used to generate the forecast distributions.

Although lack of data, as described in Section 3, and the lack of information about computers purchased recently, and yet to be retired, prevented a full comparison of these three scenarios with actual data, some preliminary assessments were made. Approximately 200 data points from the university-wide database and the School of Engineering were available for year 2005. The forecasting process as described above was repeated using means calculated by each scenario for 2005 and a sample size of 200. The resulting distributions were compared to the right-censored distribution of actual 2005 lifespans.

6. National Projections

After determining per-employee annual PC stocks and obsolete equipment generation rates for ASU, these estimates were used to create projections of the estimated national PC stock and e-waste generation for the U.S. higher education sector. It was assumed that universities would reach a maximum penetration of 1.3 computers per person (*11, 29*). Additionally, during the time required to reach that maximum, it was expected that ownership would follow a logistic curve, constructed based on the empirical case study data presented herein. Obsolete equipment generation on a per employee basis was determined for the three scenarios described above, following the method of time series substance flow analysis (*28*). To scale data up to the national level, estimates of U.S. total annual employees and enrolled graduate students were obtained and projected from the National Center for Education Statistics' annual report "Digest of Education Statistics" (http://nces.ed.gov/programs/digest/index.asp).

7. Historical Results for Computer Stock and Lifespan

The annual stocks and percent ownership by employees of all computer equipment at ASU, including desktop and laptop systems, is shown in Figure 1, for the period 1985 through 2000. This figure indicates that while ASU population (employees and grad students) is growing, the increase of the stocks of computers is not only a product of this increase but also a result of the increasing computer ownership trend. For example, in 1985, 1990, and 2000, ownership rates were 4, 36, and 110%, respectively. For the same period, however, the calculated log-normal mean lifespan for PC cohorts decreased significantly, as shown in Figure 2, with error bars representing standard deviation of lifespans within the

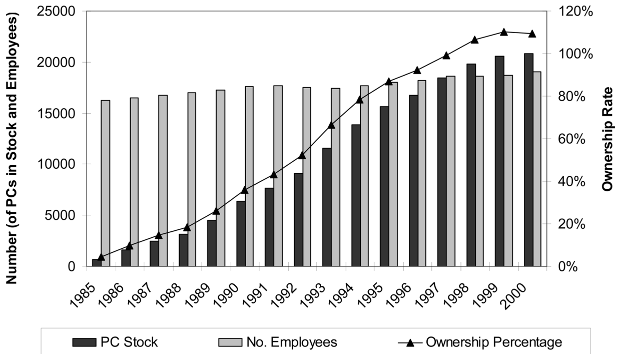

FIGURE 1. Annual computer stock and penetration rate at Arizona State University.

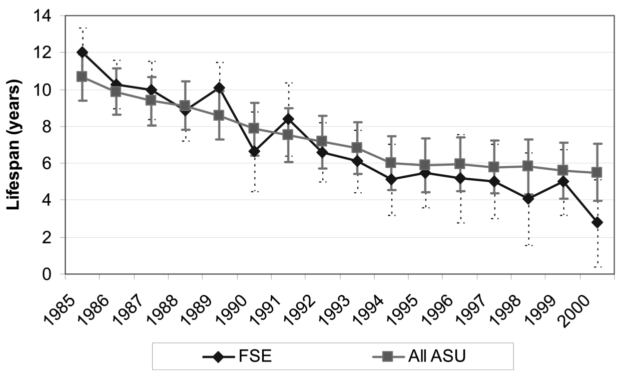

FIGURE 2. Mean lifespan of PCs at ASU and subsampled in the Fulton School of Engineering (FSE). Error bars are standard deviation among all computers in each sampling group.

TABLE 1. Lifespan Distribution Parameters

cohort purchase year	sample size (*n*)	lognormal mean	lognormal variance
1985	629	10.65	1.24
1986	792	9.87	1.27
1987	750	9.37	1.32
1988	631	9.12	1.33
1989	1282	8.60	1.33
1990	1624	7.86	1.43
1991	1259	7.53	1.45
1992	1456	7.16	1.42
1993	2245	6.83	1.42
1994	2430	6.03	1.46
1995	2405	5.88	1.44
1996	2492	5.97	1.45
1997	2850	5.80	1.45
1998	2811	5.83	1.49
1999	2824	5.62	1.52
2000	2438	5.49	1.54

cohort. Figure 2 also distinguishes between the mean lifespan of computers from the entire institution and within a subsampled department, the Fulton School of Engineering (FSE), in which strong agreement is shown between the broad and narrow sampling groups. Table 1 presents the best fitting log-normal distribution parameters for each year in consideration. As determined by Akaike Information Criteria (AIC), log-normal was the best fitting distribution for all years of data, and delta-AIC and best-fit parameters for each year are provided in SI Table S1.

The age-structured computer obsolescence curves are introduced in Figure 3, and show the cumulative fraction of obsolete equipment generated in each age class of cohorts, averaged within four periods, 1985−1988, 1989−1992, 1993−1996, and 1997−2000. Initially, the obsolescence

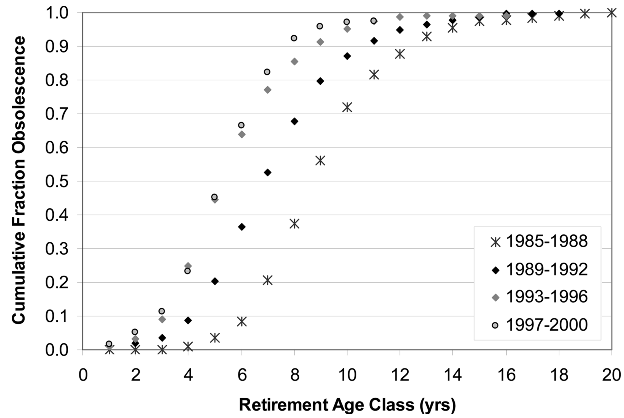

FIGURE 3. Average obsolescence curves for computer cohorts from four time periods.

curve shifts rapidly to the left, showing more rapid obsolescence over a shorter window of time. For example, for computers purchased between 1985−1988, less than 10% had been retired by the 6th year in use. However, this percentage increased to 35% for computers purchased between 1989−1992 and to approximately 65% when considering the computers purchased between 1993−1996 and 1997−2000. While the most drastic shift in the obsolescence curve was after the first two periods, the difference in curves for 1993−1996 and 1997−2000 was much smaller. The major shift perhaps reflects the decreasing use phase of PCs at the university during this time and/or a decreasing amount of time for units to be kept in storage before leaving the system boundaries. Although it may be intuitively expected that shifts to notebook computers and decreasing computer price would be directly correlated with decreasing lifespans, over this period of observation, we only observed very gradual decreases in price and no significant difference in mean lifespans among different types of computers (SI Figure S1). Although we observe increasing shares of notebooks, the annual purchase cohorts are comprised by 60% or greater of IBM-compatible desktop computers (SI Figure S2), indicating that observed trends are not necessarily linked to technology shifts between desktops and laptops.

Resulting distributions of PC lifespans for each of the four-year periods also show changing trends over time (Figure 4), specifically the decrease of computer lifespan and a narrowing of the lifespan range. For example, for computers purchased from 1985 to 1992, there was a broad spread of lifespans, indicating that the majority of obsolete equipment leaving the university for recycling, disposal, or reuse might be between 6 and 12 years old. However, for computers purchased from 1997 to 2000, it was more likely that obsolete equipment retired from the university would be five to seven years old. Year-by-year lifespan distributions were also created and are provided in SI Figure S3.

8. Forecasting Results of Computer Stock and Lifespan

It is expected that the observed trends of decreasing lifespan, shifting of the obsolescence curves, and a narrowing lifespan range may continue in the future. It is also likely that electronic equipment will continue to undergo rapid evolution and increasing adoption and use. To consider these potential trends, future scenarios of PC lifespans were created with results shown in Figure 5. Scenarios considered are (1) PC lifespan decreases linearly from 1995 onward, extrapolated to 4.7 years in 2010, (2) PC lifespan decreases on an exponential curve, extrapolated

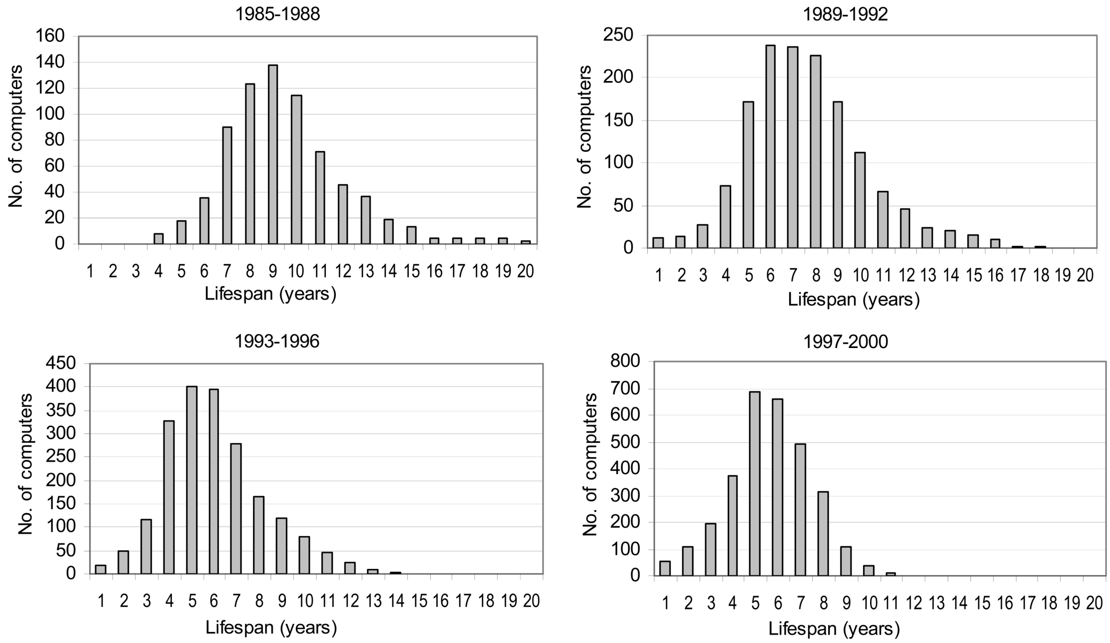

FIGURE 4. Average lifespan distributions for computers cohorts from four time periods.

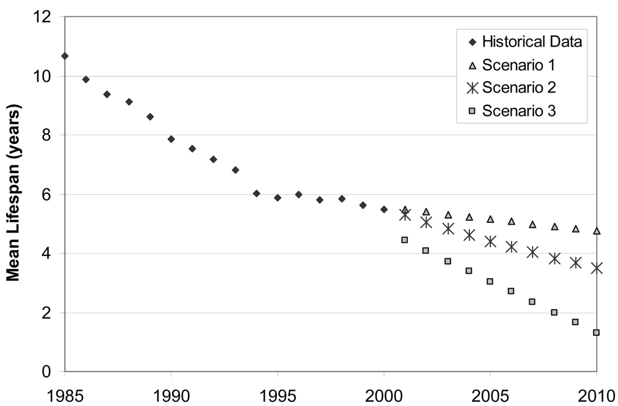

FIGURE 5. Three projected scenarios of PC lifespan change over time. Note: Scenario 1: linear (from 1995) decrease in lifespan, to 4.7 years in 2010; Scenario 2: exponential decrease in lifespan, to 3.5 years in 2010; Scenario 3: linear (from 1985) decrease in lifespan, to 1.3 years in 2010.

to 3.5 years in 2010, and (3) PC lifespan decreases linearly from 1985 onward, extrapolated to 1.3 years in 2010.

To consider the effect of decrease in lifespan on obsolescent equipment generation and to demonstrate the utility of the age-structured model lifespan, distributions for the three scenarios were created for year 2010 (Figure 6). These scenarios indicate that there are drastically different possibilities for the characteristics of obsolete equipment generated, which illustrates the challenges of recommending future e-waste management strategies for potentially highly variable waste streams. Clearly, the concerns and options for managing a waste stream comprised of 1−4 year old computers with similar technology, materials, and components (Scenario 3) would be vastly different than managing a waste stream in which computers might be anywhere between 2 and 8 years old and would likely have different generations of hardware and technology (Scenario 1).

Although it is impossible to determine a priori which scenario will be most accurate for computers purchased in the future, we can get an indication of trends using limited data available more recently. The distribution of a small sample of lifespan data collected from the university and the Fulton School of Engineering for the 2005 purchase cohort (n = 196) was compared to projected 2005 distributions of the three scenarios for the same sample size. Results (shown in SI Figure S4) indicate that this sample distribution follows Scenario 2 very closely overall for the years in which the retirement ages are known.

9. Scoping the Importance of Higher Education in E-waste Generation

The challenges described herein, associated with the management of a varied and increasing flow of obsolete computers from universities, would be magnified at a national level if trends observed at ASU were consistent across the entire U.S. higher education sector. To scope out the potential importance of this sector at the national level, computer ownership and obsolete equipment generation trends and forecasts were extended to the national level (SI Figure S5). Considering these broad projections, it is possible that higher education in the U.S. could contain a stock of 13 million computers in 2010 and be responsible for generating approximately 2.5 million obsolete computers per year. Obviously, extrapolation from a single case study is limited by the lack of other institutional benchmarks, but these estimates provide a possible upper bound on the contribution of higher education and the first approximation of this nature.

10. Discussion

Results presented herein have established empirically that evolution of PC lifespan is an important variable which can influence forecasts, management strategies, and policies for current and future challenges related to e-waste, as well as the energy use and emissions associated with the use phase of computer life cycles. In addition, two important developments of computers and their relationship with society noted in this paper—decrease of lifespan and increase in ownership—need to be considered more fully when forecasting and regulating end-of-life generation and management of computers. Prior studies intended for policy guidance, such as a recent assessment by the U.S. Environmental Protection Agency (*17*), forecast e-waste generation assuming a static lifespan applied to all years considered. Without a more complete inclusion of

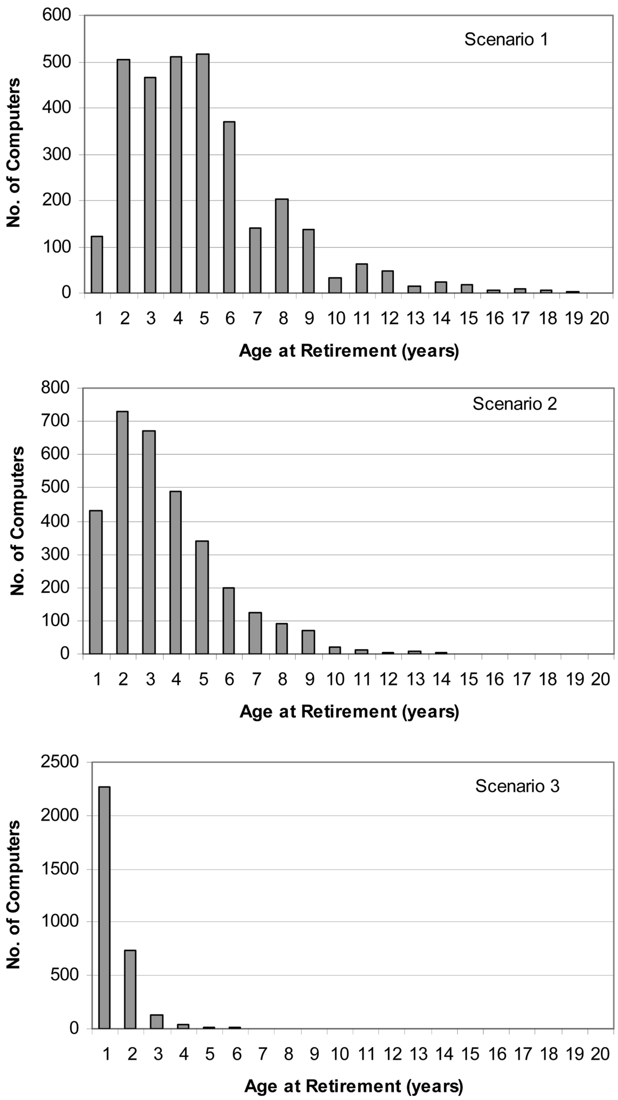

FIGURE 6. Forecast computer lifespan distribution due to changing PC lifespan, for cohorts purchased in 2010.

lifespan evolution, forecasts of e-waste generation may be significantly skewed and/or lead to oversimplified future regulations that do not adequately account for the complex characteristics of the waste flow. In addition, LCA studies that assume a single, static lifespan, rather than an evolving distribution of lifespans, may underestimate the natural variability in product use phase energy consumption. As trends in obsolete equipment storage times, user reuse patterns, and new equipment purchase intervals become more clear, the definition of lifespan can be continually improved for use in LCAs. Although further research needs to be done for different computer users, such as in residential and commercial sectors, we expect that similar trends in evolution of lifespan may be observed, implying that sustainable use and management of electronic products and e-waste at a national level will require a more in-depth understanding of the dynamic nature of lifespan and material flows for electronic products.

While this case study focused on personal computers, lifespan dynamics could affect the life cycle assessment and management of a variety of products including automobiles, buildings, and various home appliances. Dynamics are poorly understood at present. The age-structured model and forecasting approach presented here can contribute to development of methodology to account for technological progress and lifespan evolution in LCA and other types of environmental assessments.

Acknowledgments

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Supporting Information Available

Additional results and data, including disaggregated desktop and laptop comparisons, historical price changes, annual lifespan distributions, comparisons of projected scenarios with data, and the scope of computer stock for the U.S. higher education sector. This material is available free of charge via the Internet at http://pubs.acs.org.

Literature Cited

(1) *IAER Electronics Recycling Industry Report*, Update; International Association of Electronics Recyclers (IAER): Albany, NY, 2006.

(2) *Bridging the Digital Divide: Innovation Systems for ICT in Brazil, China, India, Thailand and Southern Africa*; Baskaran, A., Muchie, M., Eds.; Adonis & Abbey Publishers Ltd.: London, 2006.

(3) Warschauer, M. *Technology and Social Inclusion: Rethinking the Digital Divide*; The MIT Press: Cambridge, MA, 2004.

(4) Williams, E.; Kahhat, R.; Allenby, R.; Kavazanjian, E.; Kim, J.; Xu, M. Environmental, social, and economic implications of global reuse and recycling of personal computers. *Environ. Sci. Technol.* **2008**, *42* (17), 6446–6454.

(5) *Exporting Harm: the High-tech Trashing of Asia*; Basel Action Network (BAN) and Silicon Valley Toxics Coalition (SVTC), BAN: Seattle, WA, and SVTC, San Jose, CA, 2002; http://www.ban.org/E-waste/technotrashfinalcomp.pdf (accessed Aug 23, 2007).

(6) E-waste Chain in Guiyu, Guangdong Province. China Environmental Regulation Net. Qinghai Meng; 2004. http://www.riel.whu.edu.cn/show.asp?ID=1420 (accessed March 2007).

(7) *Recycling of electronic wastes in China and India: workplace and environmental contamination*, Technical note 09/2005 (Section 1); Greenpeace: Exeter, UK, 2005; http://www.greenpeace.org/raw/content/china/en/press/reports/recycling-of-electronic-wastes.pdf (accessed March2007).

(8) Williams, E. Energy intensity of computer manufacturing: hybrid analysis combining process and economic input-output methods. *Environ. Sci. Technol.* **2004**, *38* (22), 6166–6174.

(9) Williams, E.; Ayres, R.; Heller, M. The 1.7 kg microchip: Energy and chemical use in the production of semiconductors. *Environ. Sci. Technol.* **2002**, *36* (24), 5504–5510.

(10) Cheeseman Day, J.; Janus, A.; Davis, J. *Computer and Internet Use in the United States: 2003*; U.S. Census Bureau Special Studies: Washington, DC, 2005; pp 23−208.

(11) *Computers and Photocopiers in Commercial Buildings*; Energy Information Adminstration, U.S. Department of Energy: Washington, DC, 2002; http://www.eia.doe.gov/emeu/cbecs/pc_copier/pccopier99.html (Accessed June 2008).

(12) Choi, B.-C.; Shin, H.-S.; Lee, S.-Y.; Hur, T. Life cycle assessment of a personal computer and its effective recycling rate. *Int. J. Life Cycle Assess.* **2006**, *11* (2), 122–128.

(13) *Development of Environmental Performance Indicators for Ict Products on the Example of Personal Computers*; EPIC-ICT Consortium: University of Stuttgart, Leinfelden-Echterdingen, Germany, 2006; http://www.epic-ict.org/down/publications/EPIC_Final_activity_report.pdf (Accessed June 2008).

(14) *Lot 3: Personal Computers (desktops and laptops) and Computer Monitors*, Final Report (Task 1−8) European Commission DG TREN, Preparatory studies for Eco-design Requirements of EuPs; IVF Industrial Research and Development Corporation: Molndal, Sweden, 2007; http://www.ecocomputer.org/ (Accessed July 2008).

(15) Kang, H.-K.; Schoenung, J. M. Estimation of future outflows and infrastructure needed to recycle personal computer systems in California. *J. Hazard. Mater.* **2006**, *B137*, 1165–1174.

(16) Socolof, M. L.; Overly, J. G.; Kincaid, L. E.; Geibig, J. R. *Desktop Computer Displays: A Life Cycle Assessment*, EPA-744-R-01-004a; U.S. Environmental Protection Agency: Washington DC, 2001.
(17) *Electronics Waste Management in the United States*, EPA530-R-07−004a; U.S. Environmental Protection Agency, Office of Solid Waste: Washington, DC, 2007.
(18) Field, F.; Kirchain, R.; Clark, J. Life cycle assessment and temporal distributions of emissions. *J. Ind. Ecol.* **2001**, *4* (2), 71–91.
(19) Levine, S. H.; Gloria, T. P.; Romanoff, E. A dynamic model for determining the temporal distribution of environmental burden. *J. Ind. Ecol.* **2007**, *11* (4), 39–49.
(20) Mendivil, R.; Fischer, U.; Hirao, M.; Hungerbühler, K. A. New LCA methodology of technology evolution (TE-LCA) and its application to the production of ammonia. *Int. J. Life Cycle Assess.* **2006**, *11* (2), 98–105, 1950−2000.
(21) Reap, J.; Roman, F.; Duncan, S.; Bras, B. A survey of unresolved problems in life cycle assessment, Part 2: impact assessment and interpretation. *Int. J. Life Cycle Assess.* **2008**, *13*, 374−388.
(22) Williams, E.; Hatanaka, T. Residential computer usage patterns in Japan and associated life cycle energy use, in 2005. *Proceedings of the IEEE International Symposium on Electronics and the Environment*, Piscataway, New Jersey, 2005, 177−182.
(23) Burnham, K. P.; Anderson, D. R. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*; Springer-Verlag: New York, NY, 2002.
(24) Gotelli, N. J. *A Primer of Ecology*, 2nd ed.; Sinauer Associates, Inc: Sunderland, MA, 1998.
(25) Chari, V. V.; Hopenhayn, H. Vintage human capital, growth, and the diffusion of new technology. *J. Pol. Econ.* **1991**, *99* (6), 1142–1165.
(26) Yatsenko, Y.; Hritonenko, N. Network economics and optimal replacement of age-structured IT capital. *Math. Methods Oper. Res.* **2007**, *65*, 483–497.
(27) Davidsdottir, B.; Ruth, M. Pulp nonfiction: Regionalized dynamic model of the U.S. pulp and paper industry. *J. Ind. Ecol* **2005**, *9* (3), 191–211.
(28) Tasaki, T.; Takasuga, T.; Osako, M.; Sakai, S. Substance flow analysis of brominated flame retardants and related compounds in waste TV sets in Japan. *Waste Manage.* **2004**, *24*, 571–580.
(29) Yang, Y.; Williams, E. Logistic model-based forecast of sales and generation of obsolete computers in the U.S. *Technol. Forecasting Soc. Change* **2009**, DOI: 10.1016/j.techfore.2009.03.004.

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