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Future trends in computer waste generation in India

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ABSTRACT

The objective of this paper is to estimate the future projection of computer waste in India and to subsequently analyze their flow at the end of their useful phase. For this purpose, the study utilizes the logistic model-based approach proposed by Yang and Williams to forecast future trends in computer waste. The model estimates future projection of computer penetration rate utilizing their first lifespan distribution and historical sales data. A bounding analysis on the future carrying capacity was simulated using the three parameter logistic curve. The observed obsolete generation quantities from the extrapolated penetration rates are then used to model the disposal phase. The results of the bounding analysis indicate that in the year 2020, around 41–152 million units of computers will become obsolete. The obsolete computer generation quantities are then used to estimate the End-of-Life outflows by utilizing a time-series multiple lifespan model. Even a conservative estimate of the future recycling capacity of PCs will reach upwards of 30 million units during 2025. Apparently, more than 150 million units could be potentially recycled in the upper bound case. However, considering significant future investment in the e-waste recycling sector from all stakeholders in India, we propose a logistic growth in the recycling rate and estimate the requirement of recycling capacity between 60 and 400 million units for the lower and upper bound case during 2025. Finally, we compare the future obsolete PC generation amount of the US and India.

1. Introduction

Accelerating technological changes, consumption rates coupled with rapid product obsolescence makes electronic products obsolete (also called e-waste) very quickly. In India, e-waste is becoming a crucial waste stream in terms of both quantity and toxicity. The problem is more compounded as this enormous waste stream contains tonnes of hazardous materials, which if not disposed adequately will eventually be harmful to the humans, animals and the environment. Thrown to unsecured landfills, e-waste will eventually pollute the groundwater and the environment (Mundada et al., 2004). During the past two decades, the Indian economy has reported significant changes, as typical of any economy in transit. The Indian electronics industry has emerged as a fast growing sector in terms of production, internal consumption and export (Dimitrakakis et al., 2006). In India, the per capita PC ownership between 1993 and 2000 has grown by 604% as against the world average of 181% during the same period (Sinha-Ketriwal et al., 2005). Contrary to the world average of 27 computers per 1000 people and over 500 computers per 1000 people in the US, India in the year 2004 had one of the lowest PC penetration rate at just 9 computers per 1000 people (Moskalyuk, 2004). However, the size of India's market in absolute terms is larger than most of the high income countries (Sinha-Ketriwal et al., 2005). In a recent study, the authors Yu et al. (2010) forecast that the Asia–Pacific region may attain a PC penetration rate of around 600 computers per 1000 people by 2030. The existing system of e-waste processing in India is mostly handled by a very well networked informal sector (Sinha and Mahesh, 2007) involving key players like the vendors, scrap dealers, dismantlers and the recyclers. However, the disposal and recycling of computer specific e-waste in the informal sector are very rudimentary as far as the recycling techniques employed and safe recycling practices are concerned resulting in low recovery of materials. The process followed by these recyclers is product reuse, conventional disposal in landfills, open burning and backyard recycling (Dixit, 2007). Most often, the discarded electronic goods finally end-up in landfills along with other municipal waste or are openly burnt releasing toxic and carcinogenic substances into the air. The major sources of e-waste in India are the government, public and private sectors, retailers, individual households, PC manufacturing units, the secondary markets and illegally imported scrap (Veena, 2004). The current Indian legislation on classification of e-waste as hazardous is ambiguous with none of the laws directly referring to e-waste or it's handling (Dutta et al., 2006). Consequential to the lack of appropriate legislation, there is an alarming concern over illegal import of e-waste from developed nations. Therefore, it is imperative that all the

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stakeholders involved including the government to devise a long-term effective plan taking into consideration the unique disposition of the informal recycling sector.

Successful implementation of e-waste recycling requires the establishment of appropriate infrastructure. Factors that affect the recycling infrastructure are the amount of waste in the waste stream, the recycling technologies available, government regulations and the economics of End-of-Life (EOL) products (Kang and Schoenung, 2005). Therefore, it has become a necessity to forecast e-waste generation quantities in India so that appropriate recycling infrastructure may be planned and developed. To this end, most of the developing countries lack reliable data on e-waste generation. It is difficult to precisely estimate and predict the annual quantity of obsolete e-waste because of the lack of statistical data on their consumption patterns. The objective of this study was to forecast the future projection of computer waste in India and estimate their EOL disposal options. The requirement of such an investigation becomes more pronounced for India in so far as evaluating government intervention towards a sustained policy of enhancing the computer penetration rate in the near future. This study will also provide a road map to both national and private participation in developing the appropriate recycling infrastructure.

2. Methodology

The major objective of this investigation is to predict the future trend of obsolete computer related e-waste generation quantities as a function of time in India. For the purpose of this study, we have used a logistic function based model proposed by Yang and Williams (2009). The logistic model is further analyzed to investigate the effects it has on the computer waste generation. The logistic growth curve assumes that there is an asymptotic value to the computer adoption or penetration rate growth curve and has a characteristic "S" shape. The penetration rate is assumed to increase slowly at the beginning and reaches a maximum rate of growth at the point of inflexion. From this state onwards, there is a gradual decrease in the growth rate until the curve reaches the asymptotic value. Over the years, "S" shaped evolutions have regularly been applied for analyzing demography, biological, technological diffusion and economic models (Jarne et al., 2005). In so far as technology diffusion is concerned, such curves are used because of their ability to describe these processes and at the same time display their typical phases: growth, inflexion and saturation.

The logistic curve was first proposed by Verhulst in 1838 in the journal "Correspondence Mathematique et Physique". A century later, in 1920, Pearl and Reed rediscovered it during the course of their study on the evolution of fly population. Fisher and Pry (1971) proposed a diffusion and innovation model drawing a parallel between epidemic spread and information circulation. Past studies in technological diffusion (Frank, 2004; Boretos, 2007; Yamasue et al., 2006) include innovation such as mobile phones, computers, refrigerators and television. However, only few research papers (Yang and Williams, 2008, 2009; Yu et al., 2010; Liu et al., 2006) address and translate this technology diffusion into Waste Electrical and Electronic Equipment (WEEE) obsolete prediction. The general logistic equation for computer adoption was modeled by Yang and Williams (2008, 2009) assuming that PC population growth rate is proportional to the rate of encounter of someone without a computer and to someone owning a computer expressed in conventional logistic form as:

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

where N represents the number of computers owned per capita (penetration rate), r represents the rate of adoption or growth rate and K represents the carrying capacity. For a detailed mathematical background of the logistic equation, the readers may refer the original article by Yang and Williams (2008, 2009). The rate of adoption 'r' refers to the relative speed with which computers are adopted and for a logistic model this parameter remains constant. However, Yang and Williams (2008) in their earlier paper investigated the effects of a variable rate of change of the adoption rate and report that there is no significant difference in their analysis. The carrying capacity for this case refers to the average number of computers a person is likely to possess. It follows therefore that 'K' represents the limiting value of the output. The solution of Eq. (1) at time t is of the form:

$$N_t = \frac{K}{e^{-(rt+C)} + 1} \tag{2}$$

At reference time $t = 0$, the initial penetration rate is denoted by N_0. Thus,

$$N_0 = \frac{K}{1 + e^{-C}} \text{ or } K = N_0(1 + e^{-C}) \tag{3}$$

that is, the maximum carrying capacity K will be $(1 + e^{-C})$ times larger than N_0 or alternatively e^{-C} could be interpreted as the number of times N_0 must grow to reach K.

The value of C can be computed from the expression:

$$C = \ln\left(\frac{N_0}{K - N_0}\right) \tag{4}$$

Eq. (2) illustrates that the logistic models have three unknown parameters (K, N_0 and r), which are to be estimated. Yang and Williams (2009) argue that though in principle the value of carrying capacity (K) could be identified from statistical fits of the historical time-series penetration rates, it would be not justified for the case when the historical data-series is still in its early stage and is yet to reach their inflection point. To overcome this problem, they proposed the idea of a bounding approach by determining the lowest and the highest conceivable values of K and evaluated the logistic model for a range of outcomes within these two bounds. Skiadas et al. (1993) report that the asymptote or the saturation value (K) is the most critical factor for understanding the behavior of the system to which the logistic curve is applied.

Though time-series data on historical computer penetration rate exist for India, they remain few but unreliable and conflicting. Therefore, we follow the approach outlined by Yang and Williams (2009) to recreate a time-series of computer penetration rates based on estimates of stock, historical sales and assumptions on lifespan (see Eqs. (5) and (7)). The procedure followed was to assume a lifespan distribution L_j where 'j' represents the year after which the computer becomes obsolete and using the historical sales S_i we estimate the annual obsolete quantities (O_i) for a given year 'i' from the expression:

$$O_i = \sum [\text{Sales in the year}(i-j) \times \text{Percentage of computers that become obsolete after}`j\text{'years}] = \sum S_{i-j}L_j \tag{5}$$

Assuming that computers enter the national stock after being purchased, we estimate the possession amount or stocks in use (St_i) in year 'i' as:

$$\begin{aligned} St_i &= \text{Stocks in use in year}(i-1) + \text{Sales in year}`i\text{'} \\ &\quad - \text{Obsolete stock in year}`i\text{'} \\ &= St_{i-1} + S_i - O_i \end{aligned} \tag{6}$$

The penetration rate in year i, N_i is computed from the relationship:

$$N_i = \frac{St_i}{Q_i} \tag{7}$$

where Q_i is the population in year 'i'.

Statistical fits are performed on the generated time-series historical penetration rate in order to identify the parameter values r and N_0 of the logistic model. The approach here was to separately identify these parameters for both the upper and lower bound carrying capacity. The optimal logistic curve was identified by minimizing the sum of the squared residual (SSR) or error term λ (see Eq. (8)) between the fitted curve and the generated historical penetration rate and the corresponding best values of r and N_0 is obtained as:

$$\lambda = \sum (\overline{N}_t - N_t)^2 \tag{8}$$

where $\overline{N}_t$ is the predicted penetration rate from the logistic fit, N_t is the observed historical penetration rate and $(\overline{N}_t - N_t)$ is the residual term for a given year.

If λ possesses a minimum, it will occur for values of r and N_0 that satisfy the equations:

$$\frac{\partial \lambda}{\partial r} = 0 \text{ and } \frac{\partial \lambda}{\partial N_0} = 0 \tag{9}$$

Eq. (9) represents a system of linear equations in r and N_0.

The computer penetration rates from the logistic curve are translated to their corresponding sales using Eq. (7). The knowledge of the market share of laptops and desktops are utilized to determine their estimated sales from the projected computer sales. The projected sales figures of laptops and desktops coupled with their respective first lifespan distribution are utilized to generate the projected obsolete amounts of computers.

The next step is to determine the EOL estimates from the computed obsolete quantities. For this, we use the time-series EOL multiple lifespan material flow model proposed by Peralta and Fontanos (2006) and later used by Dwivedy and Mittal (2010). The time-series material flow model defines the extended life of a computer after it becomes obsolete. Here, the first user has the option of either storing it for an extended period of time or reusing by way of donating it to a second user; else, it could possibly be landfilled or recycled. The possible states after being stored or reused could be recycled or landfilled. The store and reuse phases can be considered as another lifespan for the computers. Also the EOL model assumes that there is no reuse possible after the storage because by this time the item under investigation has outlived its intended life. The EOL estimation model equation (Dwivedy and Mittal, 2010) is:

$$\begin{aligned} R_{U(Y,K)} &= P_1 \times O_{(Y,K)} \\ &= \text{Percentage of obsolete items of the current year that goes for reuse} \end{aligned} \tag{10}$$

$$\begin{aligned} S_{T(Y,K)} &= P_2 \times O_Y + P_1 \times P_5 \times O_{Y-Lr} \\ &= \text{Percentage of obsolete items of the current year that goes for storage} \\ &\quad + \text{Percentage reused stored of the obsolete reused from } Y - Lr \text{ years earlier} \end{aligned} \tag{11}$$

$$\begin{aligned} R_{C(Y,K)} &= P_3 \times O_Y + P_2 \times P_8 \times O_{Y-Ls} + P_1 \times P_6 \times O_{Y-Lr} \\ &\quad + P_1 \times P_5 \times P_8 \times O_{Y-Lr-Ls} \\ &= \text{Percentage of obsolete items of the current year} \\ &\quad + \text{Percentage stored recycled of the obsolete stored from } Ls \text{ years earlier} \\ &\quad + \text{Percentage reused recycled of the obsolete reused from } Lr \text{ years earlier} \\ &\quad + \text{Percentage stored recycled of the reused stored waste from } (Lr + Ls) \text{ years earlier.} \end{aligned} \tag{12}$$

$$\begin{aligned} L_{A(Y,K)} &= P_4 \times O_Y + P_1 \times P_7 \times O_{Y-Lr} + P_2 \times P_9 \times O_{Y-Ls} \\ &\quad + P_1 \times P_5 \times P_9 \times O_{Y-Lr-Ls} \end{aligned} \tag{13}$$

where, $O_{(Y,K)}$ represents the total obsolete waste disposed of type K in the year Y. $R_{U(Y,K)}$, $S_{T(Y,K)}$, $R_{C(Y,K)}$ and $L_{A(Y,K)}$ are, respectively, the number of reused, stored, recycled and landfilled items of type K in year Y. Lr and Ls are the average lifespan of reused and stored electronic items, respectively, and P_1, P_2, P_3, P_4 are % obsolete reused, obsolete stored, obsolete recycled and obsolete landfilled, respectively, P_5, P_6, P_7 are % reused stored, reused recycled and reused landfilled, respectively, P_8, P_9 are % stored recycled and stored landfilled, respectively.

The generic step-by-step procedure and the necessary information required in conducting the analysis are given below:

Step 1: Make assumptions on the life span distribution for the EEE items under investigation for the lower line, base line and upper line, respectively. The assumptions are validated by computing the historical penetration rates from the time-series data of EEE sales making use of the lifespan assumptions and the equations elucidated above. The computed values are cross-checked by separately calculating the PC penetration rate from the household and business sector using the population data and the number of computers in use in both the sectors.

Step 2: Identify the lower bound for the PC penetration rate. The lower bound penetration rate from the residential sector is estimated from the knowledge of the number of wealthy households, the household size and the population for the given year. Similarly, the contribution from the business sector on the lower bound explained in Step 1 is used to determine the overall lower bound.

Step 3: Identify the upper bound for the PC penetration rate. Here, we use the information on the proportion of the total working population for computing the upper bound of PC penetration rate from the business sector. Additionally, the proportion of total population aged between 15 and 64 years could be used to set the upper bound from the residential sector.

Step 4: Determine the unknown parameters from curve fitting the historical penetration rates to the logistic model subject to bounds. Cross-check the simulated penetration rate data for any given year with some suitable past reliable data.

Step 5: Compute the forecasted future PC sales utilizing the information of the future population projection. Convert the future PC sales to individual desktop and laptop sales. This requires data on the future increase in the market share of laptops.

Step 6: Calculate the past and the future computer waste generation quantities using the projected sales data. Cross-check the simulated values for the current year with other past studies.

Step 7: Perform the multiple lifespan EOL material flow analysis to estimate the future recycling quantities.

3. Analysis and discussion

3.1. Bounding analysis

According to CIA-World Factbook (2008) estimates for India, the annual population growth rate has been consistently decreasing since the 1990s. Further, the study reports a country comparison listing of decreasing growth rates, showing India occupying the 87th position as against 134th position of the US. As per the projection by the Registrar General and Census Commissioner of India, a growth rate of 1.3%, assuming the highest level of fertility, is possible by 2011. A low population growth rate suggests that the population is growing slowly. The present study utilizes the population projection from the Census of India, 2001.

The historical sales data of desktop and laptop computers for India are drawn from Dwivedy and Mittal (2010). The original dataseries are from the annual publications of MAIT, an association of IT manufacturers in India (see Table 1). On account of non-availability of statistical data on the reused computer market for India, this aspect was not considered in our analysis.

The accuracy of any computer waste forecasting model is dependent upon the accuracy of the estimated life span of the computer (Leigh et al., 2007). Earlier studies (Streicher-Porte and Yang, 2007; Jain and Sareen, 2006) report using primary and secondary based data from market research and questionnaire based survey to estimate the average lifespan of PCs. According to a recent study by Toxics Link, the life of a computer in India has fallen from 7 to 3–5 years. Instead of using a uniform life span, there are studies where multiple lifetime spans for estimation of outflows have been proposed (Kang and Schoenung, 2006; North Carolina Environmental Department, 1998). For the purpose of this study, we have assumed the first lifespan distribution of computers as shown in Table 2.

In order to corroborate our assumption on lifespan, we have utilized the approach outlined by Yang and Williams (2009). According to the report by Frost and Sullivan (2007), the total number of household computer stocks was 5 million in the year 2006. The population during the period was 1112 million which gives a penetration rate of 0.0045 computers per capita from the household sector. For the business sector, we assume that each information worker has a computer. In the year 2006 (Ilavarasan, 2007), the total number of IT workers (which included direct, indirect employment and ITES jobs) in India were 8.08 million. This translates to a penetration rate of 0.0073 computers per capita from the business sector. Together these two sectors yield a penetration rate of 0.012 computers per capita. This empirical data is cross-checked by combining the lifespan assumptions with the historical sales data and through the use of Eqs. (5)–(7) yielded a per capita computer penetration rate of 0.013, 0.015 and 0.016 for the lower line, base line and upper line, respectively. The two values are in very close agreement for the lower line. The reasons for higher values for the baseline as well as upper line could be the lack of sales data for the years prior to 1994, as the market was still in its infancy. The obsolete quantities during the period 1994–1998 cannot be determined resulting in marginal overestimation of stocks-in-hand and, hence, the penetration rate. After this consistency check, the computer penetration rate for the year 1994–2008 for all the three lifespan distributions are made using (Eqs. (5)–(7) and shown in Fig. 1.

Table 1
Domestic sales data of electronic devices in India (in million units).

Year	Desktop PC	Notebook PC
1994	0.240300	0.004500
1995	0.371667	0.011329
1996	0.451427	0.01596
1997	0.799058	0.01000
1998	1.027190	0.02292
1999	1.405290	0.04167
2000	1.881640	0.04167
2001	1.670880	0.044742
2002	2.293643	0.050974
2003	3.035591	0.088831
2004	3.632619	0.177105
2005	4.614724	0.431834
2006	5.490591	0.850860
2007	5.522167	1.822139

Table 2
Assumed lifespan distribution of computers.

	Average lifespan (in years)	Years in use			
		5	4	3	2
Upper line					
Desktop	4	25%	50%	25%	
Notebook	3.5	20%	20%	50%	10%
Baseline					
Desktop	3.5	20%	20%	50%	10%
Notebook	3.0		25%	50%	25%
Lower line					
Desktop	3.0		25%	50%	25%
Notebook	2.5			50%	50%

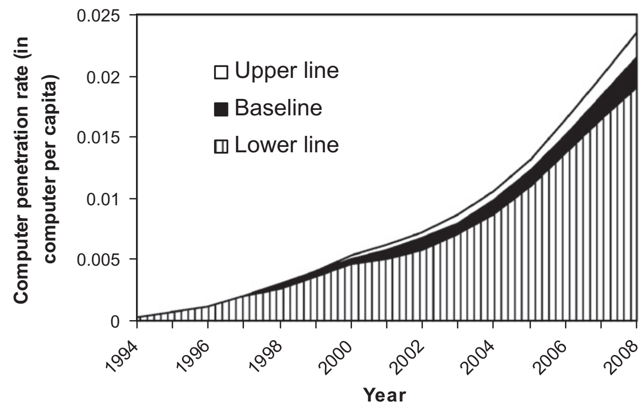

Fig. 1. Historical computer penetration rate.

A bounding analysis on the historical computer penetration rates is the next step. Yang and Williams (2009) have reported the difference between a bounding analysis from a conventional best and worst case scenario analysis. The scenario analysis reflects the range of achievable possibilities, while a bounding approach may give results which are unlikely to achieve, but are capable of giving insight into the constrained future. For estimating the bounds, we have used the approach outlined by Yang and Williams (2009).

A lower bound for carrying capacity from the commercial sector is set by assuming that all IT (Information Technology) employees possess a computer at work. The computer penetrations among wealthy families represent the lower bound carrying capacity from the household sector. As per the estimates from the study conducted by McKinsey (2007) and KPMG and IMRB (2006) for the year 2005, about 6 million of the 208 million households have an annual income exceeding 2.15 lakh Indian rupees. The National Family Health Survey (2005) estimates the mean Indian household size to be 4.8 persons per household. This translates to 28.8 million wealthy people among the total population of 1095.722 million in the year 2005 rendering a lower bound penetration rate of 0.0263 computers per capita. So the total lower bound from the residential and commercial sector yields a carrying capacity of 0.0336 computers per capita.

For the upper bound parameter estimation, we assume that all employed persons own a computer at work and every person aged from 15 to 64 years have a computer at home. The total worker population in 2001 (Census of India, 2001) is estimated to be around 400 million constituting around 39.10% of the total population. The percentage of population aged between 15 and 64 years was 63.6 of the total population (CIA-World Factbook-India). These figures are very close to the forecast by Adlakha (1997). Combining the two results yield the upper bound estimate of carrying capacity of 1.027 computers per capita.

The computed historical computer penetration data (see Fig. 1) from 1994 to 2008 are fitted to the logistic model (Eq. (2)) subject to the bounds estimated on the carrying capacity. The Nelder–Mead unconstrained non-linear minimization function of MATLAB is used for logistic function parameter estimation by minimizing the function in Eq. (8) (see Appendix).

Figs. 2–7 show the results of the logistic fit for the lower line, the base line and the upper line, respectively.

The results from curve fitting for all the lifespan distributions, shown in Table 3 prove that the lower line gives a better estimation for both the bounds on the carrying capacity. Further, the results indicate that forecasting with the upper bound gives the best fit on account of the smallest error. However, all the curve fitting errors which are obtained after optimal parameter estimation and through the use of Eq. (8) are found to be equally comparable and therefore acceptable (see Figs. 8–10).

For the case of lower line (see Figs. 2 and 3), the estimated computer penetration rate in the year 2010 will be 2.3 and 2.9 computers per 100 people for the lower and upper bound, respectively. Additionally, it is expected to reach within 1% of the asymptotic carrying capacity of 0.0336 and 1.027 computers per capita anytime during the year 2023 and 2050 for the lower and upper bound case, respectively (see Table 3).

In other words, the long-term equilibrium on carrying capacity could be achieved sometime in the next 30–57 years, 28–56 years and 27–55 years following the base year 1993 for the lower line, baseline and upper line scenarios, respectively. Our results confirm the findings of Yu et al. (2010) where they report that the Asia/Pacific region will reach the long-term equilibrium in penetration rate carrying capacity in 30–60 years. The Eleventh Five Year Plan (2007–2012) report prepared by the Department of Information Technology, Government of India outlines the market projection for computers forecasted by MAIT, and cite a penetration rate of 3.25 computers per 100 people, which is very close to our prediction. The report further states that with government intervention, the penetration rate could be enhanced to 6 computers per 100 people by the year 2012. For the year 2012, our analysis predicts a value of 5.37 and 2.94 computers per 100 people for the upper and lower bound, respectively.

3.2. Estimation of future sales and obsolete stock

The forecasted computer penetration rates are converted to their corresponding sales (see Figs. 11 and 12) by using the population projection data from 2001 Census of India for the years 2009–2026. From the historical sales data, it was observed that during the period 1995–2008, the average year-on-year increase of market share of notebook PC was approximately 2.5% of the total computer sales. Along with the extended market share of notebooks and the first lifespan distribution, the projected sales data are translated to corresponding generation of obsolete desktop and notebook PCs.

From Figs. 11 and 12, it is observed that the combined obsolete computer generation estimates for 2010 will be around 6.74–7.89 million units which is very close to the value of 7.344 million units predicted by Dwivedy and Mittal (2010). The projected obsolete computer generation estimate at the end of 2026 will be within 45–46 million units and 432–457 million units for the lower bound and upper bound, respectively. It is also observed from Figs. 11 and 12, that the projected computer sales quantity will equal the estimated obsolete generation quantities in and around the year 2026

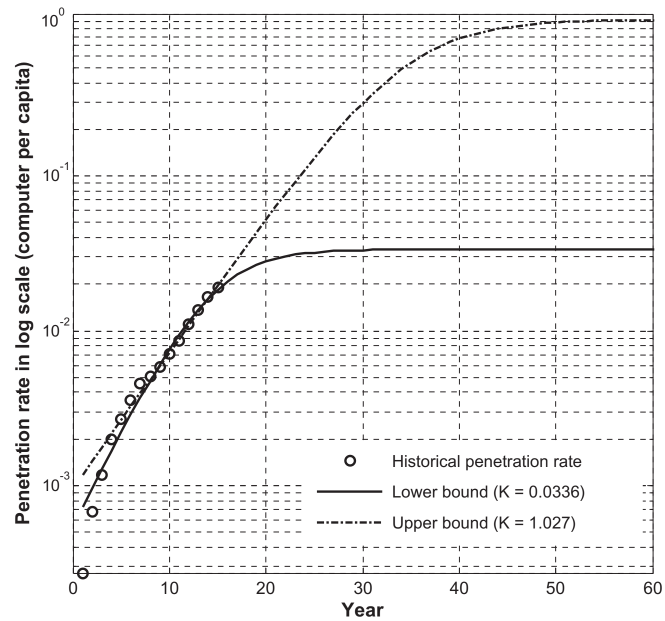

Fig. 3. Lower line penetration rate forecast.

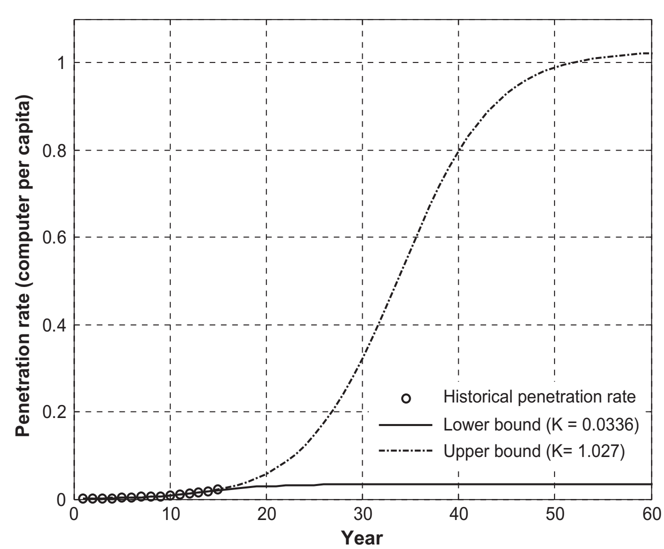

Fig. 4. Baseline penetration rate forecast.

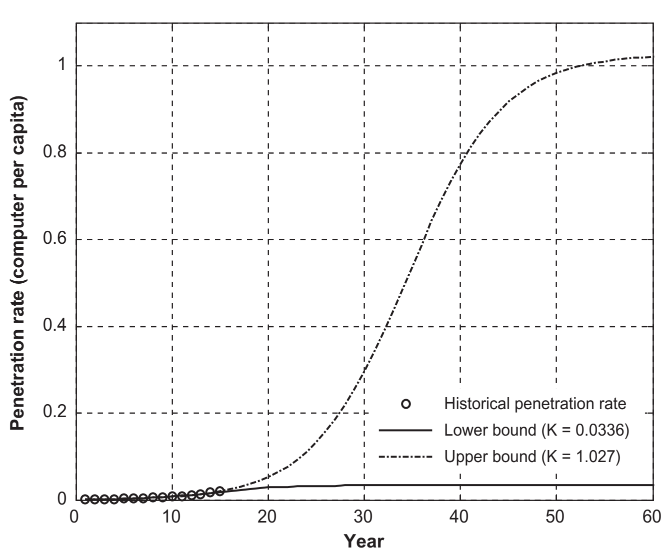

Fig. 2. Lower line penetration rate forecast.

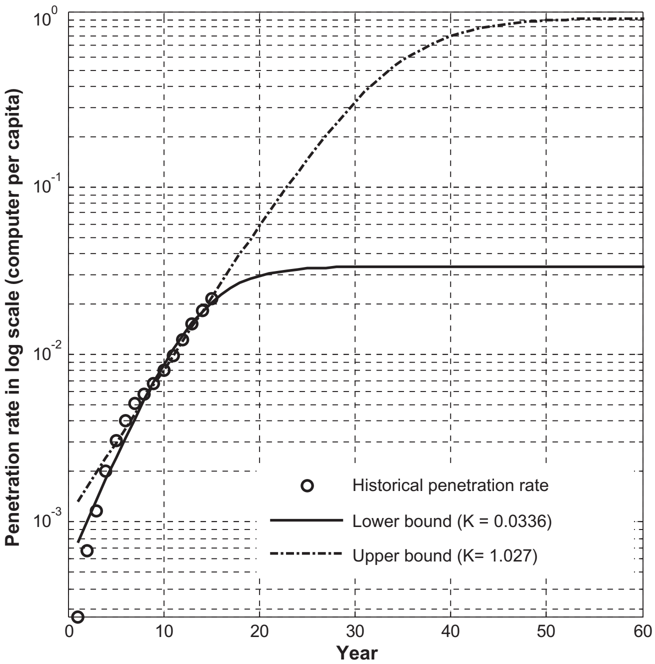

Fig. 5. Baseline penetration rate forecast.

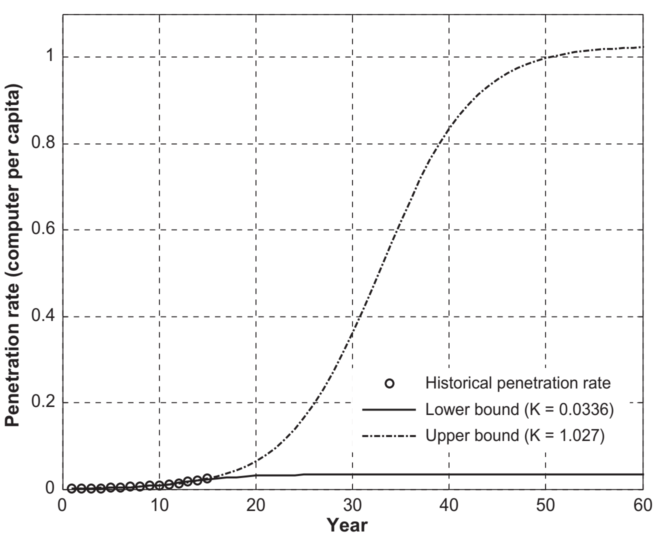

Fig. 6. Upper line penetration rate forecast.

for the lower bound case. By 2020, India's e-waste from obsolete computers are likely to increase rapidly by 500% from the 2010 levels of around 8 million units for the lower bound lower limit case. A similar study by the UNEP (2007) predicts that e-waste from old computers to rise by 500% from the 2007 levels by extrapolating the current linear growth in computer sales to estimate the future obsolete quantities.

3.3. EOL material flow analysis

The computed obsolete generation quantities are then utilized to estimate the EOL stock. The expanded EOL model shown in Fig. 13 forms the basis of our investigation. This model is simulated by making several assumptions on the EOL disposal behavior considering the fact that data inadequacy exists for a developing country like India. The underlying assumptions are taken directly from

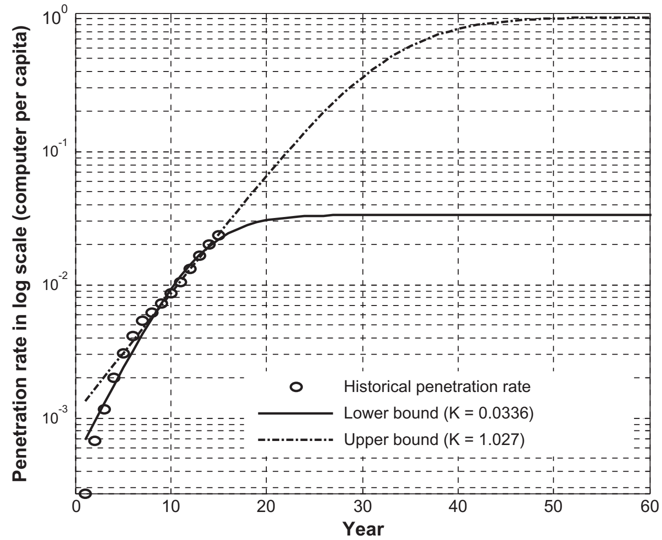

Fig. 7. Upper line penetration rate forecast.

the work by Dwivedy and Mittal (2010) where they reportedly consider two EOL scenarios. Scenario-1 represents the optimistic assumption where about 50% of obsolete computer stocks are diverted to reuse while for the pessimistic assumption represented by Scenario-2, a considerable amount of obsolete computer stock remains in storage (about 50%). The two scenarios represent the two extreme cases of EOL consumer disposal behavior. Table 4 shows the assumed parameters of the EOL model for the two scenarios. The disposal percentages and the extended reuse and stored lifespan are explicitly taken from Dwivedy and Mittal (2010).

From the aforesaid assumptions and by using Eqs. (10)–(13), the EOL model gives the quantities which are recycled, reused, stored and landfilled. The results of the EOL model indicate that during the period 2010–2020, the projected lower bound potential recycling quantity for both Scenarios 1 and 2 shall exceed 150 million units. This figure is likely to touch 300 million units for the upper bound case (see Fig. 14). The expected minimum number of reused computers for the same period will likely reach upwards of 80 and 160 million units in Scenarios 1 and 2, respectively. The total obsolete computers during this time are expected to reach a staggering 329–720 million units. The EOL estimates for every five year period in Scenario-1 and Scenario-2 are shown in Figs. 15–18, respectively.

Estimates shown in Table 5 illustrate that the average annual recycling capacity of India are close to 35% of the total obsolete PC arising assuming a constant proportion of disposal and/or recycling options. The recent findings by the MAIT-GTZ (2007) study reporting on the e-waste inventory from computers, television and mobile phones in India, predict that of the total e-waste arising, only about 40% finds its way into the recycling stream of which 95% are recycled in the informal sector.

On account of no reliable statistical data or projection on the changing consumer disposal behavior with time, the study relied on average estimates. The dynamic nature of disposal options could be captured through periodic annual surveys over a period of time from which future disposal percentages could be forecasted. Random sample populations from rural and urban India covering all income groups are to be collected to estimate their behavior. Alternatively, RFID (Radio Frequency Identification Devices) tags could be assigned to new shipments which can track the PCs over its entire lifecycle. A dedicated nodal agency supported by either the government or the manufacturing associations

Table 3
Parameter estimation from bounding analysis.

	Upper bound*					Lower Bound*				
	SSR	*K*	N_0	*r*	1% *K*	SSR	*K*	N_0	*r*	1% *K*
Upper line	0.0000046	0.0336	0.0011	0.208	55 years	0.0000082	1.027	0.000502	0.323	27 years
Base line	0.0000043	0.0336	0.00108	0.203	56 years	0.0000059	1.027	0.000562	0.3013	28 years
Lower line	0.00000314	0.0336	0.000965	0.202	57 years	0.00000355	1.027	0.000554	0.29	30 years

* The base year for all calculation is 1993.

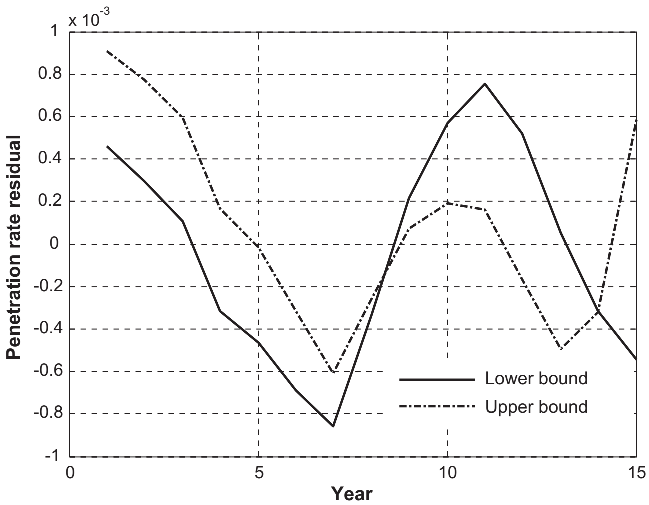

Fig. 8. Lower line residual plot.

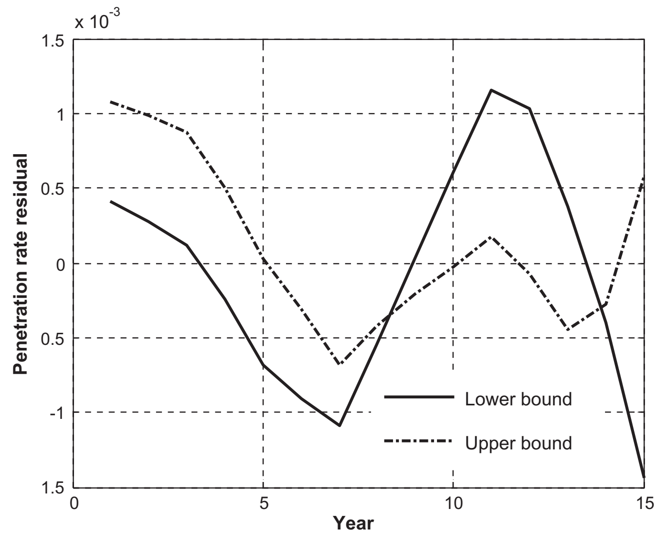

Fig. 10. Upper line residual plot.

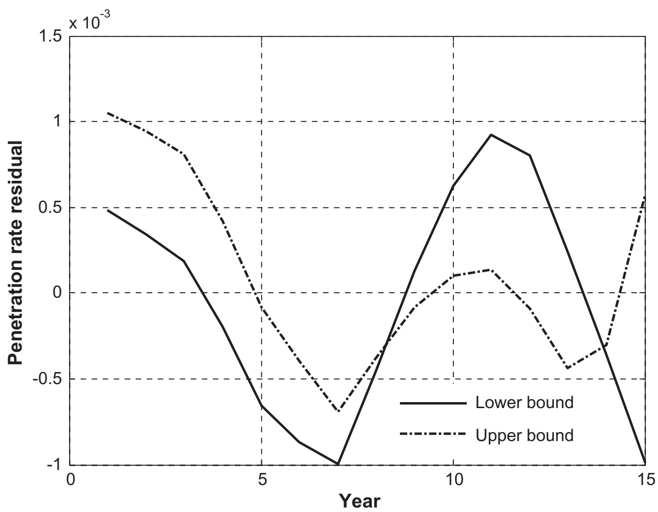

Fig. 9. Baseline residual plot.

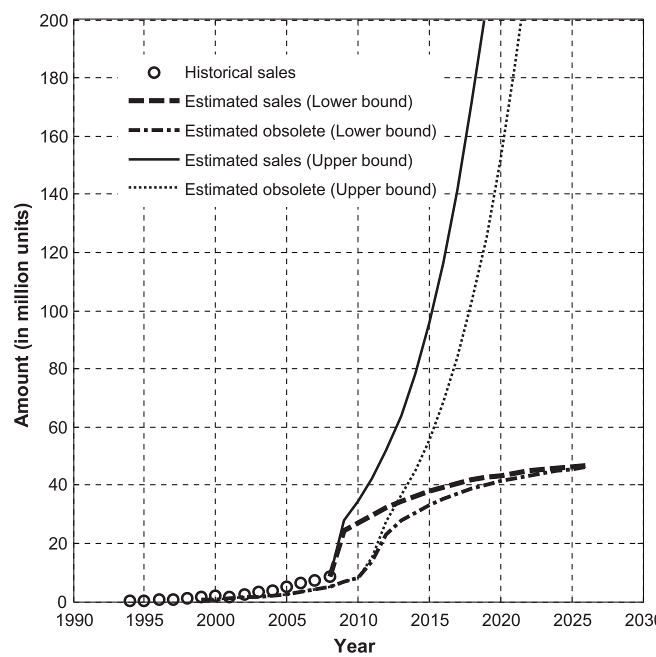

Fig. 11. Computer sales and obsolete amount.

like MAIT and other environmental NGOs could be entrusted with this activity. To utilize the forecasted disposal options, the present EOL model needs to be adjusted accordingly. This leaves some scope for future research. In India, e-waste is considered to be an important resource and an emerging business opportunity. In the last 4 years, around 10 recycling facilities have come up in the organized sector to address this problem. Though these recycling facilities are in varying levels of infancy, it is expected that in the near future, consumer attitude towards recycling will be favorable resulting in increased e-waste collection for recycling. Alternatively, this could be construed as any increase in the number of obsolete computers disposed for recycling will result in few computers being stored. This may be pursued by tracking the historical recycling volumes over time and curve fitting the past data to forecast the future. Additionally, one can use the system dynamics tool to capture this behavior using appropriate growth models

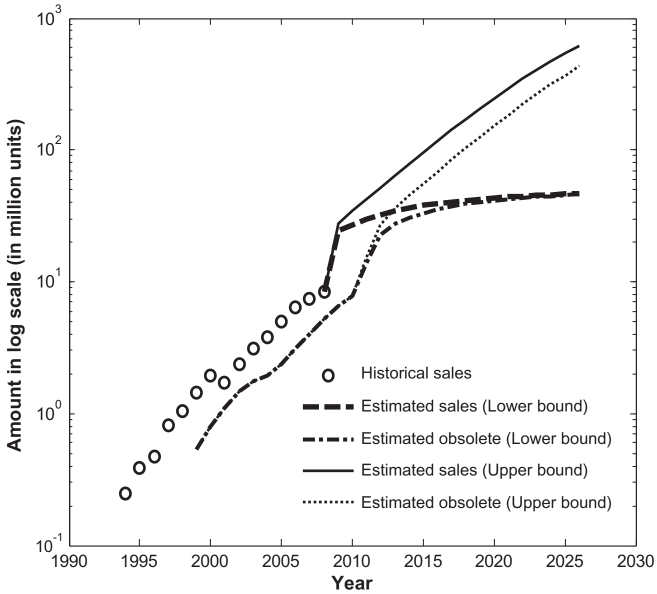

Fig. 12. Computer sales and obsolete amount.

Table 4
EOL disposal percentages for different scenarios.

EOL options	Optimistic scenario (Scenario-1)	Pessimistic scenario (Scenario-2)
Obsolete reused (P_1)	50	25
Obsolete stored (P_2)	25	50
Obsolete recycled (P_3)	20	20
Obsolete landfilled (P_4)	5	5
Reused stored (P_5)	70	70
Reused recycled (P_6)	20	20
Reused landfilled (P_7)	10	10
Stored recycled (P_8)	75	75
Stored landfilled (P_9)	5	5

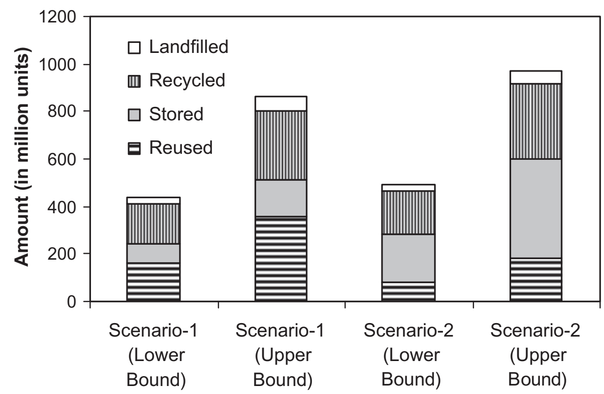

Fig. 14. EOL estimates during 2010–2020.

for simulating increasing recycling volumes and decay models for simulating the storage option. However, extensive historical data collections are necessary to freeze any of these methods. A conservative approach could be identifying the long-term equilibrium year when 95% of obsolete PCs could be available for recycling from the current levels of 40% predicted by the MAIT-GTZ study. Given that the long term carrying capacity of 1.027 computers per capita could be achieved anytime during the year 2050 (see Table 3), we assume that in the next forty years from now, India could scale-up its investment in setting-up appropriate collection and recycling mechanism for managing its annual e-waste arising to the level of 95% from its current level of 40% (see Fig. 19).

The future annual recycling capacity assuming a logistic growth is shown in Table 6. By the year 2025, India would need a recycling capacity of around 60 and 400 million computers for the lower and upper bound case, respectively, necessitating investment in infrastructure to accommodate a recycling capacity of 70%. This is fairly attainable given the fact that the current existing national systems in Europe have an e-waste recycling capacity of 60% (Yu et al., 2010). Looking at the estimates from Tables 4 and 5 the number of units available for recycling considering a variable recycling rate is close to twice those predicted from average assumptions on the recycling rate as we approach 2025.

3.4. Geographical divide: a case of US vis-à-vis India

The historical computer penetration rates of US from 1978 to 2008 recreated from the approach outlined earlier was fitted to the logistic model subject to lower and upper bound of 1.0 and 1.3 computers per capita as outlined earlier in the work by Yang and Williams (2009). All unknown model parameters from the curve fit ($r_{\text{lower bound}}$: 0.1784449581, $N_{0(\text{lower bound})}$: 0.0189767840, $r_{\text{upper bound}}$:

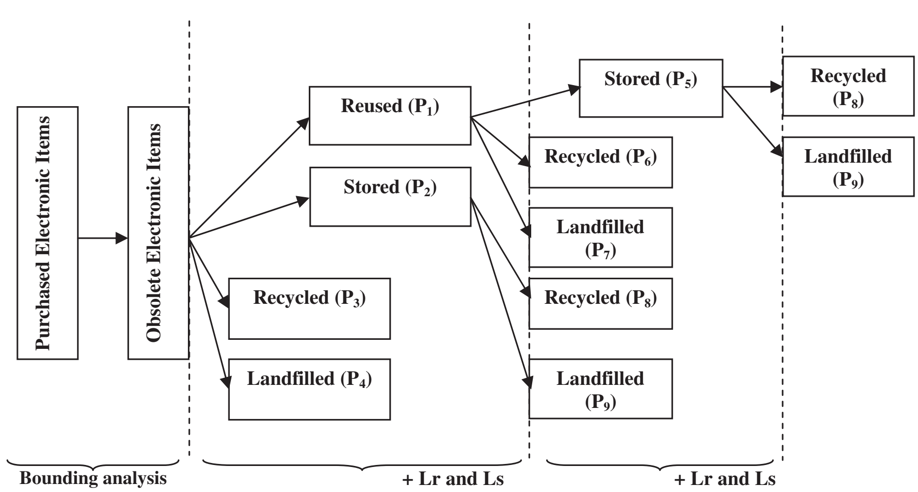

Fig. 13. Schematic representation of EOL generic model to predict WEEE estimate.

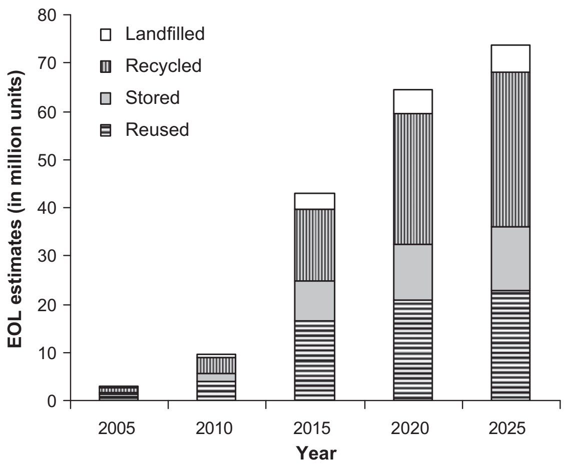

Fig. 15. Scenario-1 estimates (lower bound lower limit).

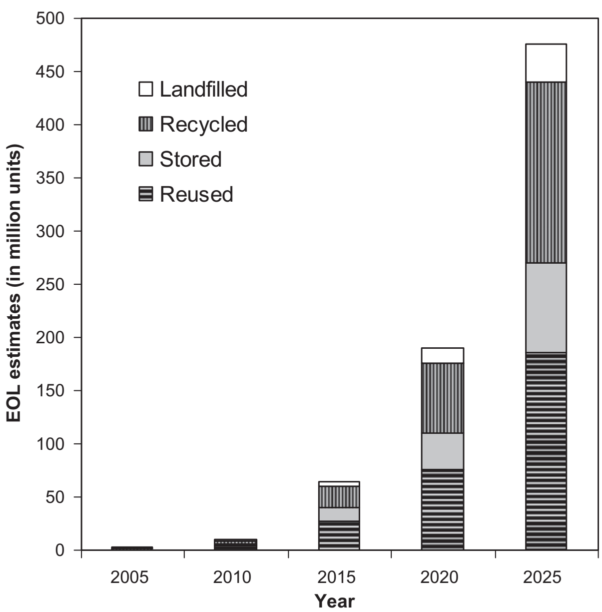

Fig. 16. Scenario-1 estimates (upper bound lower limit).

0.1466145442, $N_{0(\text{upper bound})}$: 0.0289774991, $\text{SSR}_{\text{lower bound}}$: 2.025772185680502e−002, $\text{SSR}_{\text{upper bound}}$: 8.774260786537274e−003) confirm the findings of the original authors. Yang and Williams (2009) report that the PC penetration rates in US is expected to reach its long-term equilibrium not until the year 2023 and 2033 for the lower and upper bound cases, respectively. Our analysis pegs the expected year for reaching equilibrium (99% of the assumed bounds) at 2024 and 2034, respectively, the variation though insignificant could be attributed to round-off to the nearest decimal place pursued by the original authors.

It is evident from Figs. 20 and 21 that though India starts from a low base of PC penetration rate (0.733 and 1.18 computer per 1000 people, respectively, for lower and upper bound) in the year 1994 as against the US figure of 22.6 and 33.4 computers per 1000 people in the year 1978, India in the upper bound scenario could well in all possibility overtake the lower bound per capita PC penetration rate (1 computer per capita) of the US sometime by the year 2046. The estimated number of obsolete computer inventory in India for the upper bound lower limit scenario (around 221 million

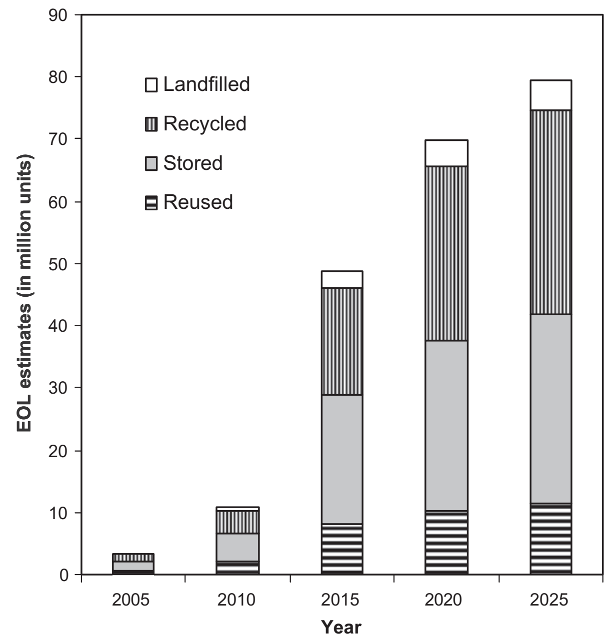

Fig. 17. Scenario-2 estimates (lower bound lower limit).

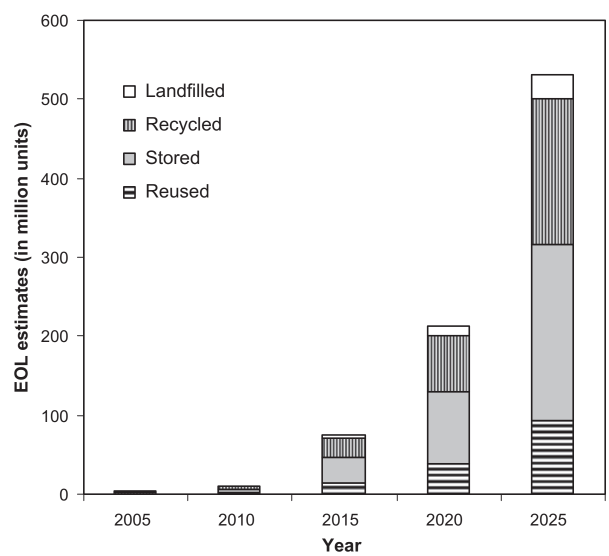

Fig. 18. Scenario-2 estimates (upper bound lower limit).

units) will be double that of the US by the year 2022 while the cross-over taking place sometime between the year 2017–2018. A similar study by Yu et al. (2010) report that the generation of obsolete PCs in the developing regions (within 400–700 million units) will double that of the developed regions (within 200–300 million units) by the year 2030, with the cross-over expected to occur between 2016 and 2018. They further report that the generation of obsolete PCs after the crossover will rise dramatically in the developing regions. For instance our study predicts, in the next 4 years until 2022 after the crossover, the obsolete PC generation in India is likely to increase rapidly by more than 100% from the projected figure of 102 million units of 2018 for the upper bound lower limit case. At the end of 2026, obsolete computer volumes in India for the upper bound case will reach in excess of 430 million units

Table 5
Percentage obsolete e-waste recycled in million units during 2010–2025.

Year	Scenario-1				Scenario-2			
	2010	2015	2020	2025	2010	2015	2020	2025
Obsolete items generated after lifespan of electronic item	7.89	33.08	41.40	45.54	7.89	55.62	152.21	370.21
Obsolete items generated after reuse/store phase (lower bound/upper bound)	2.76	19.50	38.57	46.59	3.36	18.34	33.21	39.56
	3.69	22.73	78.77	209.88	3.36	21.57	70.87	187.95
Grand total obsolete generated (lower bound/upper bound)	10.66	52.58	79.98	92.14	11.25	51.42	74.62	85.10
	11.59	78.36	230.9	580.1	11.25	77.20	223.08	558.17
Recycled quantity (lower bound/upper bound)	3.25	14.94	27.0	32.12	3.54	17.22	28.08	32.81
	3.24	20.69	66.42	170.58	3.54	23.56	72.05	184.57
Percentage obsolete recycled (lower bound/upper bound)	30.42	28.41	33.75	34.86	31.49	33.49	37.63	38.56
	27.98	26.40	28.75	29.40	31.49	30.52	32.29	33.06

Note: Figures do not sum up due to truncation after two decimal places.

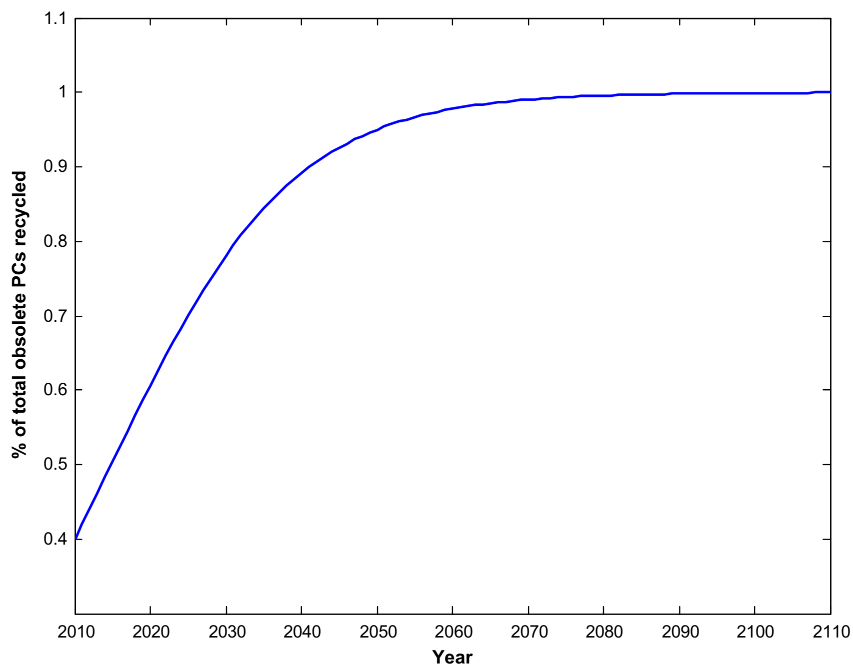

Fig. 19. Future proportion of PCs available for recycling.

Table 6
Recycling capacity with variable obsolete recycling percentages during 2010–2025.

Year	Scenario-1				Scenario-2			
	2010	2015	2020	2025	2010	2015	2020	2025
Total obsolete generated (lower bound/upper bound)	10.66	52.58	79.98	92.14	11.25	51.42	74.62	85.10
	11.59	78.36	230.9	580.1	11.25	77.20	223.08	558.17
Percentage of total obsolete that could be recycled in future	40.0%	50.33%	60.63%	70.07%	40.0%	50.33%	60.63%	70.07%
Annual recycling capacity in million units (Lower Bound/Upper Bound)	4.26	26.46	48.49	64.56	4.50	25.88	45.24	59.63
	4.63	39.44	140.0	406.49	4.50	38.85	135.26	391.12

Note: Figures are truncated after two decimal places.

which are significantly higher than double the corresponding upper bound estimate of Yang and Williams (2009) for the US.

4. Concluding remarks

This paper presents an approach to forecast the number of e-waste items generated from PCs in India. The results of the study indicate that the obsolete amount will continue to increase rapidly up to and beyond the year 2026 on account of better socio-economic conditions in both rural and urban India. In all likelihood, e-waste from obsolete computers could follow the lower bound lower line trend of our forecast, in which case, a penetration rate close to 0.0336 computers per capita could be achieved not until 2023. However, with favorable government policies directed to achieve the upper bound case, it might take another 40 years time from now to achieve the magical figure of 1 computer per capita. Given the large population trend in India and its growing economy, e-waste arising emanating from PCs will continue to rise abnormally. The management of e-waste is a growing concern cutting across all boundaries. Therefore, effective collection and recycling

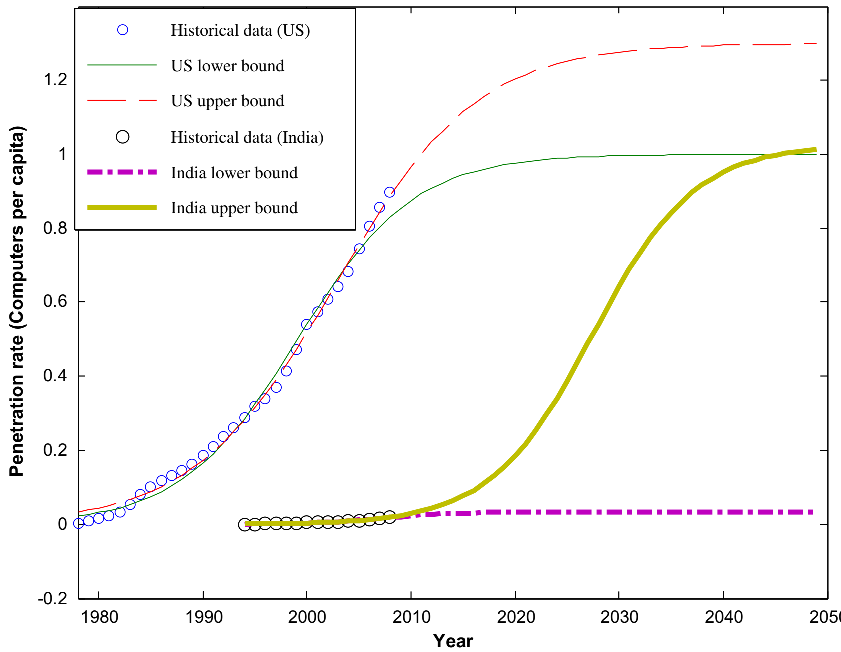

Fig. 20. Comparative growth in PC penetration rate projections.

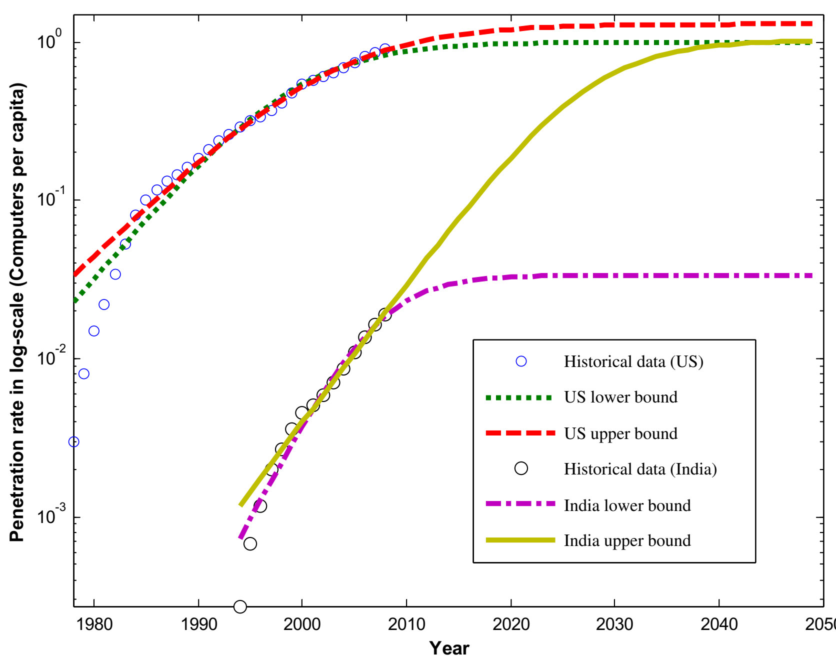

Fig. 21. Comparative growth in PC penetration rate projections.

programs needs to be developed once the necessary legal and regulatory instruments are in place. Adequate EPR regimes need to be explored and worked-out to resolve the problems emanating from such waste in India.

Acknowledgements

The authors would like to thank Professor Eric Williams, Department of Civil, Environmental and Sustainable Engineering, Arizona State University and Yan Yang, School of Sustainability, Arizona State University for sharing computer penetration rate data of the US. The authors also appreciate the suggestions given by Dr. Jagdish Bansal of BITS-Pilani, India.

Appendix

MATLAB code for logistic curve fit

```
% Create an M-file with name fitcurvelb.m
function [estimateslb, modellb] = fitcurvelb(xdata,
ydata)

    % Call fminsearch with a random starting point.
  start_point = rand(1, 2);
  modellb = @logistic;
  estimateslb = fminsearch(modellb, start_point);

function [sselb, FittedCurve] = logistic(params)
```

```
    lb=0.0336;
    r = params(1);
    N0 = params(2);
    C=log(N0/(lb-N0));
    FittedCurve = lb./(1+exp(-(r.*xdata+C)));
    ErrorVector = FittedCurve - ydata;
    sselb = sum(ErrorVector .^ 2);

  end

    sselb = sum(ErrorVector .^ 2)

  end
  % Create an M-file with name fitcurveub.m
  function [estimatesub, modelub] = fitcurveub(xdata,
ydata)

   start_point = rand(1, 2);
   modelub = @logistic;
   estimatesub = fminsearch(modelub, start_point);

  function [sseub, FittedCurve] = logistic(params)

    ub = 1.027;
    r = params(1);
    N0 = params(2);
    C=log(N0/(ub-N0));
    FittedCurve = ub./(1+exp(-(r.*xdata+C)));
    ErrorVector = FittedCurve - ydata;
    sseub = sum(ErrorVector .^ 2);

  end

   sseub = sum(ErrorVector .^ 2)

  end
  % Create an M-file with name data.m
  % Run this M-file
  clc
  xdata=[1
  2
  3
  4
  5
  6
  7
  8
  9
  10
  11
  12
  13
  14
  15
  ];
  format long e
  ydata=[0.00027291
  0.000672697
  0.001172196
  0.001996343
  0.002665728
  0.003556111
  0.004570603
  0.005100012
  0.005852456
  0.007050505
  0.008685784
  0.010975588
  0.013698532
  0.016434132
  0.019063164
  ];
  [estimateslb, modellb] = fitcurvelb(xdata,ydata);
  [estimatesub, modelub] = fitcurveub(xdata,ydata);
  r_lb = estimateslb(1)
  N0_lb = estimateslb(2)
  r_ub = estimatesub(1)
  N0_ub= estimatesub(2)
  lb=0.0336;
  ub=1.027;
  xdata1=1:1:72;
  C_lb=log(N0_lb./(lb-N0_lb));
  C_ub=log(N0_ub./(ub-N0_ub));
  F_lb = lb./(1+exp(-(r_lb.*xdata1+C_lb)));
  F_ub= ub./(1+exp(-(r_ub.*xdata1+C_ub)));
  for i =1:1:15

   F_xdata1(i)          =          lb./(1+exp(-
(r_lb.*xdata(i)+C_lb)));
   F_xdata2(i)          =          ub./(1+exp(-
(r_ub.*xdata(i)+C_ub)));
   error1(i) = (F_xdata1(i)-ydata(i));
   error2(i) = (F_xdata2(i)-ydata(i));

  end

   error1'
   error2'
   figure
   plot(xdata, error1',xdata, error2')
   figure
   plot(xdata, ydata,'o',xdata1, F_lb, xdata1, F_ub)
   p=[xdata1; F_lb; xdata1; F_ub]
   fid = fopen('exp.txt','w');
      fprintf(fid,'%4.10f \n ', r_lb);
      fprintf(fid,'%4.10f \n', N0 _lb);
      fprintf(fid,'%4.10f\n', r_ub);
      fprintf(fid,'%4.10f \n', N0 _ub);
      fprintf(fid,'%4.10f \n', C_lb);
      fprintf(fid,'%4.10f\n', C_ub);
      printf(fid,'================================
============\n');
      fprintf(fid,'%4i \ t%4.10f \ t%4i \ t%4.10f \ n', p);
      fprintf(fid,'*******************************
*************\n');
      fclose(fid);
```

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