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Service Lifetimes of Mineral End Uses

Daniel B. Mueller, Jing Cao, Elif Kongar,
Matthew Altonji, Paul-Harvey Weiner, and T.E. Graedel

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Abstract

Reliable information for the lifetime distribution (LTD) of products is essential for determining current and future waste flows, for designing end-of-life management strategies, and therefore for improving resource efficiency of materials and energy. There is, however, a lack of both, methodology to determine the probability density functions for life expectancies of products, and solid quantitative data based on case studies. In this report, we describe five approaches to determine the LTD of products using a combination of material flow modeling and survival analysis. Two of these approaches are applied to the following product categories: dwellings, passenger cars, refrigerators, air conditioners, CRT TV sets, and CRT computer monitors. The analysis was performed using data from various literature sources and a field study conducted during the summer of 2007. While the lifetime distribution of appliances is best approached with Weibull functions, passenger cars tend to follow normal distributions, and dwellings lognormal distributions. The lifetime expectancy of passenger cars has continuously increased since the 1960s, but experienced a pronounced increase for vehicles manufactured between 1985 and 1990. One important factor for this sudden increase in lifetime expectancy might be the introduction of zinc-coated steel for corrosion protection.

1 Introduction

1.1 Problem

The fate of mineral resources extracted from the lithosphere is relatively well documented by USGS and various minerals associations. This is generally not the case for materials embodied in final products, or for their end-of-life destiny (Graedel, Van Beers et al. 2004; Graedel, van Beers et al. 2005; Johnson, Jirikowic et al. 2005). The lack of reliable data on those factors limits an understanding of their entire cycles, and therefore restricts policy development for resource and waste management.

Measurements on discards and waste flows are very time consuming and expensive. In addition, the results of such samples are unlikely to be representative for an entire state or the U.S. as a whole because of regional differences in population growth and investments in capital and consumer goods.

An alternative to determining discard flows is to compute them using historic data of products entering use and estimations of their lifetimes (Zeltner, Bader et al. 1999; Kleijn, Huele et al. 2000; Müller, Bader et al. 2004; Spatari, Bertram et al. 2005). The simplest assumption for service lifetimes is a "simultaneous exit": products of a particular type all remain in the stock until they reach the average service life assumed, at which point they are all withdrawn. This is a convenient assumption for purposes of computation, but is a poor reflection of reality, and may result in inaccurate waste estimations. Common sense suggests that some assets will be withdrawn before they reach the average length of life and that some will remain active for some time longer. More realistic approaches assume that service lifetimes follow probability density functions (PDF). PDFs or lifetime distribution functions vary depending on the product category; as a result, several shapes have been suggested, such as normal, lognormal, Winfrey, or Weibull distributions (OECD 1993; Organisation for Economic Co-operation and Development. 2001; Bohm, Gleiss et al. 2002). Furthermore, the service life may also be dependent on the vintage year. For example, cars produced in the 1960s were more prone to engine failure or corrosion than newer models.

Despite the crucial role of lifetime estimations, there is a lack of quantitative data analysis to determine reliable estimates for average service lifetimes as well as accurate

shapes of the distribution function. Service lives of a large number of asset categories are used by the Bureau of Economic Analysis (BEA) to determine the size of capital stocks. The service lives used by BEA, which are derived from a variety of methods and (often old) sources, assume for most assets a simultaneous exit (single lifetime with no explicit distribution) which is constant over time (United States. Bureau of Economic Analysis. National Income and Wealth Division. 1999). For automobiles, where very good data of in-use stocks subdivided into vintage classes can be derived from registrations, BEA assumes full depreciation for vehicles older than 12 years. This assumption might be adequate for estimates of monetary assets, but it is certainly not reasonable for estimations of physical stocks and flows of goods, which do not lose weight during service lives.

More recently, EPA commissioned two studies on the management of electronic waste in the United States (EPA 2007; EPA 2007), which involved a large field study conducted by the Florida Department of Environmental Protection. This work involved sampling more than 12,000 units to determine the age distribution of various electronic products reaching end-of-life management. The age distribution of retiring products was subsequently used as a proxy for the lifetime distributions. This approach, however, does not take into account the change in product sales: For example, if historic sales of a product have increased sharply over the past years, an analysis is more likely to encounter larger quantities of younger end-of-life products than would be the case for decreasing sales. The assumption that the age distribution is equal to the lifetime distribution assumes that sales are constant, which is often not the case.

1.2 Objectives and relevance

The objective of this study is to determine service lives for a variety of products using a combination of material flow analysis (MFA) and survival analysis. The models use a wide range of literature data for production, trade, and in-use stocks, which are complemented with a field study on end-of-life flows.

The following products were analyzed:

- Dwellings
- Passenger cars
- Refrigerators
- Air conditioners
- TV sets
- CRT computer monitors

Improved service lifetime estimations can be used to directly calculate the following variables in mineral cycle systems:

- In-use stocks (growth, saturation, shrinkage),
- Discard or obsolete product flows,
- Stock replacement requirements.

These, in turn, allow us to improve our understanding of the following information

- Recycling efficiency,
- Dissipative losses to the environment (arising, for example, from corrosion or abrasion of in-use stocks),
- Flows into landfills,
- Imports and exports of used and discarded products.

Lifetime information is therefore essential in modeling material cycles, but also in developing forecasts and scenarios for future minerals demand and scrap availability (Müller 2006).

Improved data on the lifetime distribution of products will, when embedded into material flow models, enhance our understanding of mineral cycles in the past, the present, and the future, and therefore help to identify the most relevant opportunities to improve resource efficiency and to reduce environmental impacts of activities throughout the mineral cycles.

2 Methods

2.1 Definition of service lifetime

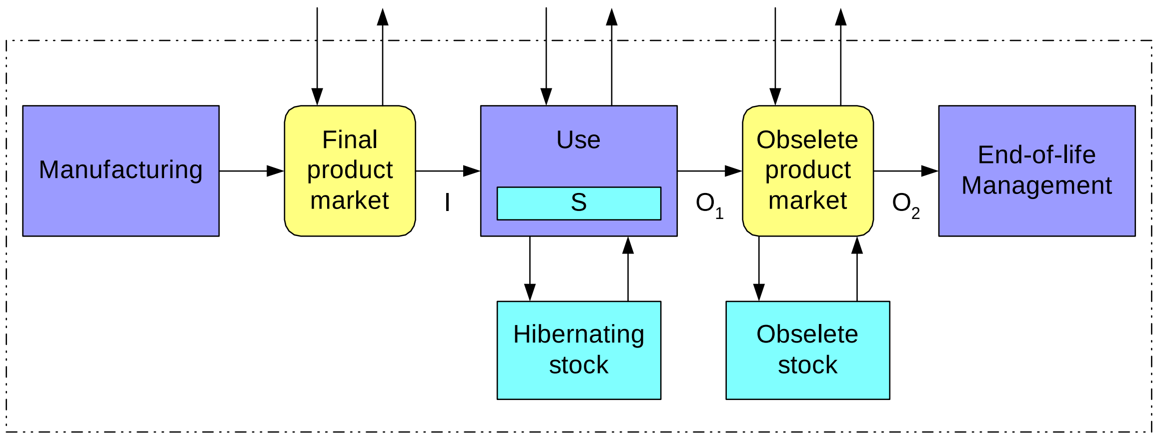

Figure 1: System of product lifecycle from manufacturing to end-of-life management.

The service lifetime of a product is defined in this report as the time span between its entry into use (I) and its exit from use (O_1). This includes the time the product is actually used and the time it is "hibernating" (for example, vacant buildings or switched off computers that remain unused for a period of their life). Measurements of products exiting use (O_1), however, are seldom performed. In these cases, measurements of products reaching end-of-life management (O_2) are used as a proxy. This includes a period in which a product may be stored in "obsolete stocks": for example, obsolete appliances stored in an attic or in illegal dumps, or abandoned structures that are not yet demolished.

There are, however, two main reasons why a product reaches its end of service lifetime: deterioration and obsolescence. Deterioration refers to the diminishing functionality of the product due to changes in initial status, such as run out, wear out, breakage and so on and so forth, simply due to disintegration or degeneration. On the other hand, obsolescence, in general, is the process of passing out of usefulness. Note that a product can be obsolete even though it has not deteriorated, and it can deteriorate without

reaching the obsolescent state. When a product is obsolete it means that the object is no longer perceived as having value, that is, a product is no longer in demand even though it may still be able to meet its functionality requirements.

Obsolescence can be classified into four categories:

Functional obsolescence usually occurs when a new product replaces an existing product, ending the demand for the current product. CDs and CD players replacing cassettes and LPs and their related products is a good example of functional obsolescence.

Systemic obsolescence is generated by a system change that does not allow the current product to function fully in the new environment. Eliminating service and maintenance for the existing product and/or introducing a new operating system to the market, thereby creating difficulties in current software usage, can be considered as examples of systemic obsolescence causes.

Style obsolescence usually occurs in high-cost low-demand products, and is usually highly correlated with the time that the product spent in the market. Fashion merchandise, high-technology objects (i.e., old model automobiles, PCs), toys (i.e., old Harry Potter movie merchandise) are examples of style obsolescence. That is, demand for the products ceases in the market place because the object loses its appeal for the customers due to the design rather than its functionality.

Notification obsolescence is predetermined in the product design. Advice to the customers as how many times or how long a product may be used to avoid health risks or to maintain optimal performance, results in the discard of functioning products. Water filters are common example.

These definitions of obsolescence are based on a conceptual lifecycle of products that may incorporate planned obsolescence. The lifetime definition used in this study, however, is independent of any such plan, and is independent of ownership. (A product may be reused several times by different owners). The service lifetime as used here is therefore defined purely in physical terms.

2.2 MFA model

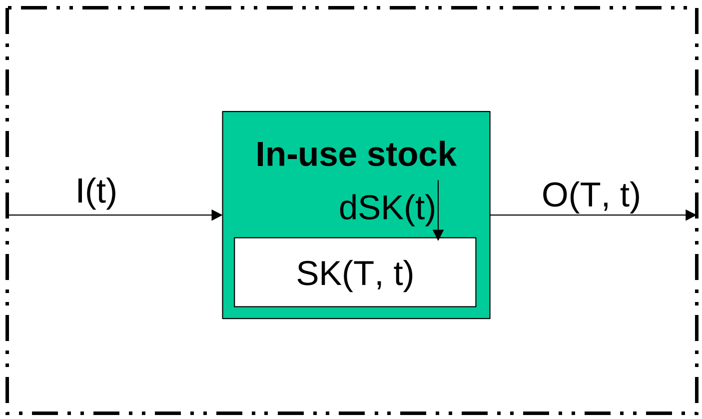

Figure 2: System of in-use stocks. I is the input into use, O the output from use, SK the stock in use, and dSK the rate of change in stock. T is the vintage year (year of manufacturing / construction), t the actual time of the system state.

The dynamics of in-use stocks can be described in terms of a mathematical model (Baccini and Bader 1996). If we assume no trade in used products and integrate the hibernating stock into the in-use stock (Figure 2), we can formulate a generic model for the in-use stock system using three equations:

$dSK(t) = I(t) - O(t$ Mass balance (

$SK(t_1) = SK(t_0) + \int_{t_0}^{t_1} dSK(t) *$ Intrinsic relation (

$O(t) = \int_0^t L(T,t) * I(t) * dT$ Model approach for constant LTD (3)

The lifetime distribution (LTD) L(T, t) is the probability density function (PDF) that an input at time T exits use at time t. It delays an input at time T (e.g., vintage year) into outputs in various years t: some products of vintage T may retire after a short lifetime, others may remain in use much longer. The total output at time t, O(t), is the sum of the

exits of all vintage classes prior to year t, or, in differential terms, the integral over all vintages.

Using this model, the LTD functions can be determined via different approaches given the data available. Figure 3 illustrates input, output and stock as a function of time for one specific vintage T.

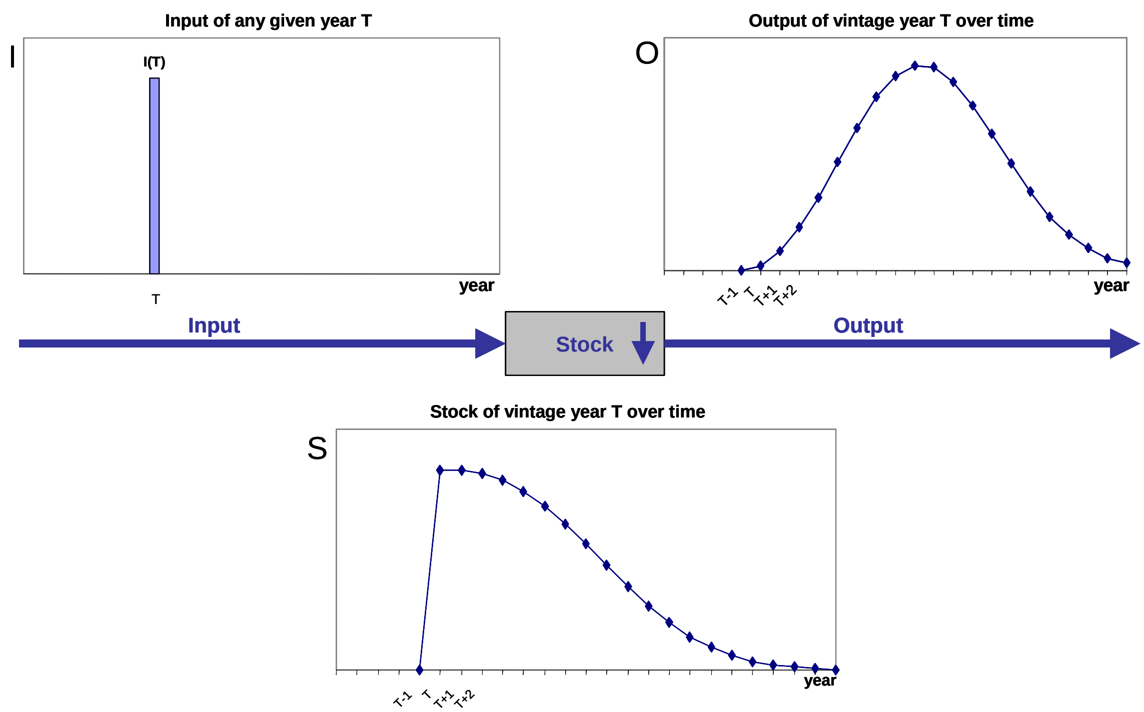

Figure 3: Input, stock, and output of an individual vintage (cohort)

2.3 Survival analysis

An alternative way to determine the LTD is the use of survival analysis. This branch of statistics is also known as *reliability analysis* in engineering or *duration analysis* in economics. Two key terms of our analysis are defined as the following:

a. Survival function S

The survival function describes the probability that the time of death T^D (or exit of use in our case) is later than some specified time t:

$$S(t) = \Pr(T^D > t) \tag{4}$$

Survival functions must be non-increasing (only deaths, no rebirths during lifetime), and they usually start with a value of 1 ($S(0) = 1$) at birth and diminish to a value of 0 as time elapses ($S(+\infty) = 0$).

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b. Lifetime distribution function L

The lifetime distribution L(t) is a probability density function that describes the rate of exit at time t. In other words, $L(t) = P(T^D = t)$. L(t) is also the derivative of the complement of the survival function:

$$L(t) = \Pr(T^D = t) = \Pr'(T^D \leq t) = d(1 - S(t))/d \tag{5}$$

2.4 Approaches for determining the lifetime distribution

In the following, we assume that all products sold domestically remain in the country during their entire lifetime. This assumption is necessary because data for used and obsolete product trade are generally poor. Typically, for the few cases where used product trade data are collected, model years (vintages) are not distinguished, which makes the data useless for purposes of lifetime determination. The impact of this simplification differs by product category and approach used. Dwellings are usually not shipped across country borders, whereas trade in used passenger cars is known to be significant (U.S. Department of Commerce 2005). For used appliances no trade statistics are available, but those products are more difficult to ship than automobiles and are therefore likely to be less significant.

It is furthermore assumed that the time of products exit use (O_1 in figure 1) equals the time these products enter end-of-life management (O_2); thus, that no significant amounts of obsolete products are stored prior to arrival in end-of-life management.

Assuming no trade and stock accumulation of obsolete products, the lifetime distribution function of products can be estimated using data for inputs I(t), stocks SK(t), and outputs O(t) in various combinations. The estimation can be done either by analyzing individual vintages or cohorts, or by treating stocks and outputs in an aggregated form. A differentiation of vintages allows the determination of changes in lifetime distributions, while the aggregated form assumes a constant lifetime distribution.

We identified five ways to determine the LTD of products. Two approaches deal with individual vintages and therefore enable the study of changes in LTD over time. Three approaches treat the vintages in a combined way and thereby presume a constant LTD.

The five approaches use different parameters (Table 1). Official data on inputs I(t) are usually available on a national level, and are calculated by domestic production and trade (mass balance on market of final products in Figure 1). Alternatively, market research institutes may provide input data on smaller scales. Data on stocks of products in use are sometimes available for individual vintages (SK(T, t)), and sometimes only on an aggregate level (SK(t)). Stock data, if available at all, may be provided for a variety of scales (national, state, county, community, street, etc.). Data on outputs from use are rarely measured. Amounts of waste flows published by EPA are usually calculated using input data and assumed lifetimes, making these data useless for a determination of LTDs. In a few cases, however, output data for specific vintage years (O(T, t)) may be obtained, for example, for dwellings. For other products, the output may be measured in terms of its age distribution at a specific year, e.g., O(T, 2007) if the measurement took place in year 2007. Such analyses are not performed on a routine basis. They are very labor intensive, and their scale is often limited to individual transfer stations (community level), or, in exceptional cases, on a state level (EPA 2007).

With the exception of the first approach, all methods presented here apply data on different scales. They therefore presume that the small-scale samples are representative of

the entire country. The discussion as to whether or not this assumption is reasonable needs to be carried out on an individual basis.

Table 1: Approaches and parameters (I(t): time series for input; SK(T, t): time series for stocks by vintage; SK(T,2007):age distribution of stock in year2007, SK(t): time series for overall stock, regardless of vintage; O(T, t): time series for output by vintage; O(T, 2007): age distribution of output in year 2007)

	I(t)	SK(T,t)	SK(T,2007)	SK(t)	O(T,t)	O(T,2007)	Products
Vintage	(X)	X	-	-	-	-	Dwellings, passenger cars (1)
	(X)	-	-	-	X	-	None
Combined	X	-	X	-	-		None
	X	-	-	-	-	X	Passenger cars (2), refrigerators, air conditioners, TV sets, monitors
	X	-	-	X	-	-	(validation)

Approach 1: Individual vintage stock

Time series of in-use stocks for a specific vintage (stock graph in Figure 3) can be transformed into a cumulative proportion of surviving stock by scaling the values with the input of the respective vintage year. If the stock has negligible numbers of exits during the build-up phase (vintage year), the scaling can be done using the initial stock size. Survival functions (e.g., for normal, lognormal, or Weibull functions) are subsequently derived by non-linear regression of the adjusted cumulative proportion of surviving data. The survival functions are then restated as LTD functions using formula (5).

Approach 2: Individual vintage output

Time series for exits from use of a specific vintage (output graph in Figure 3) can be transformed into a lifetime distribution plot by scaling the values with the weight of the initial input of respective vintage years. LTD functions are then derived by non-linear regression, and the LTD functions can be expressed as survival functions.

Approach 3: Combined vintage stock

If the stock sizes of many vintages are known for only a few years (e.g., initial and current stock size), the individual tracking of a vintage (approach 1) provides little information for the shape of the LTD function. This problem can be resolved by assuming that all vintages have the same LTDs. In this case, all vintage stock data are first scaled by their respective inputs and subsequently plotted with the time axis showing age instead of construction year. This increases the number of data on the cumulative proportion of surviving plots, facilitating the non-linear regression to derive LTD functions and survival functions.

Approach 4: Combined vintage output

The age of retired products can be measured in field studies. If it is assumed that the products have a constant LTD, products of different vintages can be combined to form a plot of the age distribution. The age distribution plot needs to be scaled by the inputs of the respective vintage years to produce a LTD plot. Input data for the actually sampled region are generally not available, and need to be estimated using, for example, national sales data as a proxy. In order to account for the different scales in waste collection and sales, the national sales data for all vintage years are reduced proportionally in such a way that the overall sales data reflect the overall sample size. The LTD plot is subsequently used as a basis for non-linear regression analysis to determine LTD functions and survival functions.

Approach 5: Combined vintage stock validation

If time series for inputs and at least one independent measurement of the overall stock size are available, LTD functions can be validated: an MFA model (equations (1-3)) can be used to calculate the historic stock, which can be compared with the measured stock at the given time. This approach assumes a constant lifetime distribution.

2.5 Approaches and data used

a) Appliances

We used approach 4 (combined vintage output) for estimating the LTDs of refrigerators, air conditioners, TV sets (CRT only), and computer monitors (CRT only).

Input data (I(t)) were estimated using historic sales data (U.S. Census Bureau 1980-2007; U.S. Census Bureau 1980-2007; U.S. Census Bureau 1980-2007; EPA 2007). The age distribution of products exiting use, O(T, 2007) was determined by a field study at the transfer station in Branford, CT during the period June 2007 – September 2007. The age of retiring products was determined by subtracting the manufacturing date from the date of arrival at the transfer station. In cases where the manufacturing date was not indicated on the appliance, manufacturers helped us in determining them by indication of model and serial numbers. The resulting useful sample sizes were as follows:

Refrigerators: 25 units

Air conditioners: 34 units

Monitors: 83 units

TV sets: 75 units

By using national sales data and local age distributions, we assume that the pattern of national sales is representative for Branford, or vice versa.

b) Dwellings

The LTDs of dwellings was estimated using a modified approach 4 (combined vintage output), which pays particular attention to the problem of data truncation. The truncation issue arose because of the longer lifetime of the buildings. In other words, even by tracking the buildings for over 100 years (which is as far as we could go in practice), we still only observed the first half of the LTD function. The model took into consideration this problem.

Dwellings were analyzed for the city of New Haven, CT. The Department of Buildings has complete historic records of building permits since 1892, which serve as a proxy for inputs (I(t)). All dwellings with vintages of 1892, 1893, 1894, 1895, 1899, 1921, and 1953 were analyzed in this study. Each of these vintages included between 50-150 buildings. The time series of these vintage stocks SK(T, t) were investigated on a dwelling-by-dwelling basis using fire insurance maps from Sanborn (formerly called The Sanborn Map Company) for the years 1901, 1924, 1956, and 1973, and an online map of real estate appraisals from Vision Appraisal (a real estate appraisal company in New England) for 2007. Since buildings with no explicit demolition year were assumed to exit use at the year of the first Sanborn map on which they no longer exist (while in reality they could have disappeared at anytime from the previous Sanborn map year up to this point), a slight overestimate could occur in our results,

c) Passenger cars

We used both approach 1 (individual vintage stock) and approach 4 (combined vintage output) for estimating the LTDs of passenger cars. The first demonstrated how the lifetime of passenger cars evolved over the years, while the latter provided us with more information on the long tail of the LTD function.

The LTD of passenger cars was studied using two complementary approaches. The first approach (individual vintage stocks) uses historical data of passenger car registrations per model year (MVMA 1973-1992; AAMA 1993-1998; WARD'S 1999-2006) in the U.S., which are available from 1961-2001, as proxies for in-use stocks per vintage year SK(T,

t). By using these data, we assume that exits from use are caused by vehicle retirement, and neglect trade in used vehicles. Since exports of used vehicles exceed imports, the retirements from use are probably overestimated, resulting in an underestimation of the LTD. The magnitude of the error, however, cannot be determined because trade data for cars do not distinguish model years.

The model year of cars is usually not identical with the calendar year, because production begins in the previous year, e.g., production and sales of cars of model year 2007 start in the fall of 2006. Therefore, assuming the first car of model year T is released to the market in October of the previous year, and the release continues at a constant rate until September of year T, we can simplify the problem by taking the middle of this cycle, April, as the release time of cars of model year T. Because the automotive stock statistics are assembled each July, this provides us with an additional three months in lifetime – when the 2007 models show up in the 2007 registration statistics, they have already been in use for three months.

Car registrations differentiate model years for cars younger than 13 years, while data for vintages older than 13 years are only available as a sum. Apart from the trade problem, these are excellent data to determine the LTD of car vintages for the first 13 years of vehicles' lives. However, many cars reach a lifetime much greater than this. In particular, these data do not allow the determination of the LTDs' skewness on the right hand side.

We therefore applied a second approach (combined vintage output) by which the shape of the right side of the LTD can be determined, although only for combined vintages. Retail sale data for passenger cars (MVMA 1973-1992; AAMA 1993-1998; WARD'S 1999-2006) are used as proxies for the input (I(t)). It is therefore assumed that all trade in new cars is done prior to retail sale. The age distribution of cars exiting use, O(T, 2005-2007), is derived from records of Seymour Auto Wrecking, an automobile salvage company in Seymour, CT, who recorded information on the cars they salvaged over the period of July 2005 – July 2007. Out of a total of 387 records, 100 were used for the analysis (records of trucks and vans or records with missing data such as unidentifiable manufacturing year were excluded). The age is determined by subtracting the model year from the salvage year. It is assumed that the age distribution of retiring cars salvaged in Seymour is

representative for the U.S.

3 Results

3.1 Introduction

The goodness of fit was measured by either R^2 or Akaike's information criterion (AIC). R^2s were used when the results were derived from the curve fitting process, i.e., the "combined vintage output" approach for passenger cars. R^2 values represent the fraction of the total variance that is explained by the model equation. Generally speaking, the higher the R^2 (closer to 1) the better the fit. The judgment of the validity of a model, however, should be drawn based on other factors as well. In other words, one can get a perfect R^2 (equals 1) by increasing the number of independent variables, but the interpretation of such model might be very difficult, or even impossible.

AICs were used when the results were derived from the distribution fitting process, i.e., appliances, dwellings, and the "individual vintage stock" approach for passenger cars and appliances. AICs are used instead of R^2 because the distribution fitting is based on the principle of Maximum Likelihood Estimation (MLE), instead of least squared-error. AIC is defined as "AIC = 2k-2Ln(L)", where k refers to the number of parameters and L refers to the likelihood (the chance of observing the samples given a probability distribution). Generally speaking, the smaller the AIC the better the fit.

For each product category, we will demonstrate our results by listing the raw data used (first graphs from the left), the survival functions (second graphs), the lifetime distribution functions (third graph), and the goodness of fit (graphs on the right). As mentioned earlier in the paper, we attempted three distribution functions for each product: normal, lognormal, and Weibull.

3.2 Appliances

All appliances were analyzed using the "combined vintage output" approach, which assumes a constant LTD (Figure 4).

Refrigerators

The expected lifetime for refrigerators varies only slightly with the assumed distribution function: 15.1 years for Weibull and normal distribution functions and 15.5 years for a lognormal distribution function. The standard deviation shows greater dependency on the chosen distribution function, and lies between 7.8 years (Weibull) and 10.5 years (lognormal). Using the AIC value as an indication, the best fit is achieved by the Weibull distribution function.

Air conditioners

The expected lifetime for air conditioners is also relatively robust between 13.5 years (Weibull) and 14 years (lognormal). The standard deviation ranges between 5.4 years (Weibull) and 8.1 years (lognormal). The Weibull and normal distribution functions show the lowest AIC values, indicating the best fit.

TV sets (CRT)

The mean lifetime for TV sets lies between 15.4 years (Weibull) and 15.9 years (lognormal), with the standard deviation being between 6.1 (normal) and 8.5 (lognormal). The best AIC values are achieved using Weibull and normal distribution functions.

The study on management of electronic waste in the United States (EPA 2007) determined the age distribution of electronics based on a similar, but much larger field study conducted in Florida. The age distribution of TV sets in Florida resulted in a mean of 17.27 years for TV sets <19”, and 13.53 years for TV sets >19”.

Computer monitors (CRT)

The mean lifetime for CRT computer monitors is 10.2 years for all three distribution functions. The standard deviation is between 4 years (Weibull and normal) and 4.5 years (lognormal). The best fit is reached using the Weibull function.

The above mentioned study on management of electronic waste in the United States (EPA 2007) with data from Florida determines the mean age of discarded computer monitors (CRT) to be 9.34 years.

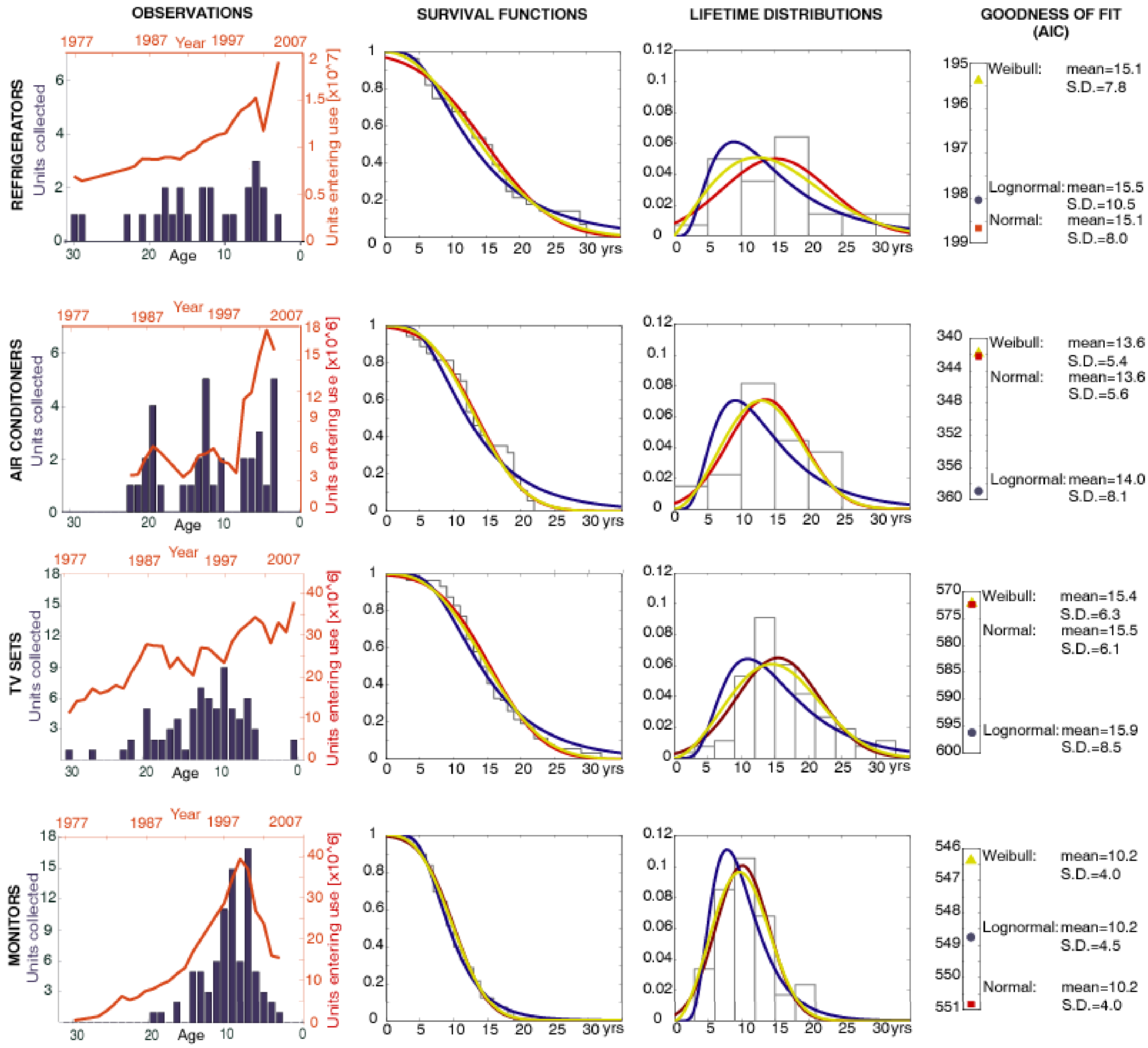

Figure 4: Lifetime analysis for refrigerators, air conditioners, CRT TV sets, and CRT computer monitors in Branford, CT, using end-of-life data for June-September 2007.

3.3 Dwellings

Figure 5 shows the results for the dwelling analysis performed for New Haven, CT. The LTD could be determined only partially: Out of the oldest dwelling vintage with a complete data set (construction year 1892), about half of the dwellings are still in use. This provides us with reasonable data to calibrate the left side of the LTD curve, but the right side remains speculative. It is therefore impossible to make quantitative statements about a potential long tail, except for the reasonable presumption that some dwellings remain in use for a much longer period of time than the average. The resulting expected dwelling lifetime therefore depends strongly on the assumed distribution function, but lies for most vintages and approaches between 100 and 150 years (lognormal distribution tends to produce the longest lifetime estimate, with Weibull in the middle and normal the shortest). Although the dwelling lifetime seems to depend significantly on the vintage class, there is no convincing evidence for a clear trend in lifetime changes. This, however, may be due to the small sample size and the relatively short period of recorded dwelling stocks.

The best fit (lowest AIC value) is for all vintages achieved using lognormal distribution functions.

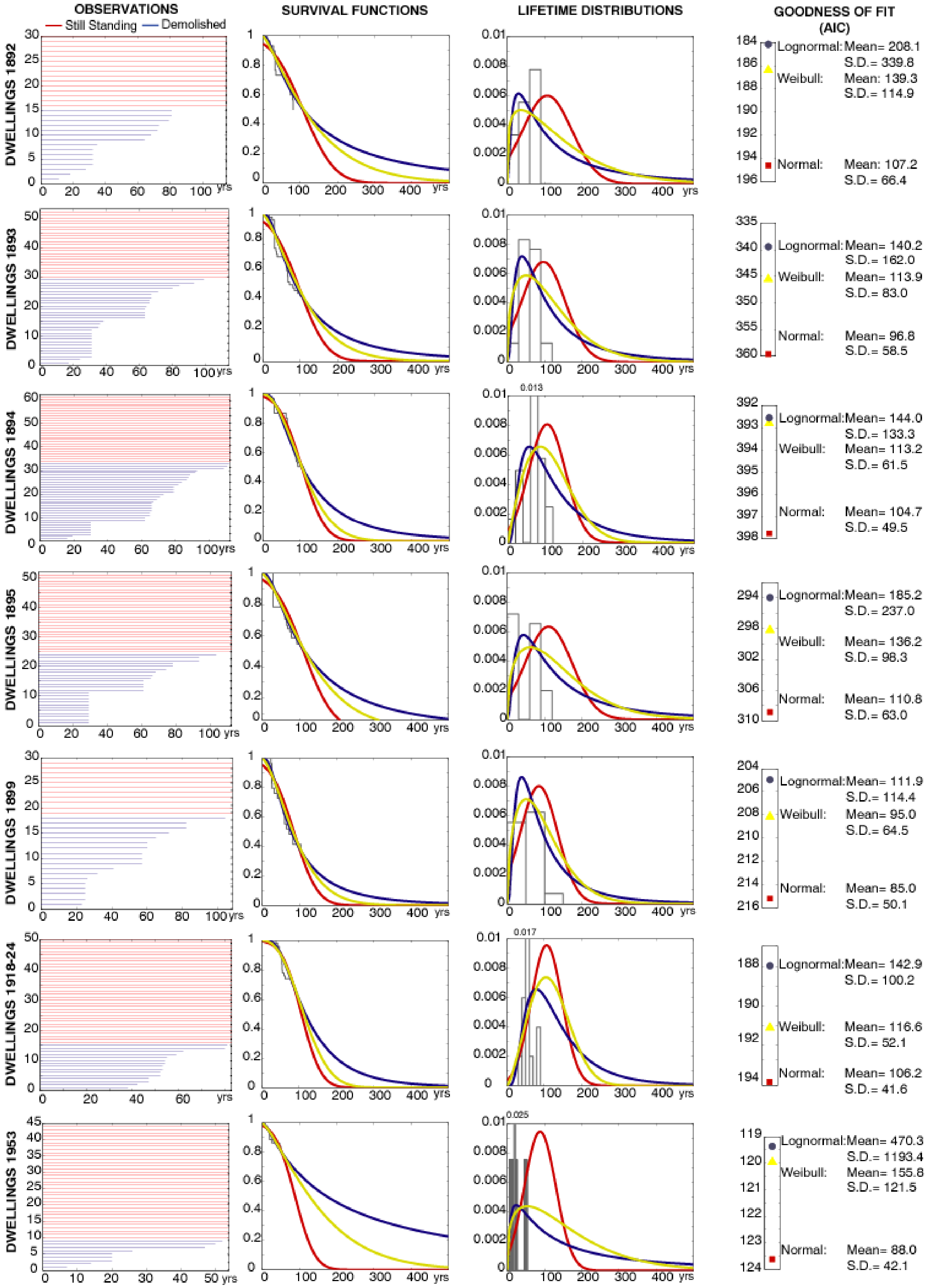

Figure 5: Lifetime analysis for dwellings in New Haven with vintages 1892, 1893, 1894, 1895, 1899, 1921, and 1953.

3.4 Passenger cars

Passenger cars were evaluated using two complementary methods, an "individual vintage stock" (Figure 6) and a "combined vintage output" approach (Figure 7).

The policy of reporting data for the first 13 years of a vintage year was in the 1960s sufficient to cover most of the lifetime curve. However, the same policy currently does not even cover the exits from use of half of the cars, which results in an increasingly poor understanding of the expected lifetime. Worse, in 2003, WARD'S has discontinued the publication of numbers of cars in operation by model year. Based on the available data, it is therefore not possible to conclude whether or not the trend of increasing lifetime expectancies is still continuing.

The analysis of individual vintages shows that the average lifetime expectancy of cars has increased considerably over the past decades: that of vintage 1965 cars was 10.6-11.3 years; this has increased to more than 17 years for cars of vintage 1990. However, the strongest increase in lifetime occurred in the years between 1985 (13.8 years) and 1990 (17.4 years).

Based on the vintages of the 60s and 70s, which are covered with the most complete data sets, the LTDs are only slightly skewed to the right. The best fit for passenger cars is obtained with normal distribution functions.

The "combined vintage output" approach conducted in Seymour, CT, results in slightly shorter lifetimes for passenger cars (15.9 years for all distribution functions). The best fit is again achieved using a normal distribution function.

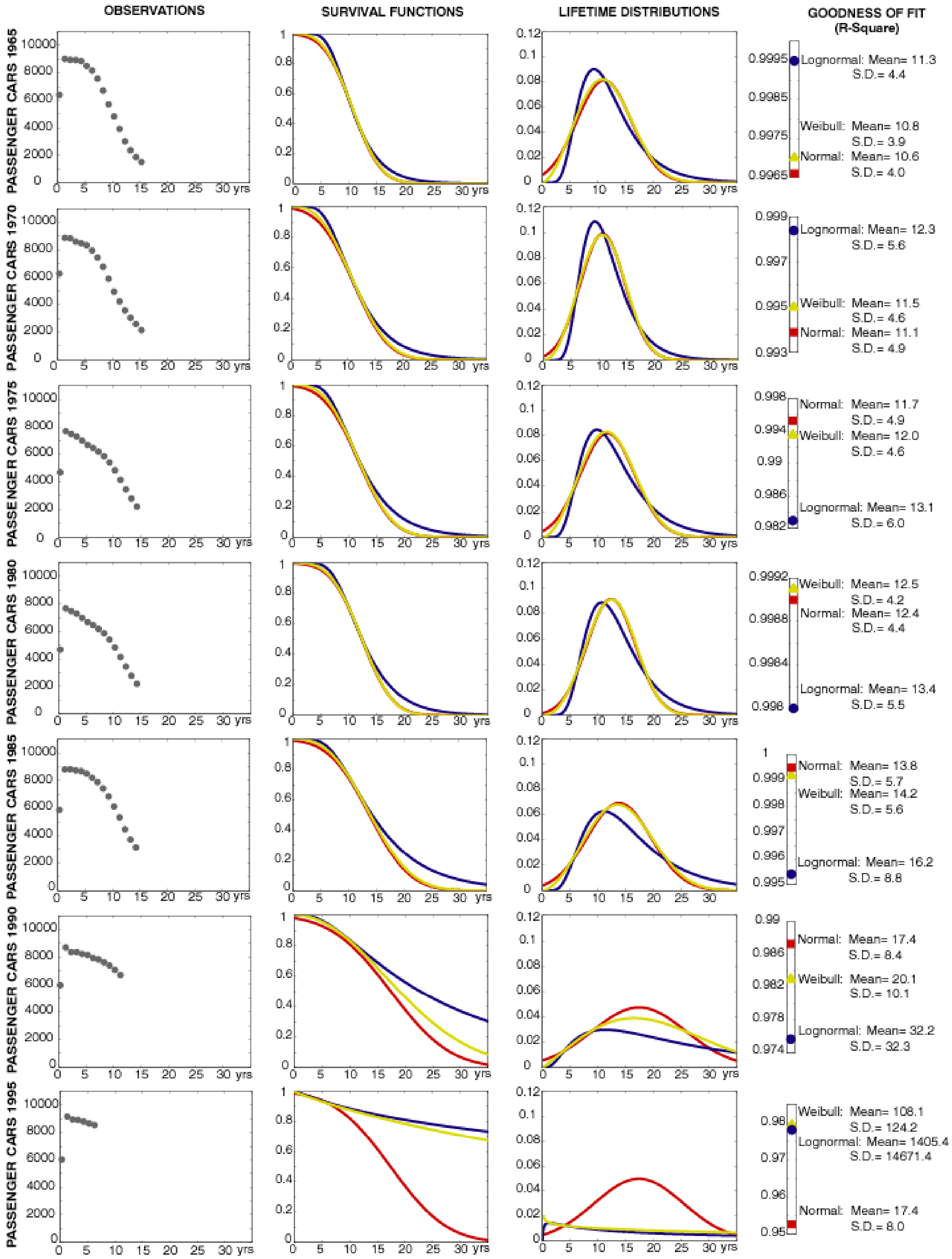

Figure 6: Lifetime analysis for passenger cars in the U.S. using the individual vintage stock approach for model years 1965, 1970, 1975, 1980, 1985, 1990, and 1995.

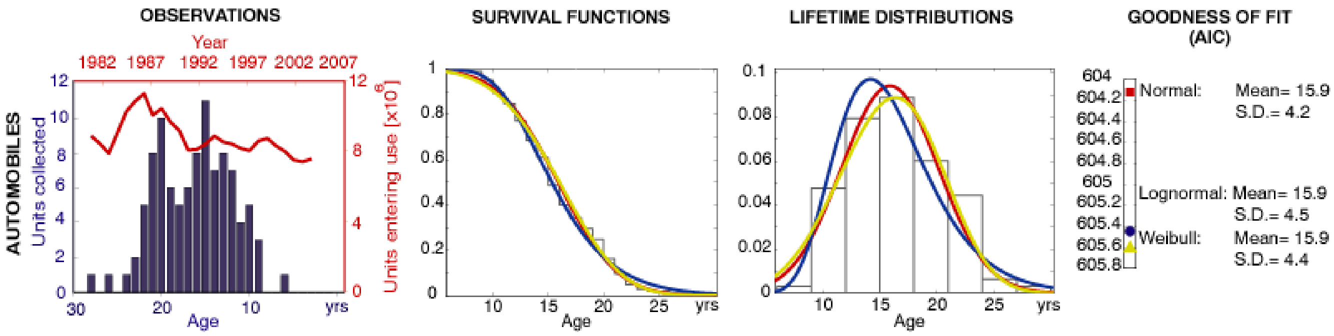

Figure 7: Lifetime analysis for wrecked passenger cars in Seymour, CT, using the "combined vintage output" approach.

4 Discussion

This study presents a first attempt to structure the task of determining the LTD of products using a combination of material flow modeling and survival analysis. Five approaches for determining LTD functions are introduced and applied for a set of commonly used products.

The results are based on a set of assumptions, which might limit their accuracy:

- Data for trade in used and obsolete products are incomplete or lacking entirely, and are neglected here. Assuming that exports exceed imports in the U.S., this results in an underestimation of the average lifetime.
- Accumulation of obsolete products prior to disposal can often not be separated from the use phase (measurement at end-of-life management), which results in an overestimation of the average lifetime.
- The sampling of end-of-life products is very time-consuming, resulting in relatively small sample sizes in our study. The study of end-of-life management of electronics conducted in Florida (EPA 2007; EPA 2007) is based on a much larger sample size. Nevertheless, the results for the age distribution of that study are very similar with our results. The age distribution, however, is a poor indicator for the LTD for products with significant changes in sales over the past years.
- Literature data for time series of vintages are very rare. For example, WARD'S has discontinued the publication of data for vehicles in operation according to their model year. This severely restricts the analysis of changes in LTDs. This change is particularly important for automobiles, for which the average lifetime has almost doubled over the last 50 years.
- All applications using end-of-life management data in this study used data on different scales, e.g., national sales data and local end-of-life data for the age distribution. This presumes that sales data for the U.S. are representative of local sales.

The shape of the LTD varies strongly with the products: The LTDs of all investigated appliances are best approached using a Weibull function, while dwellings tend to be best fitted with lognormal functions, and automobiles with normal distribution functions.

An increase in the expected lifetime could be observed for passenger cars throughout the vintages from 1965 to 1995. However, the extension of lifetime was most marked for vintages between 1985 and 1990. One important factor for this shift might be the introduction of zinc-coated steel for car bodies, which prevents cars from corroding.

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