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PCRR E-waste Stream Analysis

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Abstract

The problem addressed in this paper is that the incoming stream of "feedstock" from product take-back systems is known to be widely variable, but the type and extent of that variability have not been well defined. This paper presents an analysis of data from an incoming e-waste stream for a computer refurbisher, and analyzes the type and degree of variability. The implications for design for sustainability are presented, along with a discussion of suggested future research needs.

1. Introduction

Design for sustainability often considers the entire product lifecycle from cradle to "grave', and back to the cradle again. Some methods involve reusing products, components, or materials in some way after the end of the first consumer use phase. These methods include design for disassembly, recycling, reuse [1-5], etc. One difficulty with these methods is that the incoming waste stream is highly variable [6-8]. Unlike traditional manufacturing processes which impose tight quality control standards on raw materials, the processes must deal with an incoming stream of raw materials (used products) that vary widely in configuration, age, material, condition, etc.

This variability is one reason that design for product take-back and reuse is only in its infancy, as it makes cost effective reuse very difficult. Two developments create incentives for studying this variability in an attempt to gain insight on how to design products to improve cost effectiveness reuse. The first is product take-back legislation. Environmental regulations, such as Waste Electrical and Electronic Equipment (WEEE) and Extended Producer Responsibility (EPR), impose mandatory targets for e-waste take-back on product manufacturers [9, 10]. For example, the WEEE directive requires EU Member States achieve a certain collection target of four kilograms per person per year. The recycling and recovery targets of such collected wastes now cover product reuse, and the weight-based targets for IT and consumer electronics will increase to 80% in December 2011.These product take-back regulations "internalize the externality", transferring the economic burden of waste disposal from society at large to the manufacturer. The second motivator is the significant increase in the volume of e-waste being generated (which has increased approximately 10% every year [11]) and its residual value. Since manufacturers are increasingly being required by law to comply with take-back legislation, product design that facilitates cost effective mining of this resource would increase profitability.

This paper addresses the problem that the incoming stream of "feedstock" from product take-back systems is known to be widely variable, but the type and extent of that variability has not been well defined. This paper presents an analysis of data from an incoming e-waste stream for a computer refurbisher, and quantifies the type and degree of variability. The implications for design for sustainability are presented, along with a discussion of suggested future research needs.

The rest of the paper is organized as follows. The background for the data analysis is presented in Section 2. The method used for analyses is described in Section 3. The data collected and analysis results are discussed in Section 4, and the summary of design implications and future research needs are presented in Section 5.

2. Background

2.1 Facility

This section describes the take-back system under consideration, PC Rebuilders & Recyclers (PCRR), founded in 2000 and based in Chicago, IL. PCRR utilizes a waste stream system, as opposed to market-driven system [12]. All feedstock incoming to PCRR is from donations (i.e., no economic incentive is provided for product drop-off) and PCRR passively accepts all products.

The Goose Island Facility run by the City of Chicago and Knox Facility run by PCRR are the two take-back channels where PCRR collects the e-waste. While Knox Facility collects e-waste both from individual consumers and from companies, Goose Island Facility accepts individual consumer e-waste only. Approximately 20% of the entire feedstock comes from individual consumers and 80% from corporations.

Table 1 shows estimates of e-waste incoming to PCRR. A total of 4,500 units arrive per month, including desktops, laptops, monitors, televisions, printers and other miscellaneous items (e.g., VCRs, telephones and small home appliances). White goods are not included. Table 2 shows the detailed composition of e-waste to Goose Island, which will be analyzed statistically in Section 4.

Table 1. Estimated E-Waste Stream per Month to PCRR

Product Category	Individual Consumers		Corporations	Sum
	Goose Island*	Knox Facility†	Knox Facility	Percentage
Desktop	2.7%	2.7%	24.4%	29.7%
Laptop	0.4%	0.4%	2.8%	3.6%
Monitor	3.3%	3.3%	23.2%	29.9%
TV	1.5%	1.5%	12.0%‡	15.0%
Printer	1.3%	1.3%	10.5%	13.2%
Other	0.9%	0.9%	7.0%	8.7%
Total	10.1%	10.1%	79.8%	100%

* Individual donations accepted at Goose Island are transported to Knox Facility. (Transportation rate estimate = $0.012/lb)

† Individual donations accepted at Knox facility follow approximately the same donation trend as the Goose Island.

‡ Grey area indicates the numbers estimated based on individual donations. Referring to desktop, laptop, and monitor data, a factor of 4 is applied to the total number of individual donations.

Table 2. Average E-Waste Stream per Month from Goose Island Facility

	Average Number of Units per Month	Average Weight of Units per Month
Desktop (Tower only)	26.4%	23.4%
Laptop	3.9%	0.9%
Monitor	33.1%	40.2%
TV	8.7%	23.7%
Printer	13.1%	7.7%
Other	14.9%	4.1%
Total	100.0%	100.0%

2.2 Waste stream processing

Figure 1 shows the e-waste stream processing at PCRR. The e-waste is first sorted into four groups (i.e. desktop, laptop, monitor, and others) according to product type. Each product group passes through different recovery procedure towards four possible recovery options [13]:

- Refurbishment: A product is rebuilt to meet the minimum specifications and to be in good working order, and sold to another user.
- Reuse: A product is sold to another user without undergoing any value-adding operations. Only minimum operations (e.g., cleaning, testing the whole system) are conducted if necessary.
- Component reuse: A component is sold to the market separately from its parent system. For instance, hard drives and memory extracted from computers can be sold on the market as an individual product.
- Material recovery: A product or component is sold to recyclers where it is typically shredded and converted to raw material form. In general, units for material recovery are sold by weight. Processors (CPU), on the other hand, are sold by number.

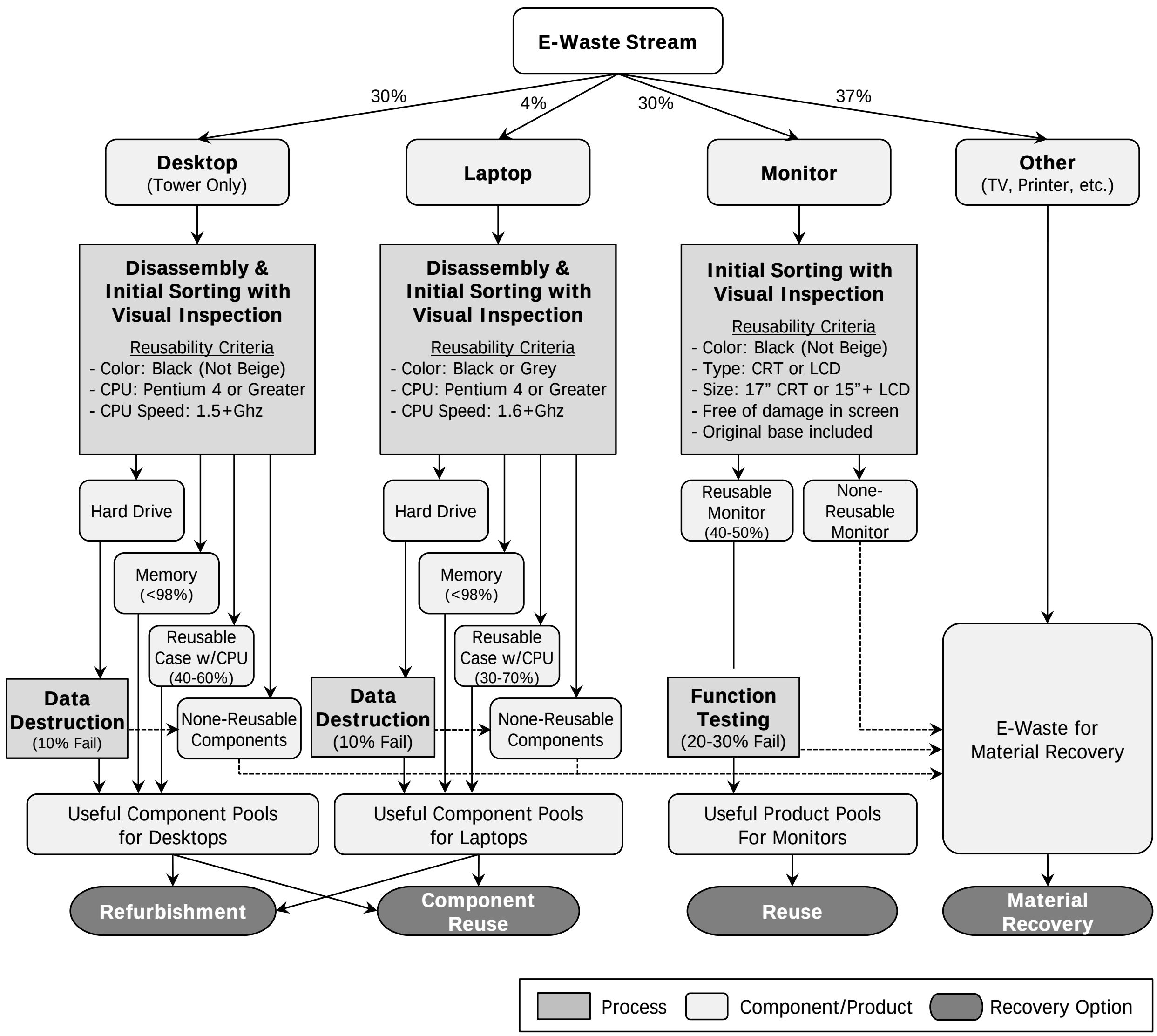


Figure 1. E-waste Stream of PCRR

PCRR refurbishes desktops and laptops. Refurbishment starts from visual inspection evaluating each PC's potential for reuse. PCRR follows an assemble-to-order system for refurbishment, and stores reusable PCs in the form of components. When a customer places an order for refurbished products, appropriate components are retrieved and reassembled. In this way, PCRR can meet various types and volumes of demands more flexibly. Therefore, all incoming PCs are first disassembled, inspected, sorted and stored as components. Basically, a computer is disassembled into three primary elements; the main case with CPU and mother board, the memory, and the hard drive. All hard drives undergo an additional step for data destruction. Components are sorted as reusable or non-reusable. For hard drives, this sorting is performed after purging the data. The criteria for making the sorting decision (called reusability criteria) are shown in Figure 1. A component is considered reusable if it meets the criteria and has no failure or physical damage. Note that the attribute of color, which is unrelated to performance, can render the main box of a desktop (or laptop) unsuitable for reuse. The reason is that customers associate the color beige with older model units. Reusable components are stored in component pools for future refurbishment or component resale (such as on eBay). Non-reusable components such as housing, wiring, etc., are stacked together on pallets are prepared for material recovery.

Figure 2 shows the computer refurbishment process after receiving orders from customers. Refurbishment starts from retrieving the necessary components from inventory. Operators then pick the appropriate components and assemble the system. If components are in short supply or difficult to disassemble (e.g., memory, wireless card), spare components can be externally procured. Compared to desktops, laptops typically require more spare components be procured, because they have a higher degree of design variety across different models and brands.

After testing the assembled hardware, operators install a new operating system and applications, then test the whole system. If the unit fails, operators attempt to fix the problem by replacing components, redo the assembly, and/or reinstall software. If the problem still cannot be resolved, the hardware is redirected to material recovery. If a computer passes all tests, it passes through virtual and physical clean-up steps and the refurbishment process is completed. Current capacity is 3 products per workbench, and 4 to 5 workbenches per operator. Each operator works in batch mode, on 10 to 15 desktop setups concurrently.

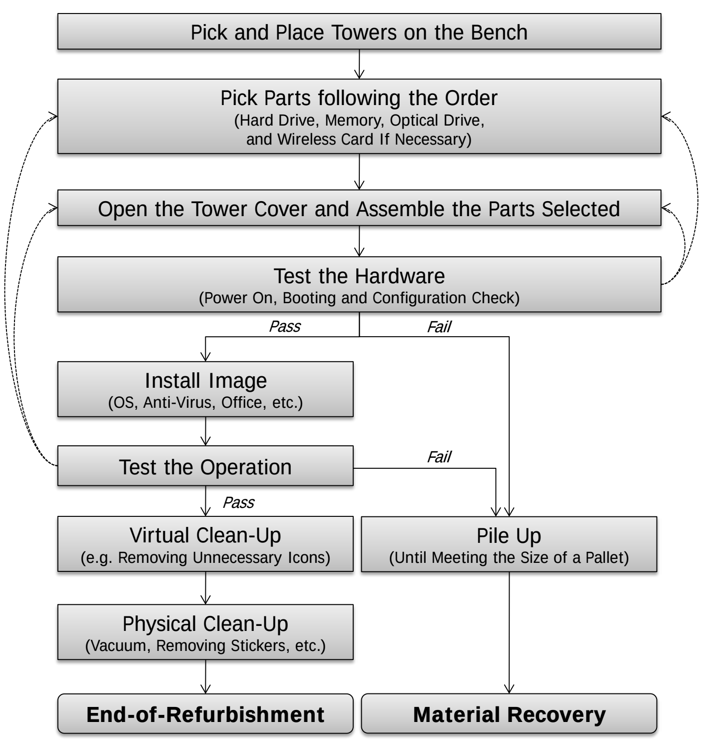


Figure 2. Desktop Refurbishment Process

PCRR does not refurbish monitors due to lack of demand and safety issues, but reuse some units to sell with refurbished desktops. The criteria for monitor reuse are shown in Figure 1. If a monitor does not meet the reusability criteria, it is sent to the recycler for material recovery. Reusable monitors that meet the criteria and pass a functional test are stored for sale bundled with refurbished desktops. Note that only black monitors are reusable for reasons of consumer acceptance. Unless specific orders for beige monitors exist, the beige units are sent to recyclers regardless of performance.

Televisions, printers, and any other items are sold to recyclers by weight. No repair or cleaning is conducted. Upon receiving these products, PCRR stores them until their total weight reaches a minimum for shipping.

2.3 Market value analysis of E-waste stream

This section presents an estimate of the potential market value of the E-waste stream incoming to PCRR.

Sources of prices of comparable components or products on the secondary include websites such as: http://ebay.eztradein.com/ebay/, http://www.recycledgoods.com/Computers-department.html, http://www.gazelle.com/ and http://www.craigslist.org. Tables 1 and 2 show the average volume of E-Waste per month from individual and business customers. Approximately 16,000 desktops and 2,000 laptops are collected each year. Table 3 shows the average selling prices and the age distribution of the collected products. A weighted average estimate reveals that the potential market value of these products lies between $680,000 and $850,000.

Table 3. Estimation of collected products age distributions and average selling price

Desktops		Laptops	
Age Distribution	Average Selling Price	Age Distribution	Average Selling Price
3 % 2 ~ 3 years 5 % 3 ~ 5 years 15% 5 ~ 7 years 35% 7 ~ 9 years 25% 9 ~ 11 years 17% 11 ~ 27 years	$ 160 ~ $ 200 $ 130 ~ $ 160 $ 80 ~ $ 100 $ 40 ~ $ 50 $ 0 $ 0	3% 1~ 5 years 7% 5~7 years 20% 7 ~ 10 years 30% 10 ~ 12.5 years 40% 12.5 ~ 17 years	$ 160 ~ $ 200 $ 120 ~ $ 150 $ 80 ~ $ 100 $ 40 ~ $ 50 $0

3. Method

This section describes the method used for analyzing the raw data to identify some design implications that can increase potential profitability of take-back operations. It provides a methodological structure to support the analytic effort and interpret the results. The method has four main steps, illustrated in Figure 3.

3.1. Step 1: Formulate hypotheses

Understanding why the data is being analyzed is the first step of the analysis process. This step can be conducted through two sub-steps:

3.1.1. Define the main issue(s) that affect the economics of product take-back operations - Analyzing the data without a specific objective is unlikely to be useful. Basic thoughts about design issues expand scientific principles that may have design implications. With a focus on a high level assessment of design opportunities, the main design related issue addressed through data analysis should be defined in this step. Generally, those are issues which most likely affect the economics of salvaging operations of take-back products.

3.1.2. Formulate design-related hypotheses - The defined issue in the previous sub-step should be expanded to formulate specific hypotheses. The hypotheses should be testable based on the available data, and their results should provide some design insights. The purpose of conducting the statistical analysis is to determine whether the data provide statistically significant evidence to reject those hypotheses or not. A result is called statistically significant if it is unlikely to have occurred by chance alone [14].

3.2. Step 2: Identify data sources

While many sources and types of data may be available, not all are useful. Based on the purpose of the analysis, the data are filtered to identify those that are useful. It should be noted that this step is based on the assumption that the analysis is going to be performed on existing data, or data that can be gathered. For a methodical implementation, this step compromises two sub-steps defined as follows:

3.2.1. Identify sources of data - The sources of the data and the conditions under which the data have been gathered should be investigated to make certain that the recorded data are representative of the population under study, and that the results of the analysis can be generalized. When an analysis cannot be done because of the quality of the data or because the data is not representative, the option of improving the data or collecting new data should be considered. Different methods for data gathering can be applied, including interviews, observation, panels of experts, surveys, etc. Different statistical methods can be used for analyzing the data based on different methods of data gathering.

3.2.2. Filter data based on design-related hypotheses - Not all of the recorded data might be related to the analysis of design issues. After verifying the quality of the data and defining the objectives of data analysis, the next step is to filter the data in order to define the appropriate data fields. In addition to choosing the appropriate fields, before conducting the statistical analysis, data screening methods can be used to identify miscoded data, outliers, missing and other messy data.

3.3. Step 3: Choose the required statistical methods

After formulating hypotheses, the appropriate statistical method for testing those hypotheses is selected, using the following sub-steps:

3.3.2. Choose the required statistical method - The type of the data, the number of groups of data, distribution, whether the data are paired or unpaired, the purpose of the analysis (the question/hypothesis under study), etc., are considered to select an appropriate statistical method. For example, if the purpose of the analysis is to test the relationship of an outcome continuous variable with a combination of some other determining variables, the linear regression analysis is chosen. Other methods are employed under other circumstances [15, 16]. Before applying a statistical method the underlying assumptions should be verified. If the data do not meet the assumptions then some data modifications may help. For example if the data do not satisfy the normality assumption, which is required for conducting Analysis Of Variance (ANOVA), then it may be possible to solve the problem by transforming the data.

3.3.3. Choose the statistical package - There are many statistical computing packages including SAS, GENSTAT, SPSS, Minitab, Excel, etc. Each of them has its own advantages and disadvantages. The selection of the package is specified by the nature of analysis that will be done.

3.4. Step 4: conduct the analyses and derive design implications

Two sub-steps of Step 4 are to conduct the analyses and derive design concepts.

The analyses are conducted in this step based on the hypotheses/questions determined in Step 1, after which the results will be interpreted to derive meaningful implications out of the results.

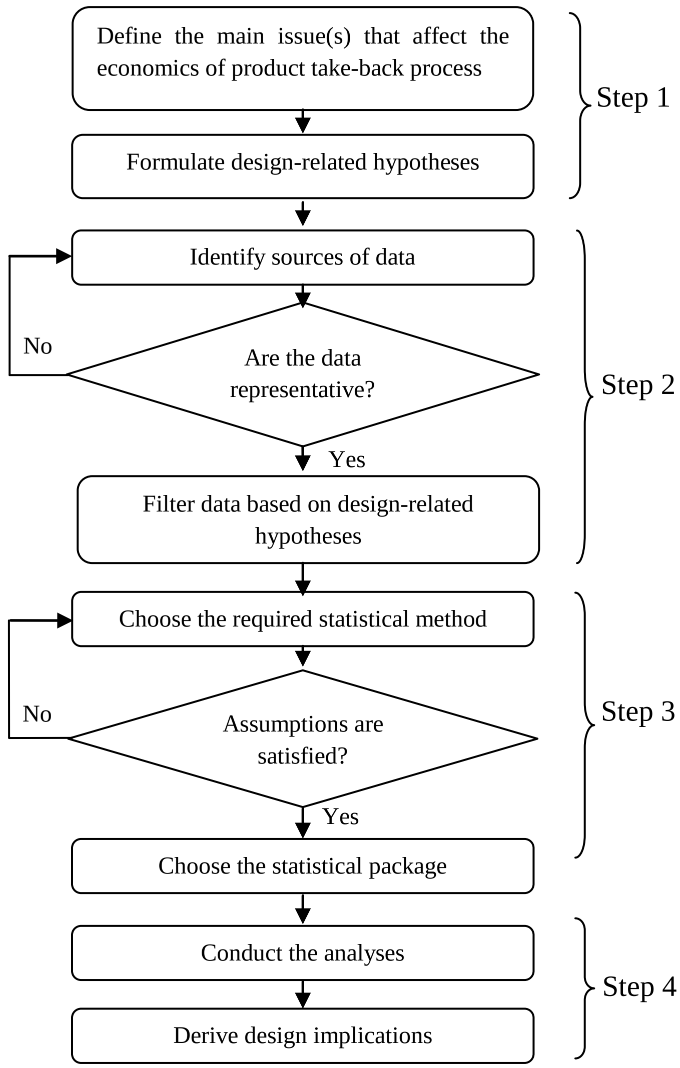


Figure 3. The procedure of the statistical analysis

4. Results and Design Implications

In this section the method presented in section 3 is applied to analyze the data gathered at the Goose Island facility, (an e-waste collection site for PCRR), and design implications are discussed. Only the main steps of the method are listed here.

4.1. Step 1: Formulate hypotheses

As stated in Section 3 the first step of data analysis is to define the main question to be addressed through analysis. The purpose of this work is to address the following issue:

What is the type and extent of variability in the incoming stream of "feedstock" from product take-back systems?

Basic thoughts about design issues expand hypotheses that may have design implications. For example, one possible design for sustainability strategy is modularization, where product modules can easily be removed, replaced and upgraded, or updated by the consumer. Thus, the entire product does not enter the e-waste stream; only those modules which are upgraded. The question of whether or not the current e-waste stream shows any evidence that consumers upgrade components separately (e.g. monitor of a desktop), rather than as a whole leads to hypotheses 1 and 2 below.

Hypothesis 1. Is there a statistically significant difference between electronic types in average count of e-wastes collected per day?

Hypothesis 2. Is there a statistically significant difference in the average age between different electronic types?

Furthermore, product brand is a factor that may influence the range of variability of incoming e-waste. Based on the available data, the weight and age of e-waste can be tested through hypotheses 3 and 4 as two design features related to product brand.

Hypothesis 3. Is there a statistically significant difference between electronic brands in weight of a specific product type (Desktop, Monitor, TV)?

Hypothesis 4. Is there a statistically significant difference between electronic brands in age of a specific product type?

4.2. Step 2. Identify data sources

The data analyzed here have been collected in Goose Island facility located in Chicago, IL, USA, that accepts e-waste from individual customers. More than 15 data fields were recorded for each unit collected, including date and time of return, source of return (zip code), weight, manufacturing date, serial number, etc. Not all of those data were required for the purpose of this research on analyzing the variability factors influencing the design implications, so the recorded information has been screened to six data fields: date, product type, Brand, manufacturing date, model number and weight.

4.3. Step 3. Choose the required statistical methods

For the purposes of this analysis, one-way analysis of variance (ANOVA) has been applied. ANOVA in its simplest form presents a statistical test of whether the means of multiple groups of data are equal or not [17]. While conducting ANOVA the errors of measurement should be independent and normally distributed with a zero mean and also the means may vary from one group of data to other group, but the variance must be constants in all groups under study [18]. To conduct the analyses MINITAB known as a software package for quality improvement is selected.

4.4. Step 4. Conduct the analyses and derive design implications

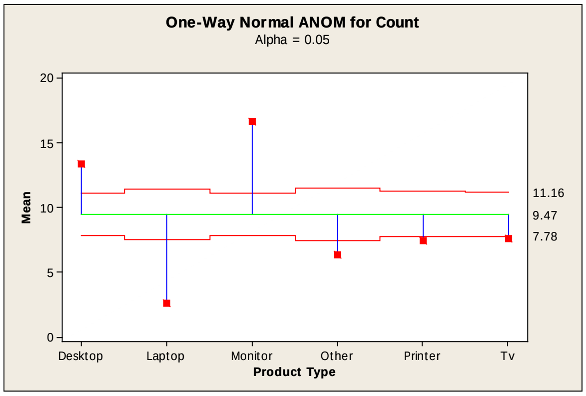
In this step the main sources of variability identified in the first step are investigated more and the results of some statistical analysis are presented.

4.4.1. Variability in Product Type - Consumers typically purchase PC as a bundle of components, such as a desktop unit, monitor, keyboard, and sometimes a printer. One sustainable design strategy is to configure products in such a way that the refurbisher or consumer can replace and upgrade separate components, leaving other components that do not require an upgrade out of the e-waste stream until some later date. The e-wastes received by PCRR are classified into six categories: Desktop, Laptop, Monitor, Printer, TV and other miscellaneous items.

A one-way ANOVA is a suitable statistical method to analyze the data collected during 202 days (23 months, from Nov. 2007-Sep. 2009) to determine whether the average count of e-waste collected per day is different for each electronic type or not. Before applying ANOVA, the underlying assumptions including normality and the equality of variances were verified. The result of “test for equal variances” shows that the variances of the number of e-waste collected per day for each product type are not the same. A graphical representation of "Analysis of Means" in figure 4 shows how the average count collected per day for each product type differs from the overall average of 9.47 items per day.

$H_0: \mu_{count,\ CPU} = \mu_{count,\ Laptop} = \mu_{count,\ Monitor} = \mu_{count,\ Other} = \mu_{count,\ Printer} = \mu_{count,\ TV}$

$H_1: There\ is\ a\ difference\ in\ average\ count\ between\ electronic\ types.$



Level	N	Mean	StDev
Desktop	197	13.376	10.906
Laptop	150	2.633	2.212
Monitor	199	16.608	13.956
Other	141	6.362	10.179
Printer	182	7.434	9.051
Tv	190	7.605	6.733

Figure 4. The average and StDev. of count collected per day for different e-waste

Figure 4 shows that monitors, with a mean 16.60 per day, have the highest frequency, and laptop with 2.63 numbers per day has the lowest. Product size, price and market size may influence the rate of return of different products. For example, customers may wish to keep an expensive laptop, but are keen to discard a big 19" cathode ray tube (CRT) monitor.

At PCRR, 90% of the monitors received have CRT technology and 60% are beige in color, which does not satisfy customer demand even in the refurbished market. As a result, a high volume of monitors are sent for material recycling. According to Smith et al. (1995), although components of the end of life product can be reintroduced into secondary markets, no market for reused monitors was identified [19]. If designers can anticipate this type of obsolescence, they should aim at *design for recyclability* or *material compatibility* to reduce the future cost of recycling.

Figure 4 shows the difference between the number of monitors disposed by customers and the number of CPUs. This indicates a willingness to upgrade just one portion (or module) of the desktop computing product. Design strategies that respond to this willingness -- making it easier for consumers to upgrade memory, the operating system, the CPU, and user-interface elements -- have the potential to simultaneously satisfy customer demand and decrease e-waste. One design strategy might be the use of common connectors that facilitate upgrades, such as connector designs that could survive at least one generation of improvements in data transfer speed.

4.4.2. Variability in Age - Computing technology evolves at a rapid pace. The older e-waste is, the more difficult it is to refurbish or reuse in a cost effective manner. This subsection analyzes the age of e-waste, and also explores the question of whether there is a difference in age among product types. If there is a difference, designers might focus their efforts on achieving commonality in a strategic fashion. If e-waste age for a particular product type varies significantly, a potential strategy is to design for "generational commonality," where components can be reused across multiple generations. On the other hand, if e-waste age falls within a narrow range then sharing components across products within one (or few) generation, "contemporary commonality", might be more fruitful.

Irrespective of age, the percentage of e-waste that has failed physically is quite low. For the hard drive, the failure rate is only 10%, for memory only 2%, and CPU failure is extremely rare. Thus, physical reliability is very high, and the main obstacle in refurbishment is technical obsolescence, rather than component failure. At PCRR 94% of e-waste desktop units are more than 5 years old (which is the average useful life time of a PC), presenting a significant challenge in the realm of technological obsolescence. Rai and Terpenny (2008) suggested "piggybacking" as an effective strategy in dealing with technological obsolescence. They defined piggybacking as "a strategy that enables renewed functionality of a technologically obsolete product through the integration or add-on of a secondary device or component. Not to be confused with upgrading strategies, piggybacking requires a device that fits adjacent to, upon, or within the existing product (parent product) architecture" [20].

Age of returned products is based on manufacturing date. The average age along with the technology cycle can give refurbishing company some insights about the possible end of life options (re-use, remanufacture, recycle, etc). For example if a product becomes e-waste before it becomes obsolete, it can be resold in the secondary market and re-use can be considered as a potential end of life decision.

The focus of this subsection is on comparing the average age of different product types. Before applying ANOVA, the assumption of the "equality of variances" has been tested. The result shows that Television with average age 15.20 years has a higher StDev (6.70) compare to other groups of products violating the equality of variances assumption, so ANOVA was conducted only for Desktop, Laptop, Monitor and Printer. The resulting p-value of 0.000 (which is less than the significance level, 0.05) shows that there is a statistically significant difference in average ages between different product types. The results are summarized in Figure 5.

$$H_0: \mu_{age,\ Desktop} = \mu_{age,\ Laptop} = \mu_{age,\ Monitor} = \mu_{age,\ Printer}$$

$$H_1: There\ is\ a\ difference\ in\ average\ age\ between\ electronic\ types.$$

```
                                     Individual 95% CIs For Mean Based on
                                     Pooled StDev
Level       N    Mean  StDev  ----+---------+---------+---------+-----
Desktop  1474   9.160  3.048        (--*-)
Laptop    122  11.095  3.389                                  (-------*------)
Monitor  3127   9.950  3.241                      (*-)
Printer   648   8.733  3.613  (--*--)
                              ----+---------+---------+---------+-----
                                8.80      9.60     10.40     11.20
```

Figure 5. The ANOVA result of the average age for different e-waste

Printers exhibit the shortest average age, while laptops exhibit the longest. It should be noted that the average age of TV is omitted from ANOVA, and is even higher than laptops. Not having proprietary data and being cumbersome to store can be two reasons for the short average age of printers. On the other hand, as laptops are easy to store, have a higher price and may contain proprietary data, they have a higher age.

Rose et al. (1998) categorized the printer as a product with a short life cycle and rapidly changing technology [21]. In the work conducted by Diggleman et al. (2003) for the study of end of life electronics in Wisconsin, it was assumed that the life cycle of TVs is approximately 15 years old [22], which is supported by the data presented here.

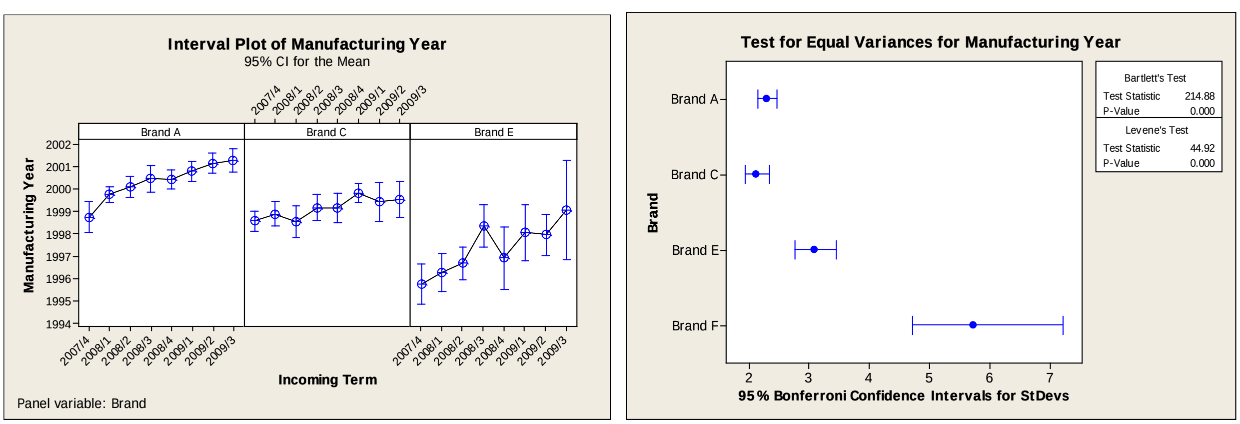
The time when the products are received by the recyclers may be different from the time when customers stop using them. Analyzing the length of storage time from collected products can be helpful in investigating the customer behavior in returning the products. Based on the information on 90 units of hard drives collected from corporations and 646 units coming from individual customers at PCRR, the average storage time is 0.82 years for corporate and 1.40 years for individual customer data.

Another consideration is the variability in age, to determine the degree of product variety and its variability among different *incoming terms*. To do this analysis, PCRR desktop data are classified into eight groups according to each desktop's return date. Here, manufacturing year is chosen as an indicator of product variety.

If there is a high variability of manufacturing years in incoming returned products, longer term "generational commonality" should be considered for higher profit in product recovery. On the other hand, if there is lower variability of manufacturing years in incoming returned products, then "contemporary commonality" is better suited for product recovery. In other words, manufacturers do not need to consider longer term generational commonality.

To provide more detailed suggestions for design for sustainability, data are stratified by brand name. Stratification of the data by manufacturing brand reveals how different brands work. Figure 6 shows that different brands exhibit different variances for manufacturing year. In Figure 6(a), Brand E tends to have a large variance of manufacturing year within a term, whereas Brand A and C have relatively small variances. Figure 6(b) considering all terms at once provides a clearer comparison. Brands E and F exhibit large variances for manufacturing year, which indicates that these two brands need to deal with a wide range of product variety across multiple generations at the same time. However, Brands A and C are not burdened by this feature, owing to less variety throughout product generations.

Designing brand E and F for generational commonality and brands A and C for contemporary commonality may result in higher product recovery profit. The battery of the laptop is an example where considering commonality can increase its recovery profit. Laptop batteries do not have a standard shape and dimension, which make it difficult to reuse for other laptops. So considering component compatibility such as interface, dimensions and architecture can increase the reusability of this component between different generations.



(a) Interval Plot of Manufacturing Year (b) Result of Test for Equal Variances

Figure 6. Variances of Manufacturing Year for Different Brands

4.4.3. Variability in Brand -There are more than 400 different brands (496) across the different product types in the current data set. This further hinders cost-effective refurbishment, as each brand exhibits different design materials, geometries and configurations. Figure 7 shows a Pareto Chart of the percentage of Desktops received with different brands. The figure illustrates that seven major brands account for the 83% of the total number of desktops. The remaining brands are clustered as “Other.” Similar Pareto charts can be used to represent the variability of brand for Monitors, Laptops, printers and TVs.

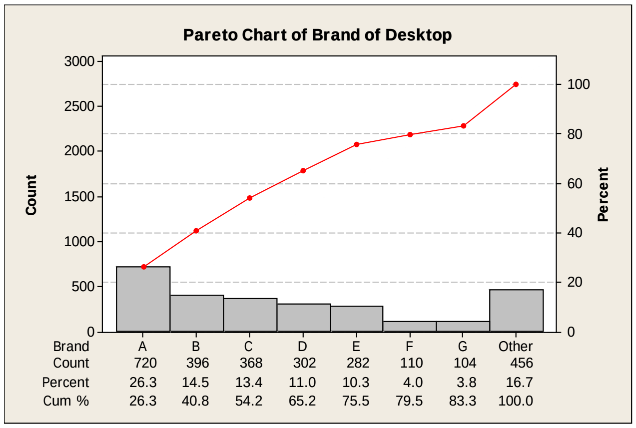


Figure 7. Pareto Chart of different brands of Desktop

The aim of this subsection is to concentrate on the effect of brands on the weight and age of e-wastes collected. Two hypotheses have been tested for each product type to find out whether there is a significant difference in the average weight (the average age) of a product between different brands or not.

Figure 8 shows the hypothesis and the ANOVA result for the average age of four different brands of Desktop. In order to satisfy the assumption of the equality of variance, other brands have been removed.

$H_0: \mu_{Age\ of\ Desktop,\ brand\ A} = \mu_{Age,\ brand\ B} = \mu_{Age,\ brand\ C} = \mu_{Age,\ brand\ E}$

$H_1: There\ is\ a\ difference\ in\ average\ Age\ of\ Desktop\ between\ different\ Brands$

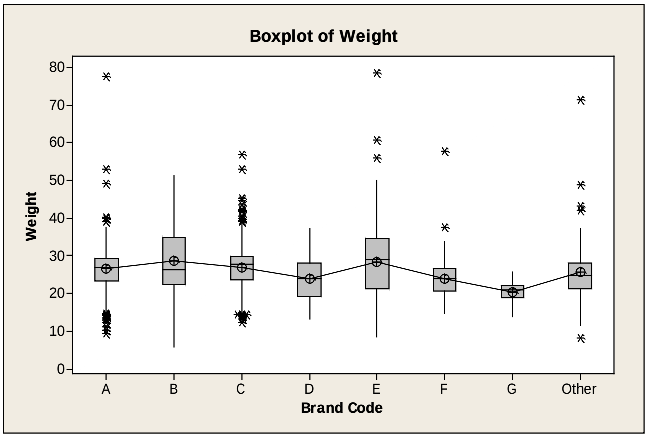
```
                                Individual 95% CIs For Mean Based on
                                Pooled StDev
Level    N    Mean  StDev  ---+---------+---------+---------+------
A      636   7.870  2.176  (-*)
B       33   9.414  2.599           (--------*--------)
C      354   9.063  2.047             (--*-)
E      252  11.269  2.901                                  (--*--)
                           ---+---------+---------+---------+------
                            8.0       9.0      10.0      11.0
```

Figure 8. The ANOVA result of the average age of different brands of Desktop

Another hypothesis is whether the average weights of different brands of Desktop are different or not. Since the standard deviations of the weight of different brands are different, ANOVA cannot be conducted. However the Box plot presented in Figure 9 illustrates the average weights of different brands.

$H_0: \mu_{Weight\ of\ Desktop,\ brand\ A} = \mu_{Weight,\ B} = \mu_{Weight,\ C} = \mu_{Weight,\ D} = \mu_{Weight,\ E} = \mu_{Weight,\ F} = \mu_{Weight,G} = \mu_{Weight,Other}$

$H_1: There\ is\ a\ difference\ in\ average\ weight\ of\ Desktop\ between\ different\ Brands$

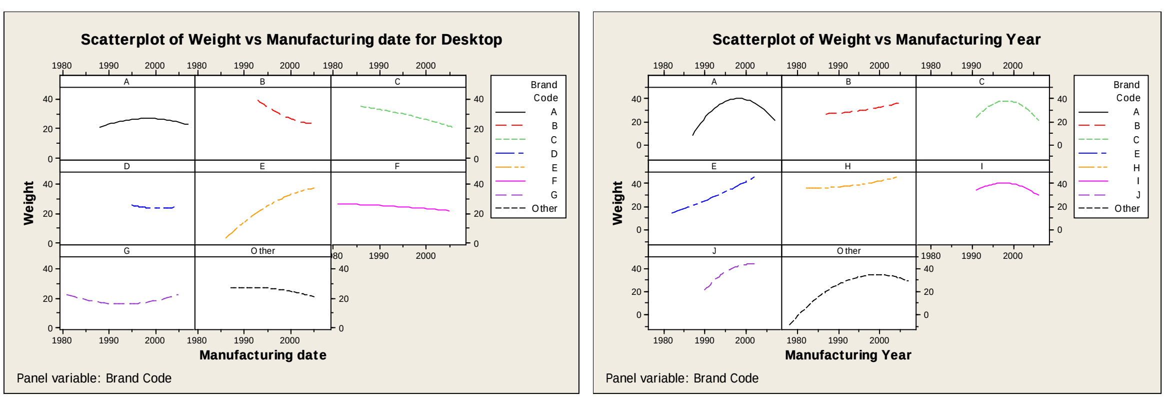


Level	N	Mean	StDev
A	636	26.346	5.339
B	33	28.630	9.822
C	354	26.848	6.024
D	25	23.728	6.519
E	252	28.137	8.868
F	71	23.897	5.891
G	12	20.267	2.892
Other	91	25.420	7.781

Figure 9. The mean, StDev and the Box plot of the weight of different brands of Desktop

Similar analyses can be performed to compare the average age and weight of different brands of other products including monitor and TV.

Analyzing the weight trend of different brands of a product provides an interesting insight. Figure 10 (a) and (b) illustrate the weight trend of Desktop and Monitor respectively.



(a) (b)

Figure 10. The Weight trend of different brands of Desktop (a) and Monitor (b) applying Quadratic Regression

In general most of the brands except brand E show a decreasing or flat trend for Desktop's weight. On the other hand, most of the brands of monitor show an increasing trend due to increasing interest toward larger CRT monitors, followed by a downward slope as LCD monitors began to substitute for CRT monitors in 1999 [23]. Brand E shows an increasing weight trend of monitor. Investigating the model numbers of this brand indicates that the increasing trend is most likely related to the integrated all-in-one PC models coming to market.

5. Summary

This paper has quantified the nature and variability of an incoming e-waste stream. A set of hypotheses were developed and tested related to the cost-effectiveness of product take-back operations. The results of the analyses regarding variability in product age and weight clarified the potential role of product design in increasing the profitability of take-back operations, especially design for commonality.

Product take-back requires consideration of a wide variety of product type simultaneously. Accordingly, value recovery is influenced not only by individual product designs but also by the interactions between designs, i.e., the interchangeability of components across multiple models and brands. When designing a product, thus, it is desirable to consider the design of other products that are (or will be) related. In this regard, it is worth considering how the range of product variety that reaches the end-of-life stage at the same time.

Then PCRR desktop data were classified into eight groups according to each desktop's returning date. Manufacturing year was chosen as an indicator of product variety, since desktop design is rapidly changed or upgraded with a cycle of less than a year [24].

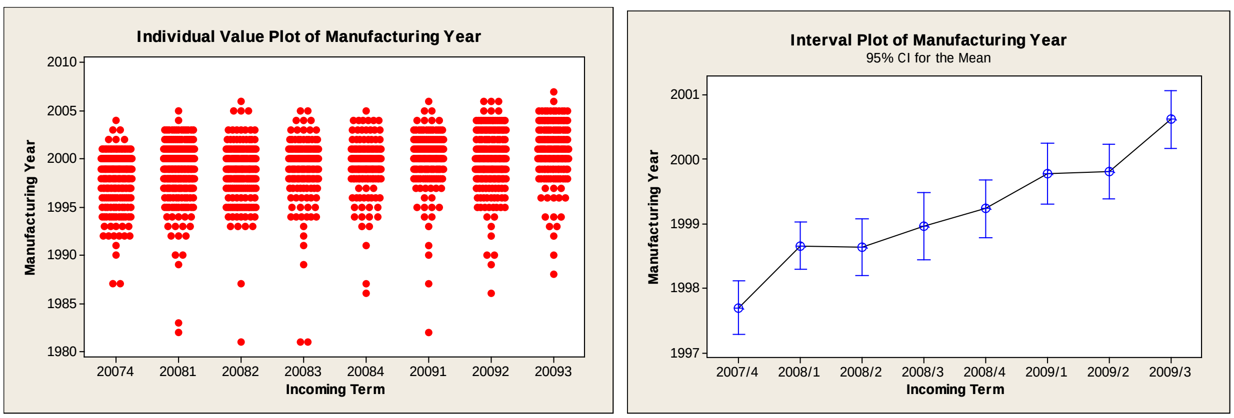


Figure 11. Individual Value Plot and Interval Plot of Manufacturing Year

Figure 11 shows the individual value plot and interval plot of manufacturing year for eight incoming terms, from the fourth quarter in 2007 to the third quarter in 2009. The descriptive statistics given in Table 4 show that the products returning to a refurbisher each quarter have a wide range of manufacturing year, up to 25 years. One thing of interest here is the variance of manufacturing year in each term (quarter). Because Levene's Test for equal variances shows p-value as 0.776, different incoming terms are regarded to have equal variances. The variation of manufacturing year for returned products in every term is approximately 3 years (pooled standard deviation = 2.99). In other words, 95% of the returned products in every term has manufacturing year that are within two stand deviations ($\mu \pm 2\sigma$ = average manufacturing year ±6 years).

Table 4. Descriptive Statistics of Manufacturing Year for Different Incoming Terms

Incoming Term	2007/4	2008/1	2008/2	2008/3	2008/4	2009/1	2009/2	2009/3
Number	185	255	186	157	153	157	210	171
Mean	1997.70	1998.65	1998.63	1998.96	1999.24	1999.77	1999.80	2000.61
StDev	2.87	2.95	3.00	3.29	2.81	3.01	3.06	2.96
Variance†	8.22	8.68	8.98	10.81	7.88	9.04	9.38	8.76
Minimum	1987	1982	1981	1981	1986	1982	1986	1988
Maximum	2004	2005	2006	2005	2005	2006	2006	2007

† Levene's Test result (Test statistic = 0.58, p-value = 0.776, pooled StDev = 2.99)

The variance of manufacturing year gives the reason why multiple generations of products need to be considered simultaneously in the design stage. Unfortunately, current approaches for design for sustainability have focused on improving single product design. Therefore, more methods for design for sustainability need to be developed to consider and improve multiple generations of products simultaneously.

To decrease storage time and recovery profit, design commonality across multiple generations might be employed. Specifically, a product could be designed to be compatible and expandable with components from older-generation products. Many recovery systems store e-waste by first disassembling them into groups of components. Some e-waste is too old to refurbish, even though it is fully-functioning. However, newer products might be designed to be able to reuse older-generation components. For example, a PC designed to have two slots for hard drives can reuse old 20GB hard drives to meet the minimum hard drive specification for the refurbished PC, that is, 40GB. Similarly, PCs with multiple slots for memory expansion can facilitate the reuse of 256MB memory from older-generation products, while satisfying minimum specifications for refurbishment (i.e., 512MB, for example).

Future research should address the specific cause of product obsolescence. One line of research would be to determine more specifically why customers purchase new computer products. The reasons will range from technical obsolescence (for example, speed or memory inadequate for new software or internet applications), physical obsolescence (inability to obtain needed replacement components), compatibility with coworkers or peers, or equipment failure.

Another line of research is to develop models to predict future trends in the e-waste stream. If the current waste stream problem and resulting legislation had been anticipated earlier, we might have avoided the current disposal problem. Will variability in waste stream in terms of age decrease or increase over time? Will customers upgrade more frequently since prices have decreased and they have better/less expensive means of data back-up? Or will more consumers practice direct reuse by deploying obsolete units to lower level functions, such as demoting a primary PC to a printer server for a home network? These are valid research questions for the future in the sustainable product research area.

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