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Evaluating Electronic Waste Recycling Systems: The Influence of Physical Architecture on System Performance

by

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Bachelor of Science in Mechanical Engineering
Franklin W. Olin College of Engineering, 2006

Submitted to the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degree of

Master of Science in Technology and Policy

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Abstract

Many different forms of electronic waste recycling systems now exist worldwide, and the amount of related legislation continues to increase. Numerous approaches have been proposed including landfill bans, extended producer responsibility (EPR) and advance recovery fee (ARF) funded recycling systems. In order for policymakers and system architects to establish the optimal recycling system for their location, they need to know how to evaluate the performance of existing systems, and furthermore, how to use this information to design new systems. This thesis addresses the question: How does the physical system architecture of e-waste systems influence system performance? Specifically, it focuses upon the physical system architecture of collection site density and distribution. This thesis presents a systematic methodology developed with the Materials Systems Laboratory for characterizing recycling systems. Case studies of existing e-waste systems operating in Switzerland, Sweden, the Netherlands, Norway, Belgium, the Canadian province of Alberta and the US States of California, Maine and Maryland are examined for correlations between the environmental and financial performance of existing systems with respect to both the context and the architectural options of those systems. The case study analysis furthermore informs the construction of a model of e-waste systems. This model, which examines architectural choices in collection, transport, processing and system management of e-waste, is used to predict the environmental and financial performance of theoretical e-waste systems for a given location. The model was intentionally developed to be both broad, in order to encompass all pieces of recycling systems, and general, such that many different types of systems, both real and hypothetical, can be analyzed. Following an application of the model to several different combinations of system architecture and context, policy recommendations are made regarding the construction and evaluation of e-waste systems in various locations.

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Table of Contents

List of Figures

List of Tables

1 THE GROWING IMPORTANCE OF RECYCLING ELECTRONIC WASTE

Figure 1: Images of E-waste taken by Elretur in Norway. (Elretur 2004-2007).

1.1 What is electronic waste and why should it be treated differently from other waste?

For the purposes of this thesis, electronic waste, or e-waste, refers to the electrical and electronic products which have reached the end of their useful life and are ready for recycling or some other form of disposal. Such products include IT and telecommunications equipment such as computers, televisions, cell phones, and PDAs, as well as large and small home appliances including refrigerators, air conditioners, washing machines, and toasters. In the Waste Electrical and Electronic Equipment (WEEE) Directive, the European Union formally categorizes such e-waste into the 10 categories shown in Table 1. Further clarification regarding which products fall into each of these 10 categories can be found in Appendix A.

Table 1: WEEE Categories (The European Parliament and the Council of the European Union (2003)

Categories of E-Waste Covered by the EU WEEE Directive
1. Large household appliances
2. Small household appliances
3. IT and telecommunications equipment
4. Consumer equipment
5. Lighting equipment
6. Electrical and electronic tools (with the exception of large-scale stationary industrial tools)
7. Toys, leisure and sports equipment
8. Medical devices (with the exception of all implanted and infected products)
9. Monitoring and control instruments
10. Automatic dispensers

Figure 2: 23,000 Refrigerators and Freezers (<1 month of collection) waiting for treatment in Norway. (El Retur 2004-2007)

E-waste poses challenges distinct from many other types of waste due to its content. Most electronics contain hazardous materials such as antimony, arsenic, cadmium, chromium, cobalt, lead, mercury, selenium, beryllium, and brominated flame retardants (BFRs). (Lincoln et al. 2007, Musson et al. 2000, and Musson et al. 2006) As a result, there are risks to human health associated with placing such products into landfills or incinerators where these hazardous elements can enter air and water streams. Electronics also tend to contain substantial quantities of precious metals such as gold, silver and platinum. The concentration of gold in a circuit board may be 40 to 800 times greater than that found in natural gold ore. (Bleiwas 2001) Therefore, mining e-waste for such metals can be more efficient than mining the earth. However, despite the potential for inherent environmental benefit in mining e-waste, historically, the high costs of separating the aggregated materials in e-waste have limited the growth of e-waste recycling markets. Thus, in the absence of legislation, e-waste recycling systems have been limited to private recycling of high-value waste with only limited, voluntary consumer participation. In the United States, it has been estimated that currently less than 20% of e-waste is being recycled. (US EPA 2007a) The remainder that is not in individuals' basements or other storage locations is being sent to landfills. Unfortunately not all of the small percentage of e-waste collected by recyclers is being handled responsibly. Significant quantities of e-waste are exported to areas of the world with lax environmental, health and safety controls, where the cost required to manually dismantle components is extremely cheap. Images taken by the Basel Action Network of unsafe treatment of exported e-waste are shown in Figure 3. Given the undocumented, and in some areas illegal, nature of such exports it is impossible to quantify the amount of e-waste which follows such undesirable paths. (Carroll 2008) However, the amount of US e-waste being exported to Asia has been estimated as between 50% and 80% of that collected for recycling. (Silicon Valley Toxic Coalition in Pontoniere 2002)

Figure 3: Images of Exported E-Waste Treatment. Source: Basel Action Network 2005.

As the sales of electronic products continue to increase worldwide, the magnitude of the potential human health and environmental problems associated with disposing of e-waste will continue to increase as well. Figure 4 below presents the growing volume of sales for some common electronic product categories in the United States as estimated by the US Environmental Protection Agency (2007b). Unless the market prices for materials recovered from electronics rise to the point where it becomes economical for businesses to recycle such goods in a safe manner, policies are necessary to prevent future human health and environmental damage.

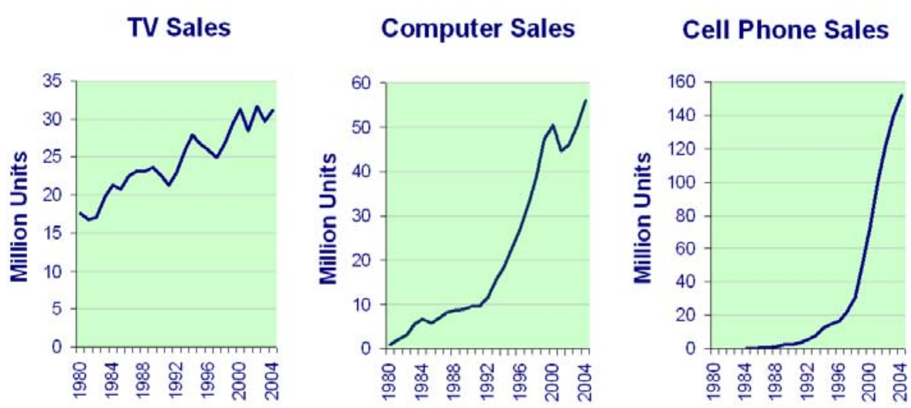


Figure 4: Growth in US sales of electronics suggests a future growth in e-waste
Data from: United States Environmental Protection Agency, 2007b, Approach 1

1.2 Optimizing e-waste system architecture remains a challenge

The fundamental goals of any e-waste recycling system are to collect e-waste so as to divert it from landfill or hazardous disposal, and process it such that its component materials are recycled. The performance of a recycling system is therefore characterized in terms of both environmental efficiency (e.g. the amount or percentage of waste recovered or reused) and economic efficiency (e.g. the costs of the recycling system). Ultimately, both environmental and economic metrics are a function of both a given recycling system architecture and the context in which the system exists. Contextual factors include the amount of waste generated, population density, labor rates, trade restrictions and other regulations. As no single architecture can provide the optimal performance in all contexts, the system architecture for a given location should be chosen with respect to its unique contextual factors.

E-waste recycling systems now exist in many locations worldwide and the amount of related legislation continues to increase. The US does not yet have national e-waste legislation, but a sparse patchwork of legislation exists at the state level. Seventy-nine (79) pieces of e-waste legislation were introduced in 33 states in 2007, compared with 54 bills introduced in 27 states in 2006. (Gast 2008) Thus, the amount of state level activity appears to be rapidly increasing. Numerous approaches to e-waste management have been proposed including landfill bans, extended producer responsibility (EPR) and consumer advance recovery fee (ARF) funded recycling systems. With the enactment of the WEEE (Waste Electrical and Electronic Equipment) directive in the European Union in 2003, all EU member states are now required to provide an e-waste system. The WEEE directive mandates that electronics manufacturers, or importers of electronics into the State, assume financial responsibility for the transportation and processing of the e-waste; as such, it is considered an EPR system. As a result of this directive, there are now many types of national e-waste systems in existence in Europe. However, despite the growing quantity of e-waste systems, there is still no consensus on how to best construct such a system. The systems currently in existence take many different forms and operate in significantly diverse contexts. There are still more differences between the systems in operation than there are similarities. Thus determining the system architecture best suited to achieve any particular set of e-waste goals remains a significant challenge.

1.3 Central Research Questions

Given the hazards associated with improperly handled e-waste and the wide variety of available solutions, policymakers are left with the question:

What is the best system architecture for collecting and treating electronic waste?

If policies are necessary to prevent e-waste from damaging human health and the environment, they want to know: What is the anticipated environmental performance of a proposed e-waste system architecture in my jurisdiction?, What are the costs associated with this architecture? and ideally, Given my constituency, which system architectures will drive the most economically-efficient and environmentally-sound material recovery?. To answer these questions, policymakers need to know how to evaluate the performance of existing systems, and furthermore, how to use this information to design new systems. One objective of this research was therefore to develop a methodology for comparing the performance of different recycling system architectures.

Studies of existing e-waste systems have suggested that their environmental efficiency can be substantially increased by simply increasing the percentage of e-waste recovered. (NERIC 2007a, UN University 2007, Ökopol 2007) For example, a 2007 United Nations University report (Table 1 in UN University 2007) estimates that on average across the EU, excluding monitors, only 27.8% of telecommunications equipment (Category 3) at end-of-life is being collected. It furthermore notes that, “The most interesting finding, however, is that there are very large differences in performance by different Member States per sub-category. This indicates that there is much room for improvement in collection performance." and "The two key environmental findings are that from an environmental point of view, it is beneficial to collect more WEEE and to treat it more effectively." (UN University 2007) Additionally, a recent press release by the Public Interest Network for WEEE stated that:

> Producers are widely using separate collection systems established by municipalities, but in most cases without paying the full price of the service. This creates unfair competition for EEE producers that are taking up their responsibility individually. In many countries, there is insufficient information about the total cost of collection, transportation and treatment of WEEE. (Martin 2008)

These quotes demonstrate a need to better understand what mechanisms can increase collection rates and their associated costs. Thus, in addition to proposing a new framework for recycling system comparison, this thesis will attempt to answer the following questions focused on increasing the quantity of e-waste collected and processed:

How do aspects of the system architecture of e-waste recycling systems influence system performance?

and specifically,

How does the system architecture of collection site density and distribution influence system performance?

The proposed answers to these questions are addressed to the policymakers, electronics manufacturers, e-waste recycling system managers, and other stakeholders who are involved in the design and operation of e-waste recycling systems. This thesis proposes both a framework for e-waste system design and evaluation, and an e-waste recycling system model which can be used to predict the performance of hypothetical e-waste recycling systems. Furthermore, this thesis argues that collection site density and distribution significantly impact e-waste system performance.

1.4 Literature Review of Existing E-Waste Recycling System Analysis

Several reports have already been commissioned by various governments and organizations to examine existing e-waste recycling systems. The majority of these reports focus on presenting an overview of existing e-waste recycling system characteristics with a discussion of possible e-waste recycling system architectures and the associated trade-offs. (US DoC Technology Administration and Office of Technology Policy 2006, Savage et al. 2006, Arcadis 2007, NEPSI 2002, NERC 2002, Ökopol 2007, UN University 2007) The US EPA (2007a) and the UN University (2007) estimate the quantity of e-waste being generated in the United States and Europe, respectively. Few, however, take the next step of making recommendations regarding the implementation of specific e-waste recycling systems. When they do make recommendations, the recommendations are typically a summary of stakeholder consensus points as to how legislation should be structured. The recommendations that do exist tend to either state broad theoretical goals (e.g., the system should treat all stakeholders fairly) or anecdotal (e.g., collection site operators should have access to a cell phone). (NERC 2002) The NERIC Patchwork Study (NERIC and NCER 2006) offer some estimations of the economic dead weight losses associated with the operation of multiple state level e-waste programs instead of a unified national program. Some of the most prominent European reports reviewing the implementation of the WEEE directive contain more specific recommendations regarding the EU-wide WEEE legislation (Ökopol 2007 and UN University 2007), but do not address how individual member state implementations might best be modified. Similarly, the UK Department of Trade and Industry (DTI) reports (UK DTI Global Watch Mission 2005 and 2006) make only high level legislative recommendations to the UK government. There is little help available for new system architects of e-waste recycling systems in determining how to best apply the lessons learned from existing systems to their own context.

Among the recommendations in the above mentioned literature, with respect to e-waste collection, the US Department of Commerce summarized the consensus of the stakeholder meeting it held in recommending that legislation should include the following content:

> • Set performance goals such as targets for percent or weight per capita for collection and recycling.
> • Provide flexibility for local and regional solutions in collection methods, such as using collection incentive payments, not mandates or a centrally proscribed collection process. (Wu 2005)

Both of these recommendations can be implemented at a government level; however they will not provide the desired outcomes if the stakeholders responsible for collection do not know how to use the flexibility prescribed in the second point to their advantage. The NERC (2002) and UNEP (2007) studies provide some guidance to e-waste operators at the local level; however there is little additional literature available to help the managers of local and regional implementations determine how to best collect their e-waste. The lessons learned from other, more traditional, forms of recycling (bottles, cans, paper, tires, etc) can supplement the advice available in e-waste literature. For example, an Ohio EPA study (Ohio EPA 2004) of drop-off recycling participation and performance provides useful benchmarks for individuals' likelihood to participate in mandatory drop-off recycling programs. However, the most commonly recycled household products are typically made from a single material and thus are easier, and less costly, to recycle than complex electronic goods. Therefore such studies may be applicable to e-waste recycling participation rates, but not necessarily costs. Participation data specific to e-waste recycling is very limited. Most notably, Nixon (2007) presents results from a survey of California households regarding their willingness to recycle e-waste and (Bohr 2007) estimates the costs associated with e-waste collection points from numerous interviews of collection station personnel.

This literature review suggests a need to help those people implementing an e-waste system predict the performance of systems with different architectural options in their context. The proposed framework and model for analyzing recycling systems are generalizable to a number of different cases; however this document will focus on how they can be used to evaluate options regarding the physical sites of collection centers.

1.5 Literature Review of Recycling System Modeling

Reverse logistics models have been previously generated to analyze how products can be collected efficiently, thus allowing for future reuse, remanufacturing, or recycling. Fleischmann et al. presented an overview of existing recovery models, and found that "nearly all the models proposed so far are one-product, one-component models." (Fleischmann et al. 1997) For example, Realff, Ammons, and Newton (2004) modeled the economic implications of operating a used carpet recovery system within the US using a known list of potential collection and processing site locations. This model has more than one component, but relates to only one, single-material waste type. Fleischmann et al. also compares general characteristics of product recovery networks with traditional logistics structures and moreover derives a classification scheme for recovery networks. (Fleischmann et al. 2000)

With respect to end-of-life product processing, modeling efforts have focused on a variety of different approaches, from manual disassembly to mechanical separation, examining which processing approaches and related operating parameters should be used. Boon et al. (2003) models the profitability of recycling car bodies as a function of the car's material composition, and the processor's choice of how many parts are manually disassembled before shredding. Models for determining the economically optimal processing sequence for material recovery are presented in Sodhi, Young and Knight (1999) and Johnson and Wang (1998).

Some works have investigated the costs of complex durable goods (CDG) recycling more comprehensively, focusing on entire facilities or systems operating in a particular geographical or operational context. For example, work by Kang and Schoenung (2006) uses a technical cost model to examine the costs and revenues associated with the operation of a full e-waste recycling system in California. Using scenario-based cost models, Caudill et al. (2003) examine an electronics recycling system in the Seattle-Tacoma urban area in Washington State, specifically analyzing the effectiveness of various collection approaches, for example collection at a central drop-off facility versus collection at 20 "big box" stores. In work by Bohr (2007), recovery of WEEE in Europe is modeled, with economic models approximating a central European system.

The e-waste system model presented in this thesis aims to extend the above research to enable quantification of both the economic and environmental performance of electronics recycling systems for arbitrary instances of system context and system architecture. This flexibility enables the analysis of a variety of different systems, from the different state systems in the United States to the different country systems in the European Union. In addition, and perhaps more importantly, this flexibility allows for theoretical systems to be modeled and evaluated in a given context. As more states and countries design and implement electronics recycling systems, this ability to evaluate theoretical systems, and the effects of system input choices on these systems, will help to provide insights into critical system design decisions prior to implementation.

Furthermore, the models presented here take a broad system view, both in terms of the system functions considered, and in terms of the stakeholders considered. Explicitly accounting for the economic and environmental impacts of different stakeholders – from the consumers who generate end-of-life electronics to the consolidators who collect electronic waste to the system managers who oversee the system – provides a level of disaggregation that allows systems to be evaluated with regards to both their overall impacts as well as their impacts on particular stakeholders. A similar disaggregation of functions and stakeholders was developed in previous work by Gregory and Kirchain (2007).

1.6 Methodology Overview

In pursuit of answers to the proposed questions in Section 1.3, this work employs a two-part methodology. First, a framework for comparing recycling system is presented that builds upon previous work by Gregory and Kirchain (2007). As shown under Methodology Part 1 in Figure 5, this framework organizes data from empirical studies of existing systems into system architecture, context, and performance categories. The performance of recycling systems, normalized by context, can then be examined as a function of architectural choices. This framework is fully described in Chapter 2. One result of using this framework was learning that both due to the lack of data, and the variety of system architectures in existence, empirical data alone is insufficient to answer the central research questions of this thesis. A recycling system model was therefore developed using the data gathered for the empirical studies. This model is used to predict how changes in system architecture or context affect the performance of a recycling system. The overall recycling system model is comprised of three smaller models:

1. a collection model, which projects the mass of e-waste collected, cost of operating collection sites and the costs and environmental impacts of transporting e-waste as a function of the geo-economic context and the chosen number of available collection and processing points;
2. a processing model, which calculates the amount of various materials recovered from the recycling process and the associated revenues and costs to the system;
3. a management and financing model, which accounts for the overhead costs of operating an e-waste system.

The relationship between each of these smaller models and the associated inputs and outputs of each is depicted under Methodology Part 2 in Figure 5. These models are intentionally meant to be both broad, in order to address entire recycling systems, and general, such that many different systems, both real and hypothetical, can be analyzed. These models are fully described in Chapter 3. The conclusions derived from testing both the comparison framework (Chapter 2) and the system models (Chapter 3) are discussed in Chapter 4.

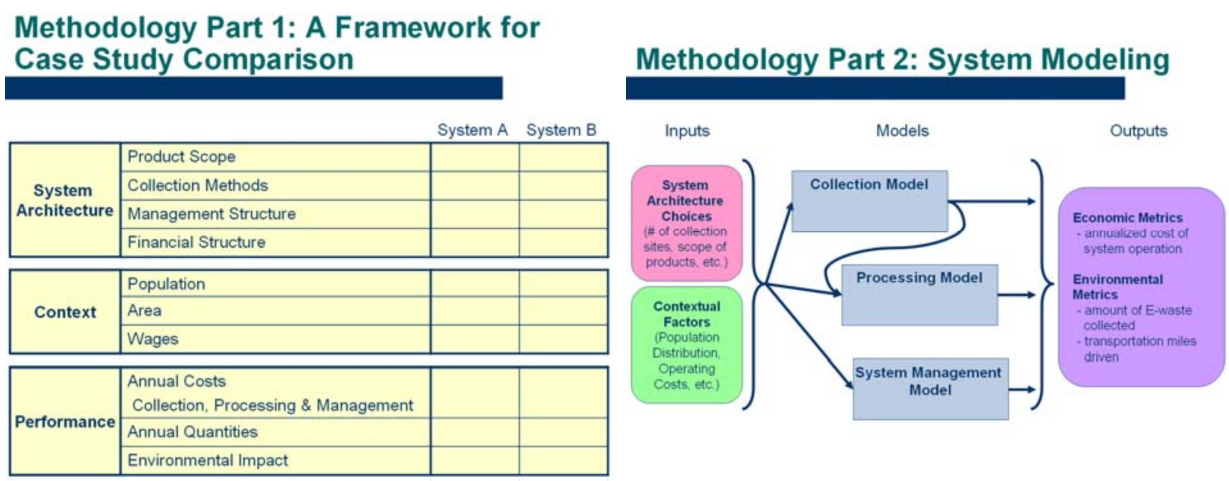


Figure 5: Overview schematics for the 2-part research methodology employed.

2 A FRAMEWORK FOR COMPARING RECYCLING SYSTEMS

Recycling systems differ in the scope of products they collect, how products are collected, how they are processed, how they are financed, the geography they cover, the labor rates paid to employees and many other important details. Given these many variable components of recycling systems, it is hard to compare existing systems. To aid the process of comparison, a framework for describing the characteristics of recycling systems is outlined in Figure 6. This framework groups system characteristics and performance metrics into 3 categories: System Architecture, Context, and Performance. System Architecture describes the design characteristics of the e-waste system. Contextual factors define the geo-economic landscape in which the e-waste recycling system operates, and unlike system architecture, cannot be directly modified. Finally, performance metrics are used to evaluate the system. A successful e-waste recycling system will achieve environmental goals with economic efficiency. Therefore, proposed performance metrics include an economic analysis of system costs, the quantity of goods processed, and measures of environmental impact such as energy usage. This chapter will outline the primary characteristics of recycling systems, and explain how these characteristics are organized into the proposed framework. Then data describing five European countries, three American states, and one Canadian province are applied to the framework to demonstrate its utility.

Framework for Comparing of Recycling Systems

		System A	System B
System Architecture	Product Scope		
	Collection Methods		
	Management Structure		
	Financial Structure		
Context	Population		
	Area		
	Wages		
Performance	Annual Costs Collection, Processing & Management		
	Annual Quantities		
	Environmental Impact		

Figure 6: An outline of the framework proposed for comparing recycling systems. The characteristics of a recycling system are organized into 3 categories: system architecture, context, and performance.

2.1 Characteristics of Recycling System Architectures

Within the category of system architecture, there are a wide range of solutions available to system architects to satisfy desired system functions. This multitude of options results in a diverse set of potential (and, in fact, extant) system architectures. The primary options available to system architects can be categorized into product scope, collection methods, management structure, and financial structure. Each of these four categories will be further defined within this chapter. The majority of the sources for the data within this chapter are organized in Figure 7. In addition to the four major architectural categories outlined here, e-waste recycling systems may differ in their choice of transportation logistics and physical processing methods chosen for reuse, recovery, and recycling of the material. The implications of these transportation and processing decisions are beyond the scope of this thesis.

To supplement the information presented here, the following literature is recommended for those interested in learning more about the range of possible system architectures.

- US DoC Technology Administration and Office of Technology Policy (2006)
- Savage, M., S. Ogilvie, et al. (2006)
- Ökopol et al. (2007)
- UN University (2007)

2.1.1 Product Scope

Electronic products vary in hazardous content, high-value content, and ease of recycling. As a result, the scope of products accepted for recycling within current e-waste recycling systems also varies widely. As such, the scope of products included in current e-waste systems varies significantly. For example, the European Union now requires the recycling of a broad group of electronic products. The WEEE directive of the European Union, defines 'EEE' as "equipment which is dependent on electric currents or electromagnetic fields in order to work properly" (The European Parliament and the Council of the European Union 2003), but is colloquially described as "anything with a cord." Thus, each EU member country must handle all types of e-waste, but may choose to separate certain types of e-waste into different systems. For example, in the Netherlands, ICT-Milieu handles the Category 3, IT and Telecommunications Equipment, while NVMP is responsible for all other categories of Dutch e-waste. In other locations around the world, the scope of e-waste products handled within mandated systems is much smaller. The US state of Maine began a system in January 2006 which only collects display devices including TVs, computer monitors, and laptop computers. As some product types are more profitable to recycle than others, the scope of products included in an e-waste system will have a significant impact on the system costs. Likewise, the environmental benefits realized through the operation of an e-waste system are dependent upon the scope of products included.

2.1.2 Collection Methods

Table 2: Common Options for e-Waste Collection

- Permanent Drop-Off Sites with Regular Hours
- Special Collection Events
- Retail Stores
- Regular Curbside Pick-Up
- As-needed Scheduled Pick-Up

Before a processor can recover materials from e-waste, the e-waste must first be collected from those ready to dispose of it. Thus, these individuals must be aware of and choose to participate in an e-waste recovery system rather than dispose of their e-waste in their traditional trash.

Existing collection methods offered for household waste are often different from those available to businesses. A system architect may include e-waste collection as a part of regular curbside pickup within a municipality, require consumers to bring their e-waste to designated drop-off collection points, use retail stores for new electronics as collection points, have products shipped back to their original manufacturer, or any combination of these methods. Curbside pick-up of household e-waste is rare, but several existing e-waste systems require each municipality to provide a local collection point. Most often, this results in adding e-waste to the scope of products already collected at existing recycling or transfer stations.

Where retailers are used as collection centers, some jurisdictions require that all electronics retailers collect all e-waste, whereas others only mandate collection of waste from current customers. In Switzerland, all electronics retailers are required to take-back, free-of-charge to the customer, all household waste electronic goods brought to them. (SWICO

Recycling Guarantee 2006) In Portugal and the Netherlands, retailers are only required to accept waste items from customers who are either buying a new similar item from that store, or can prove that the waste item was originally purchased in that store. (NEPSI 2002)

2.1.3 Management

Table 3: Common Options for e-Waste Management

• Government Entity
• Third Party Organization
• Associations of Electronics Manufacturers
• Associations of E-Waste Processors/Recyclers

Every recycling system has some form of management structure responsible for coordinating both the monetary and material flows through the system. This can be done by producers, recyclers, governmental entities, or third party organizations. System management responsibilities can include establishment and collection of recycling fees, contracting transportation logistics firms and processors, setting and enforcing processing standards, enforcing sales bans (for noncompliant producers), and advertising to increase public awareness of and participation in the system. Systems often differ with respect to the number of transportation, processing, and other options they provide to those held financially responsible. For example, Sweden requires all logistics and processors be hired through El-Kretsen, the Swedish e-waste system manager, whereas Germany has over 20 system managers each choosing their own logistics and processing providers. Thus, in Sweden, the electronics manufacturers held responsible for the majority of the e-waste system finances must pay the bills distributed by El-Kretsen if they wish to sell their products in Sweden. In Germany, the producers may choose to participate in any one of several e-waste recycling systems. There is disagreement over whether competitive structures such as that in Germany are more or less economically efficient than a consolidated structure such as Sweden's. (US DoC Technology Administration and Office of Technology Policy 2006)

2.1.4 Financial Structure

Table 4: Common Options for e-Waste Financial Structures

• End of Life (EOL) Fees ("Pay as you Throw")
• Advance Recovery Fees (ARF)
• Extended Producer Responsibility (EPR)
• Collective Producer Responsibility (CPR)
• Individual Producer Responsibility (IPR)

For many electronic products, the value of the materials recovered through recycling is not enough to cover the costs of such processing. Thus, most e-waste systems require external funding to operate. Recycling systems may be financed directly by the government, by the consumers of electronic products, either at the time of product purchase or product disposal, or by the manufacturers of the products.

End-of-life (EOL) consumer fees are used in many areas of the United States, such as Massachusetts. Alternatively, locations including California and Switzerland use Advance Recovery Fees (ARFs) to collect money from consumers at the time of the new product's purchase. Switzerland's SWICO e-waste system was originally financed by EOL fees, but switched to an ARF system in 2003.

Extended producer responsibility (EPR) systems hold manufacturers responsible for financing specific aspects of the e-waste recycling system. Within EPR systems, there are a variety of ways in which the manufacturers can fund the system. Most existing European collection systems allow multiple producers to share responsibility for their collective waste, which is referred to as collective producer responsibility (CPR) and is a specific type of EPR. Thus, rather than holding each producer responsible for only those goods which that producer manufactured, producers may band together in order to manage their collective, unsorted goods.

Collective producer responsibility organizations have the potential to achieve greater financial economies of scale than manufacturers operating individually. Sweden and Germany use collective responsibility models whereby manufacturers periodically split the current costs of the e-waste system according to their share of current market sales. Other systems, such as NVMP in the Netherlands, simply tax each new electronic item as it is brought into the country for sale.

Conversely, Maine, in the US, applies the principles of individual producer responsibility (IPR), tallying the brand of each waste product collected and then charging the manufacturer for its unit share of the current waste. Any brand documentation or sorting of collected products adds cost to a collection system, but has the potential to incentivize design for recycling by holding producers individually accountable for the end-of-life treatment of their own products. Like Maine's system, ICT-Milieu in the Netherlands once charged manufacturers according to the brands of equipment collected. However, in 2003, ICT-Milieu switched to a current market share model amid member company complaints regarding the high costs associated with the original system. (US DoC Technology Administration and Office of Technology Policy 2006)

2.2 Testing the Framework: A comparison of existing e-waste systems

2.2.1 Selecting Empirical Data for Analysis

Empirical data from existing electronics recycling systems in five European countries, three American states, and one Canadian province was collected and applied to the evaluation framework to test its utility. From those jurisdictions which have made their performance data available, this specific data set was chosen to demonstrate the variety of architectural options in use.

The European countries included in the test of the framework are Belgium, the Netherlands, Norway, Sweden and Switzerland. The North American systems included are those in the US States of California, Maine, Maryland and the Canadian province of Alberta. Together these systems cover a variety of possible architectural and contextual variables. Switzerland's SWICO system is the oldest national e-waste recycling system in the world, having begun operation in 1994. Conversely, Maine and Maryland both began their state-wide e-waste recycling systems in 2006, and represent the newest e-waste systems for which performance data was available. E-waste systems financed with advance recovery fees are represented here by Switzerland, California, and Alberta, whereas each of the other systems chosen is primarily financed by manufacturers. Chosen systems requiring that retail electronics stores collect e-waste regardless of whether or not a new sale is made include Norway's Elretur and

Switzerland's SWICO. The Netherlands' ICT Milieu and Belgium's Recupel only require free take-back from customers purchasing new equipment, and the other systems chosen do no systematically use retail stores as collection centers at all. Interestingly, although El-Kretsen does not use retail stores for collection, it is known for annually collecting the greatest mass of e-waste per capita in the world. (UK DTI Global Watch Mission 2006) Regarding the scope of e-waste collected, Elretur in Norway, El-Kretsen in Sweden, and Recupel in Belgium are each responsible for handling all types of e-waste, whereas each other system handles only a fraction of electronic waste product types. The scope of e-waste collected in the North American jurisdictions is considerably smaller than the scope of any of the European countries studied. All 5 of the European systems examined are similar in that for each type of e-waste there is only one e-waste recycling system available. Within these systems there is competition among the companies hoping to provide transportation and processing services. However, the existing system has a monopoly on administering the e-waste system itself. This is common to among the systems established in Europe prior to the EU WEEE Directive. As of this writing, performance data was not yet available for national e-waste recycling systems, such as those in Germany and Portugal, where multiple systems are competing to manage e-waste within an e-waste category. There are unique aspects of each system, but describing them is difficult in the absence of a structured framework.

2.2.2 Applying Empirical Data to the Framework

Data describing the context, system architecture, and performance of each system were collected from a variety of sources listed in Figure 7. These sources included the websites for each system, annual reports, published literature reviews of e-waste systems, government statistics, and personal discussions with system managers and affiliated government representatives. Obtaining comparable data for each location was difficult and required the compilation of many sources. Financial data beyond the fees charged to consumers and producers was particularly difficult to obtain. Most existing e-waste systems are currently not publicly disclosing the costs associated with their operation. Selections of the data collected and their sources are shown in Figure 7.

Using the table in Figure 7, differences in system performance relative to system architecture and contextual factors can be examined for insight into the influence of system architecture options on system performance. As an illustration of the utility of the framework, this thesis will focus specifically on identifying the factors which influence an environmental metric, the quantity of e-waste collected by each system. This method of comparison provides insight into the relative performance of systems and allows system architects to incorporate new information into the design of their systems.

Comparison of Recycling Systems - 2006 Data

				Switzerland SWICO	Sweden (EU) El-Kretsen	Netherlands (EU) ICT Milieu	Belgium (EU) Recupel	Norway Elretur	California USA	Maine USA	Maryland USA	Alberta Canada
System Architecture	Product Scope	WEEE Category 3. IT and telecommunications equipment	*Monitors*	✔	✔	✔	✔	✔	✔	✔	✔	✔
			Laptops	✔	✔	✔	✔	✔	✔	✔	✔	✔
			Desktops	✔	✔	✔	✔	✔			✔	✔
			Other	✔	✔	✔	✔	✔			✔	✔
		WEEE Category 4. Consumer equipment	*TVs*	✔	✔		✔	✔	✔	✔	✔	✔
			Other	✔	✔		✔	✔				
		All other EU Categories of WEEE (1,2,5-10)			✔		✔	✔				
	Collection Methods	Retail Store Take-Back?		Yes	No	Old for New	Old for New	Yes	No	No	No	No
		Total # of Collection Points		~6,000	950	~7,000	2904	2500	442	160	18	223
		# of Non-Retail Collection Points		431	950	605	537	unknown	442	160	18	223
	Financial Structure	Who finances the majority of the system?		Consumers (ARF)	Producers	Producers	Producers via ARFs	Producers	Consumers (ARF)	Producers	Producers & Government	Consumers (ARF)
Context	Population	Population	(million)	7.5	9	16.3	10.5	4.7	36.4	1.3	5.6	3.4
		Poulation Density	(per square km)	190	22	489	348	15	90	16	174	5
	Area	Area of Jurisdiction	(sq km)	39,770	410,934	33,883	30,278	307,442	423,971	91,647	32,134	640,045
	Wages	Average Recycling Wage (2004 values)	USD/hour	26.34	14.98	16.34	14.74	23.11	13.46	10.04	15.01	12.54
	Timing	Date each program began operating		1994	Jul-01	Dec-99	Jul-01	Jul-99	Jan-05	Jan-06	Jan-06	Oct-04
Performance	Estimated Annual Costs (Financial)	Collection	(USD/kg)	0.05	unknown	unknown	0.06	unknown	↑	unknown	↑	0.04
		Transportation	(USD/kg)	0.13	unknown	unknown	unknown	unknown	0.37	unknown	0.17	0.07
		Processing	(USD/kg)	0.41	unknown	unknown	unknown	unknown	0.55	0.26	↓	0.59
		System Management	(USD/kg)	0.09	unknown	unknown	unknown	unknown	0.15	0.11	0.08	0.11
		Total Annual Cost (estimated)	(USD/kg)	0.68	N/A	N/A	N/A	N/A	0.70	N/A	0.08	0.81
			(USD)	29 million	N/A	N/A	N/A	N/A	61 million	N/A	unknown	2.3 million
	Annual Quantities (Environmental)	Amount of Category 3 Waste Collected	(million kg)	28.1	27.6	18.1	12.2	10.9	16.8	0.5	0.8	1.9
			(kg per person)	3.8	3.0	1.1	1.2	2.3	0.5	0.4	0.1	0.5
		Total Amount of WEEE Collected	(million kg)	42.1	149.9	18.1	76.1	68.3	58.1	1.8	2.9	2.9
			(kg per person)	5.6	16.5	1.1	7.2	14.6	1.6	1.4	0.5	0.8

Figure 7: A comparison of e-waste recycling systems in 2006 using the proposed framework. California and Maryland were assumed to have the same percentage of Category 3 e-waste in their total e-waste collected as Maine.

Contextual data from:
US CIA (2008)
US Census Bureau (2006)
Eurostat (2007)
LABORSTA (2008)
US Department of Labor (2004)
Statistics Canada (2006a)
Statistics Canada (2006b)

European System Architecture and Performance Data from:
El-Kretsen (2007)
SWICO Recycling Guarantee (2006)
ICT Milieu (2007)
Recupel-ICT (2006)
Elretur (2007)
Ökopol (2007)
UN University (2007)
NEPSI (2002)
UK DTI Global Watch Mission (2006)
Savage et al. (2006)

North American Architecture and Performance Data System Data from:
Gregory and Kirchain (2007)
Gregory and Kirchain (2008)
NERC (2002)
US DoC Technology Administration and Office of Technology Policy (2006)
NERIC (2006)
NERIC (2007b)
NERIC and NCER (2007) – Slide 39/54
Alberta Recycling Management Authority (2007a)
Alberta Recycling Management Authority (2007b)

2.3 Analysis of Empirical Data

Before comparing performance metrics of each system, it is important to note some of the differences between each system's architecture and context shown in Figure 7. Contextually, of the systems being compared, California's system covers by far the largest population, yet has a lower than average population density. The geographical areas of California, Sweden, Norway and Alberta are also an order of magnitude larger than those of the other systems. As will be demonstrated in Chapter 3, within most existing system architectures, the costs of operating collection sites and processing e-waste are dominated by labor. Thus, differences in average wages between jurisdictions can significantly influence a system's economic performance. At over 20 US Dollars per hour, Switzerland and Norway pay workers a much larger average wage than the other jurisdictions studied.

With respect to system architecture, the scope of products collected by the North American systems is much smaller than that of the European systems. California and Maine both limit their collection to display devices (TVs, monitors and laptop computers). Maryland adds desktop computers to this list and Alberta adds both desktop computers and other peripheral equipment, primarily printers. The European systems studied here additionally include all other telecommunications equipment (computer accessories, telephones, fax machines, etc) in their scope. With respect to collection methods, the group of systems evaluated here represents three different options for using electronic retail stores as collection points. Switzerland and Norway require that electronic retailers take-back, free of charge to the individual, all e-waste brought to them, whereas the Netherlands and Belgium only require this for customers purchasing new items. Sweden and the North American systems do not systematically use the retail stores at all. Of the nine systems evaluated, Sweden does, however, provide the largest number of non-retail collection points. Non-retail collection points includes any non-retail location in which e-waste can enter the system; most non-retail collection points are existing municipal waste disposal sites where e-waste is also accepted. The number of collection points is an important architectural choice as it determines the level of convenience provided to individuals eligible for using the e-waste system. Research has shown that the more convenient recycling is, the more likely people are to recycle. (Ohio EPA 2004 and Nixon et al. 2007) Finally, with respect to financial structure, Switzerland, California and Alberta are primarily financed with consumer ARFs, whereas the rest of the systems evaluated are primarily financed by the electronics producers.

Figure 8 depicts a normalization of the total number of non-retail collection points used in each system to the contextual variables of population and geographic area. The geographic area of the Netherlands is approximately the same as that of Switzerland, and both provide several thousand collection points. However, given that the population of the Netherlands is more than twice that of Switzerland, SWICO provides many more collection points per person than ICT-Milieu. Per person, SWICO provides a significantly greater number of collection points than any of the other systems. However, per unit area, the Netherlands' ICT-Milieu provides the most collection points. The low population density of Sweden and Norway is readily apparent in that their systems have a comparable number of collection points per person compared to the other European systems, but have very small numbers of collection sites per area. All of the North American systems currently provide many fewer collection sites for e-waste with respect to both population and area. This fact may be primarily attributable to the nascency of these systems. The number of collection points within the European e-waste systems generally grew over time, and it is not unreasonable to think that the North American systems will likewise increase their numbers of collection points. Given the hypothesis that participation increases with the availability of collection sites, the data in Figure 8 suggests that Switzerland should be collecting the most e-waste, and furthermore that the European systems generally should collect more e-waste than the North American systems.

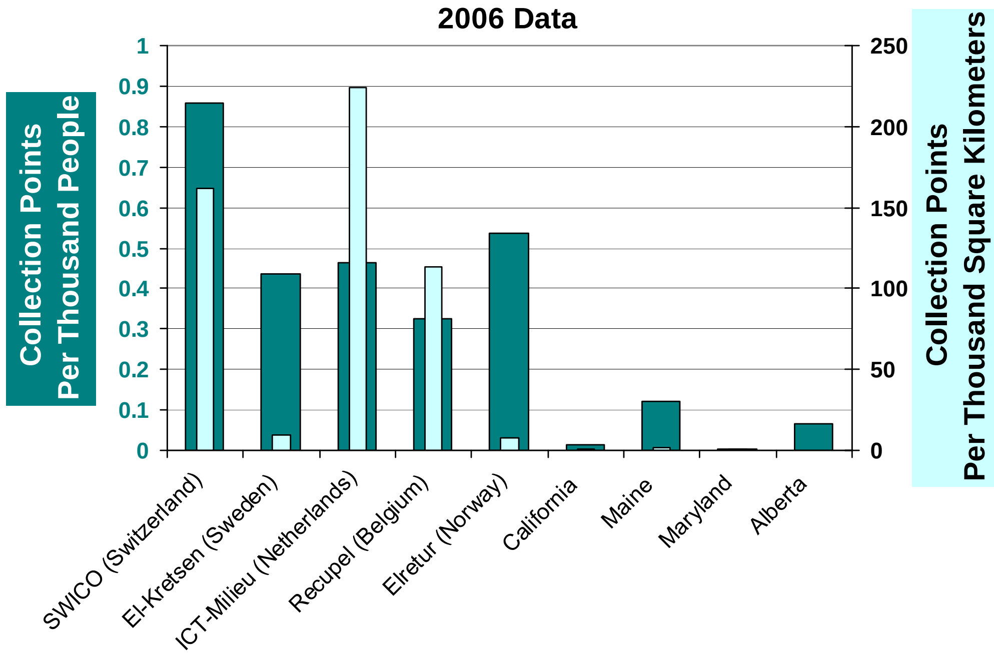


Figure 8: E-waste collection points provided per capita and per unit area. The wide, dark bars correspond to non-retail collection points per thousand people shown on the left axis. The narrow, light bars correspond to non-retail collection points per thousand square kilometers shown on the right axis.

Having examined contextual and architectural differences between the systems, the system performance can now be examined. A simple, and commonly used, metric of environmental performance is mass collected per capita. Figure 9 shows this metric for each of the nine systems on an annual basis since 1994, when the first e-waste system began operation in Switzerland. The mass of waste collected in each system is normalized by the population of that region in the year the waste was collected. In order to compensate for differences in the scope of products collected by each system, only the mass of products which belong to the EU-defined category 3 E-Waste, IT and Telecommunications Equipment, is included. The Netherlands' ICT-Milieu only collects category 3 equipment and thus, this category was chosen as the greatest common scope of each country-wide system. This category includes notebook and desktop computers, monitors, printers, other computer accessories, telephones and fax machines. None of the US State systems are currently accepting all of the items which fall into this category under the EU definition. However, they do all accept computer monitors, which dominate the mass collected in this category in all systems. Estimated masses of the most common category 3 e-waste products are listed in Table 5

The percentage of e-waste collected in California and Maryland that falls under WEEE category 3 is not published, whereas it is published for Maine. Therefore California and Maryland were assumed to have the same percentage of category 3 e-waste in their total mass collected as Maine. (NERIC 2006 and NERIC 2007b) This, however, may be an underestimate of the category 3 quantity in Maryland because Maryland collects desktop computers and peripherals, which are category 3 items that Maine and California do not collect. The exact percentage of category 3 e-waste in Norway was unknown for the years 2004 and 2006, but was assumed to maintain the average 16% by mass of their total e-waste observed from 2000 to 2005. (Elretur 2001, 2002, 2003, 2004, 2006) Over these same three years (2004-2006), Sweden and Belgium's systems collected comparable equipment with category 3 percentages of 16-18%, and 14-16% respectively. (El-Kretsen 2005, 2006, 2007 and Recupel-ICT 2006)

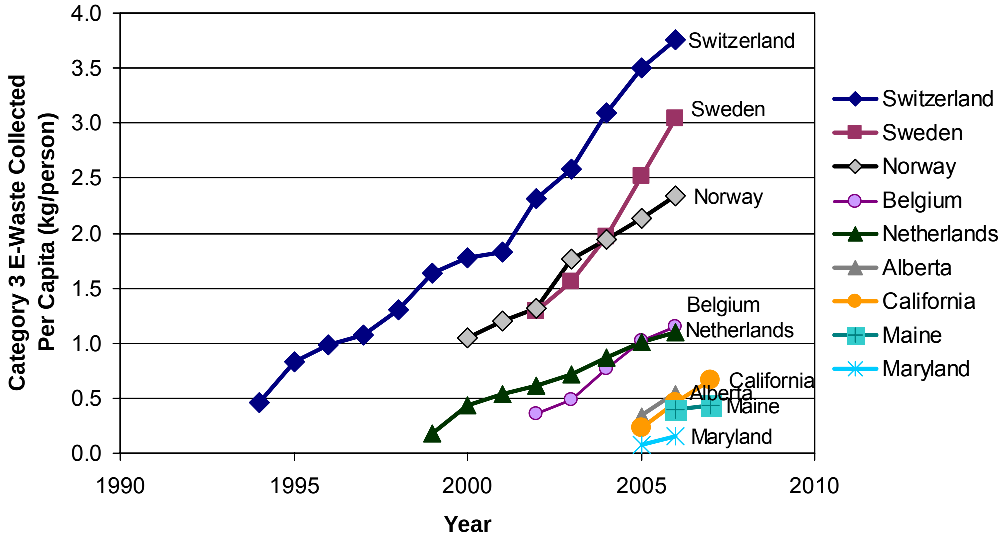


Figure 9: Mass (in kg) of category 3 (telecommunications) waste collected per capita on an annual basis.

Table 5: Mass Estimations for Category 3 Electronic Products. (US EPA 2007a)

	Average Product Mass (kg)
CRT Monitors	18.14
CPUs	9.98
LCD Monitors	7.26
Laptops	3.63
Peripherals	6.80

Figure 9 demonstrates that all existing systems, even Switzerland's SWICO which has been in operation since 1994, are continuing to increase the average amount of e-waste they are collecting per person. However, it is not readily apparent if this result is an artifact of increasing collection effectiveness in each system or due to an increasing consumption and disposal of electronics products. To answer this question, Figure 10 shows the mass of category 3 e-waste collected in each jurisdiction normalized by the number of PCs in use in each jurisdiction. "PCs in use" refers to the total number of personal computers, new and old, that have not yet reached their end-of-life, in a given country during a particular year. (Euromonitor International 2008) The rate of growth in computer usage per capita over time is similar in all jurisdictions. PCs in use was chosen as a representative metric of the amount of electronics in use in each jurisdiction, even though the e-waste systems collect products other than PCs. This scale does however provide insight into the relative quantities of electronics in use in each jurisdiction.

A time lag corresponding to the lifetime of computers is expected between growth in usage of electronic equipment and retirement of that equipment. Because PCs in use includes both old computers and ones just recently purchased, the average time to end-of-life for PCs in use will be less than the 7 years frequently used as an estimate of the total lifetime of a computer system. (US EPA 2007b) Therefore, Figure 10 presents the mass of Category 3 E-Waste collected normalized by the quantity of PCs in use in each jurisdiction both 3 years and 5 years earlier. Notably, the figures for both the 3 and 5 year delay show comparable trends: slower annual growth rates than those observed in per capita mass collection. This indicates that e-waste mass, at least within this context, is growing roughly in step with the rate of consumption of new electrical and electronic equipment.

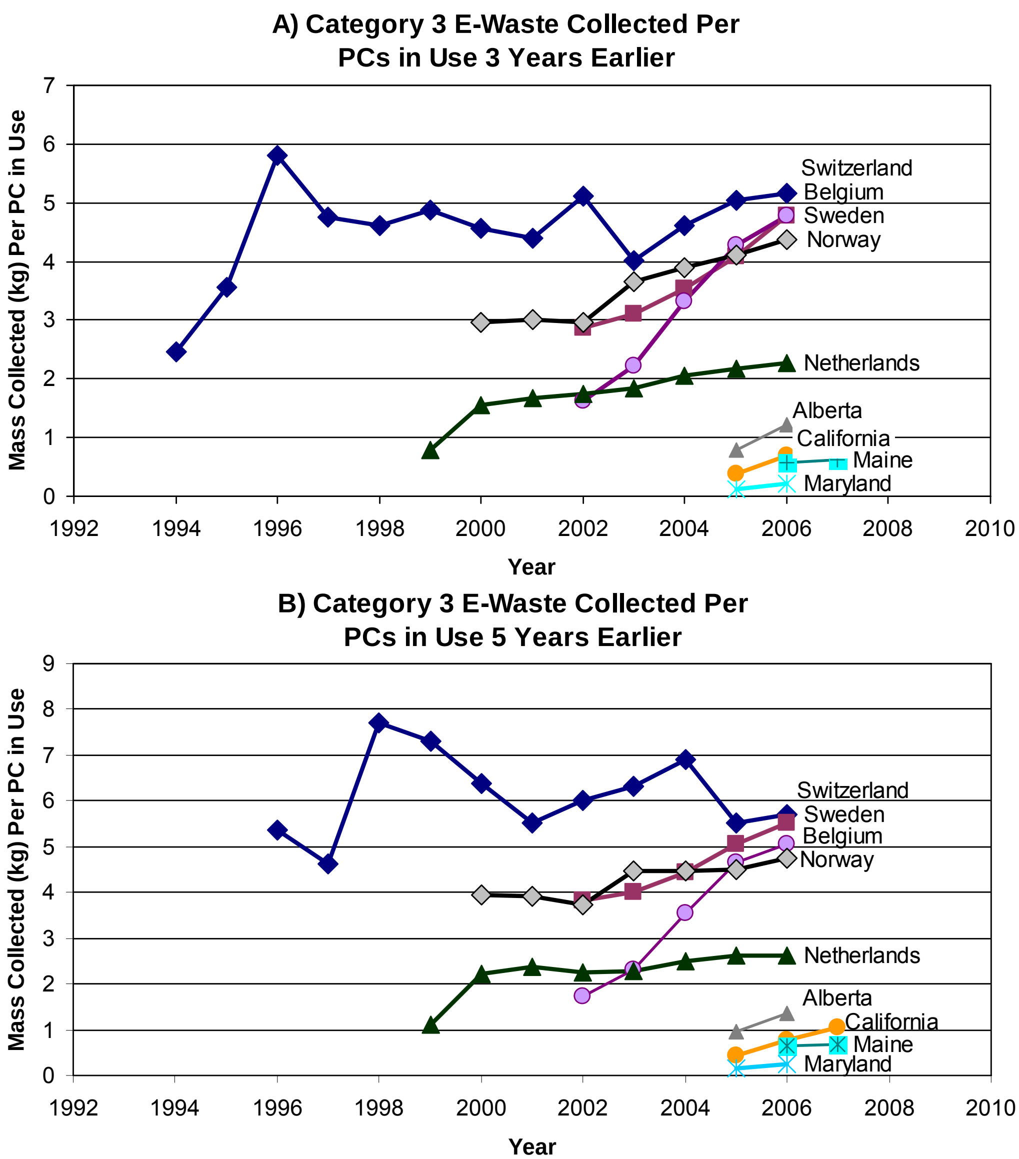


Figure 10: Mass (in kg) of Category 3 E-Waste collected on an annual basis per PCs in Use 3 and 5 years earlier. The number of PCs currently in use is an indicator of the quantity of electronics which will be retired in the future. In A) the mass of category 3 e-waste collected each year is divided by the quantity of PCs estimated to have been in use 3 years earlier. In B) a 5 year time delay is applied. Both A) and B) show the same general trends within each system.

Unlike Figure 9, Figure 10 suggests that collection in Switzerland and the Netherlands, two of the oldest systems, has reached a plateau relative to the amount of PCs in use, an indicator of e-waste available. However, Belgium's collection rate, and to a lesser extent Sweden's collection rate, appears to still be growing rapidly. Over the last few years, the e-waste collection systems in Belgium and Sweden have dramatically increased the amount of Category 3 equipment collected relative to that in use. With only two or three years of collection data currently available, little can be observed with respect to the American systems other than the fact that they appear to be gradually increasing collection relative to computer use as well.

In order to determine if these quantities collected are influenced by the availability of collection points, the performance data (mass of e-waste collected per capita) from Figure 9 is combined with the architectural data (number of collection points available) from Figure 8 to produce Figure 11 and Figure 12. Figure 11 and Figure 12 are identical other than Figure 12 displays multiple years of data whereas Figure 11 only displays data for the year 2006. Figure 11(A) and Figure 12(A) depict mass collected per capita plotted against the number of non-retail collection sites available normalized by population, whereas Figure 11(B) and Figure 12(B) show mass collected per capita plotted against the number of non-retail collection sites available normalized by geographic area. Furthermore, Figure 11 presents only data from 2006 whereas Figure 12 presents multiple years of data. Systems at the top of these graphs have collected the most Category 3 e-waste per capita.

Generally speaking, it is safe to assume that the goal of e-waste systems is to collect as much e-waste as possible. Therefore systems desire to be as far up the vertical axis as possible. Given that there is a cost associated with running each collection site, it is desirable to collect e-waste with as few collection sites as possible. However, it is unlikely that any systems will be plotted in the upper left portion of these graphs because systems often require more collection sites (movement to the right) in order to collect more e-waste (movement up). Figure 12 demonstrates how several systems have increased the mass of e-waste collected over time. Each data point for a system represents one year of data, with the highest collection amount corresponding to the most recent data available (either 2006 or 2007 as indicated). This figure shows that several systems have been able to increase the amount of waste collected each year without increasing their number of collection points substantially. In fact, Norway has increased the amount of e-waste collected while reducing the number of collection points available over time. However, despite the upward trend each system shows with time, all of the systems remain clustered in the lower-right half of the graph. This suggests that there is still a limit on the amount of e-waste that can be collected for any number of collection points, and this limit does increase as the amount of collection sites increases.

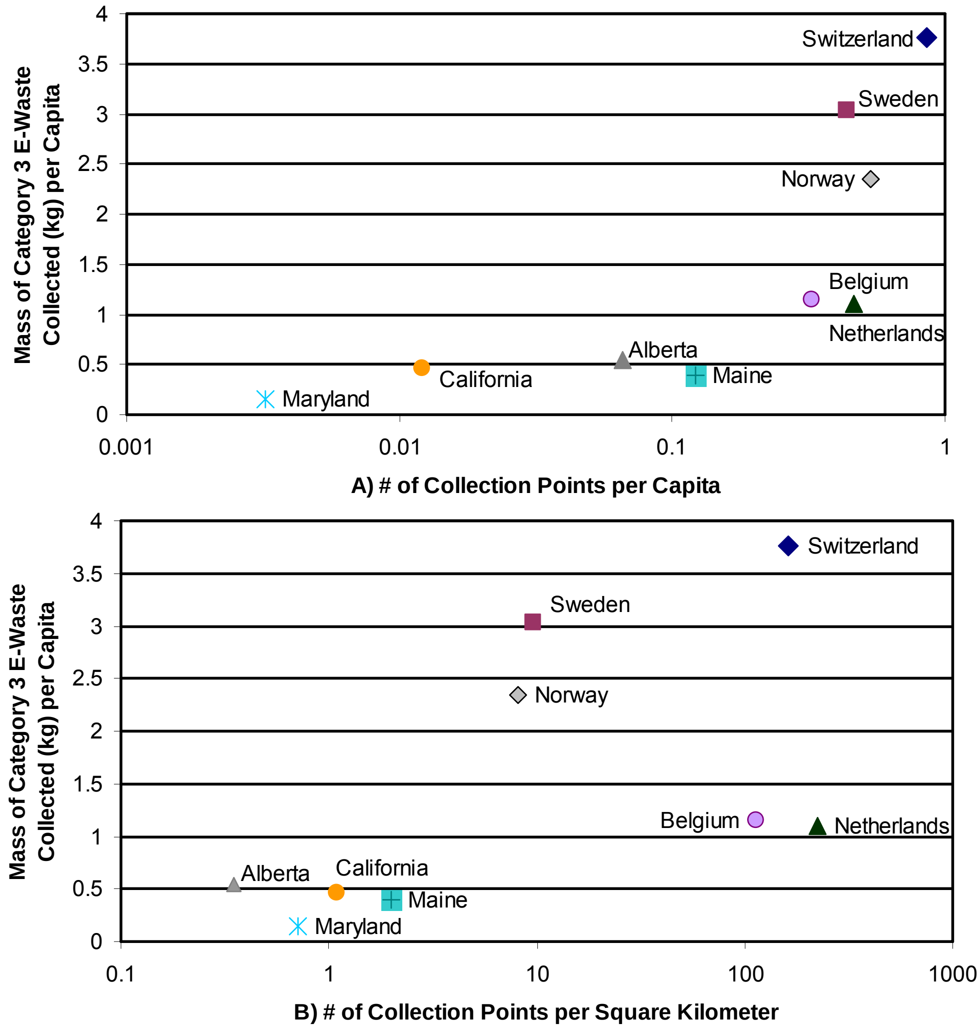


Figure 11: Mass of Category 3 E-Waste (kg) per capita collected in 2006 vs. the number of collection points in 2006. In (A), the number of collection points is normalized to population, and in (B) points are normalized to area. Note: These graphs are plotted on a semilog scale in order to visualize differences in the values for the North American systems.

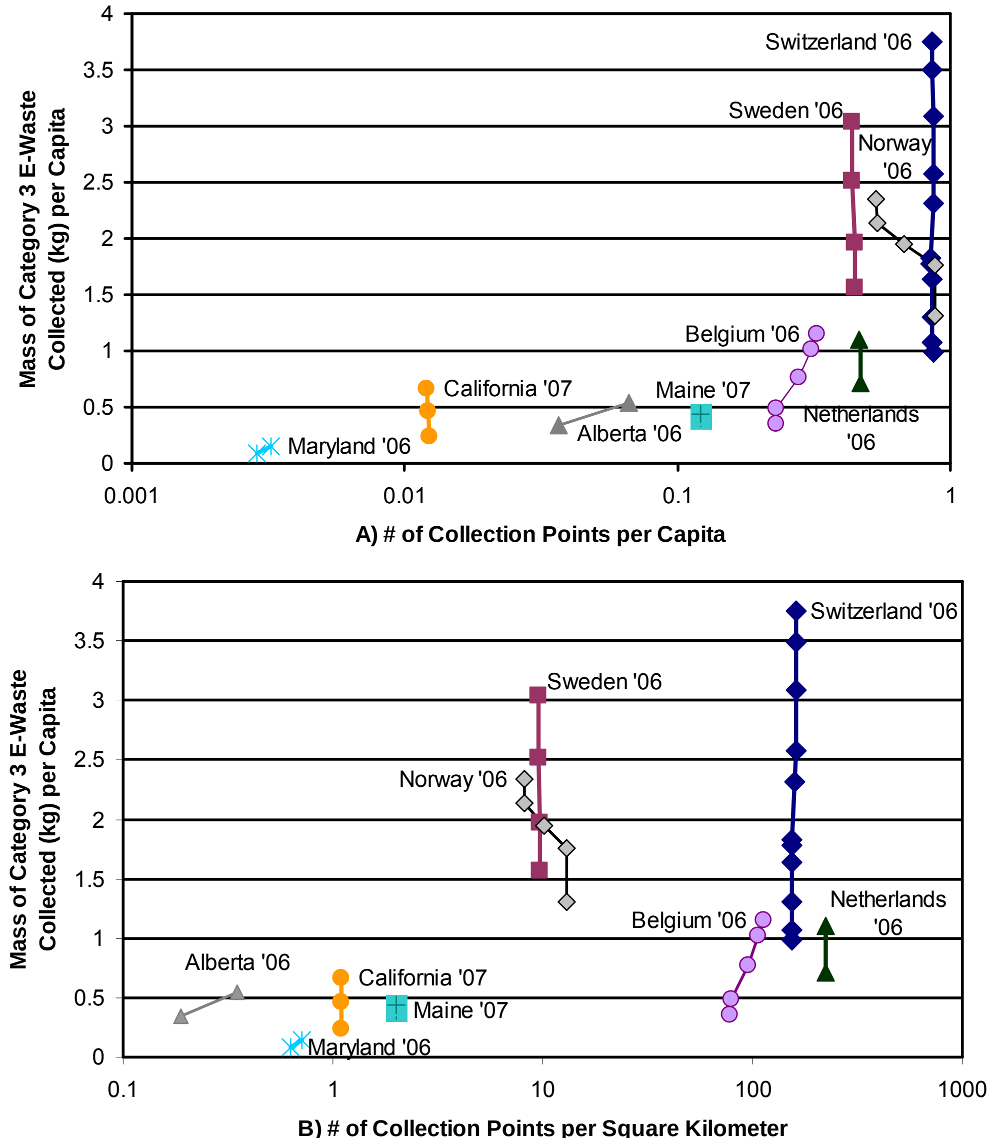


Figure 12: Kg of Category 3 E-Waste per capita collected on an annual basis over time vs. the number of collection points. In (A), the number of collection points is normalized to population, and in (B) points are normalized to area. Multiple points attributed to the same system refer to different years of operation. Note: These graphs are plotted on a semilog scale in order to visualize differences in the values for the North American systems.

In both Figure 11 and Figure 12, the measure of collection points per capita in (A) appears to be the more relevant metric than collection points per area in (B) because there is a stronger correlation between each system's horizontal and vertical position in (A). This is unsurprising given the large differences in population density of the systems evaluated. The perceived performance of Sweden and Norway, both with large areas of largely unoccupied land, are the most significantly affected systems. When measured per unit area it appears as though these systems have been able to achieve a much greater ratio of e-waste collected to collection point density than the other systems. However, when the number of collection points is instead evaluated per person, these two countries appear to collect e-waste in similar ratios to the more densely populated states.

Figure 13 is analogous to Figure 12, but the y-axis plots mass collected per PC in use 5 years earlier, as opposed to mass collected per person. As described for Figure 10, PCs in use is used as metric that is indicative of the amount of e-waste available in each state which could possibly be collected by an e-waste system. With the exception of Switzerland, each country has continued to increase the amount of category 3 e-waste collected each year per PC in use 5 years earlier. The amount of e-waste collected in Switzerland per PC in use has instead oscillated, which was illustrated more clearly in Figure 10. Since Switzerland's e-waste collection system is the oldest of those shown, it would not be surprising if other systems also begin to see slight negative growth in waste collected per PC in use as their systems mature. Figure 13 also continues to demonstrate the fact that the European systems are collecting much more e-waste than the North American systems. Neither the normalization of collection points per capita nor per area appears to be more relevant than the other in this case. However, given the prior problems noted with comparing these systems per unit area, the measure per capita likely remains the more informative measure here as well.

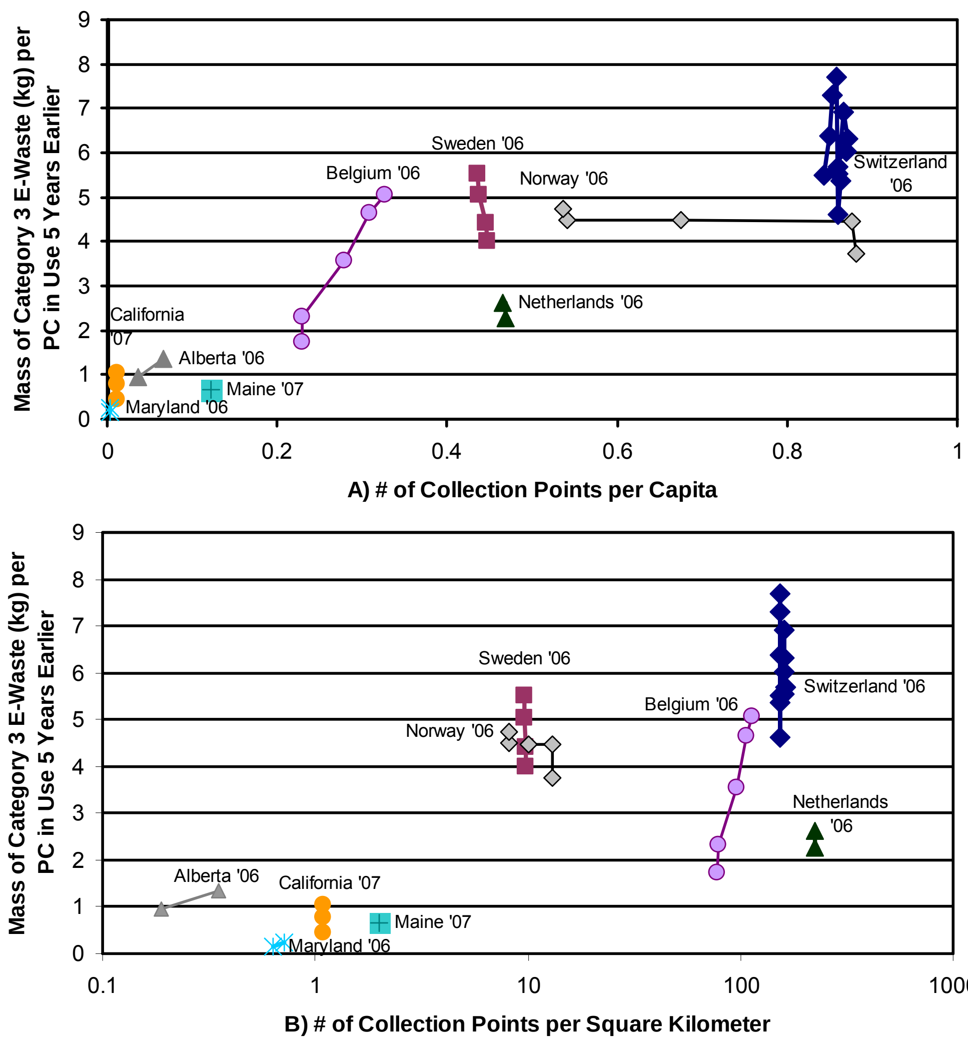


Figure 13: Mass of Category 3 E-Waste (kg) per capita collected overtime vs. the number of collection points. In (A), the number of collection points is normalized to population, and in (B) points are normalized to area. Multiple points attributed to the same system refer to different years of operation.

2.4 Conclusions from Analysis of Empirical Data

System architecture and contextual factors vary significantly between locations of e-waste recycling systems. This variation in existing system characteristics, together with the limited data available to describe current e-waste recycling systems, limits opportunities to isolate case study variables as necessary to gain insight into their effects on system performance. The framework presented here does, however, facilitate the comparisons of different e-waste recycling systems. Grouping empirical data into the categories of system architecture, context, and performance aids the process of examining multiple possible connections between architecture and performance, both normalized to context, and can illuminate the factors that are most likely to influence each performance metric.

Implementing the proposed framework for comparing recycling systems with several existing e-waste recycling systems has illuminated key factors regarding the relationship between system performance and architecture. First, while the amount of e-waste collected per capita per year is increasing, the mass of e-waste collected per electronic item in use may have reached a plateau in the older systems. Second, there appears to be a correlation between the number of collection points and the amount of e-waste collected, although it is not a direct correlation (e.g., Norway has increased the quantity of e-waste collected while decreasing the number of collection points offered). Third, there are some notable differences between the quantities of e-waste collected in European and North American systems, which may be due to differences in product scope or the number of years the programs have been running. Finally, when comparing systems in countries with very different population densities, the number of collection points available per capita appears to be a more relevant metric than collection points available per area as a predictor of mass of e-waste collected per capita.

In order to better understand how choices in system architecture affect the performance of the system, the knowledge gained through case study data collection must be abstracted to a model in which individual options can be exercised independently. Thus, the case studies completed here are used to inform the development of the model presented in the next chapter.

3 E-WASTE SYSTEM MODELING

The models presented here were developed in collaboration with Jeff Dahmus, Elsa Olivetti, Jeremy Gregory, and, to some extent all of the MIT Materials Systems Laboratory, Chris Murphy of the MIT/WHOI Joint Program and Edgar Blanco of the MIT Center for Transportation and Logistics. The analysis presented herein, however, is exclusively the work of the author.

As demonstrated in Chapter 2, with the range of possible system architectures and the important role of regional characteristics (context), understanding the determinants of system performance is challenging. To address this issue, a modeling framework to project the economic and environmental performance of complex durable good (CDG) recycling systems, based on contextual and architectural characteristics, has been developed.

The modeling framework presented here comprises three sub-models to comprehend the three main functions of most recycling systems: collection, processing, and system management. These three functions are modeled using a variety of modeling techniques and serve as a bridge between inputs related to system context and system architecture, and outputs related to economic and environmental performance. Unlike many existing models, the model presented here takes a broad system view, both in terms of the system functions, and the stakeholders included. Explicitly accounting for the economic and environmental impacts of different stakeholders provides a level of disaggregation that allows systems to be evaluated with regards to both their overall impacts as well as their impacts on particular stakeholders. The model presented here is also general, allowing many different system formats, both real and hypothetical, to be analyzed.

This chapter will describe the details of each sub-model, and then demonstrate the model's functionality in multiple geographic contexts. Specifically, it will be shown how the model can be used to predict how changes in the numbers of collection sites and processing sites affect the annual amount of e-waste collected, and the annualized cost of operating the chosen system architecture within a chosen context. The examples shown demonstrate how the model can be used both to evaluate and improve existing electronics recycling systems, as well as to design and implement new systems.

3.1 E-Waste Model Structure

As described in Section 2.1, there are many components to a recycling system. First, an e-waste recycling system must collect e-waste from constituents of the system's jurisdiction. This typically involves individuals or businesses with e-waste transporting this waste to a collection facility. The costs associated with this initial transportation are typically borne by the individual owning the e-waste. Therefore their distance to the nearest collection site may influence their likelihood to bring their e-waste into the system. From there, the e-waste may travel to a consolidation center on its way to a processing facility. The processing center then dismantles the e-waste and recovers materials which can be resold. Thus, the processing step includes some revenue to offset the cost of material recovery. These steps and the associated monetary flows are coordinated by some form of system management. The overall e-waste recycling system model described herein is therefore comprised of these three smaller models:

1. a collection model, which projects the mass of e-waste collected, cost of operating collection sites and the costs and environmental impacts of transporting e-waste; this is calculated as a function of the geo-economic context and a chosen number of available collection and processing points;
2. a processing model, which calculates the mass of various materials recovered from the recycling process and the associated revenues and costs to the system;
3. a management and financing model, which accounts for the overhead costs of operating an e-waste system.

The relationship between each of these smaller models and the associated inputs and outputs of each is depicted in Figure 14.

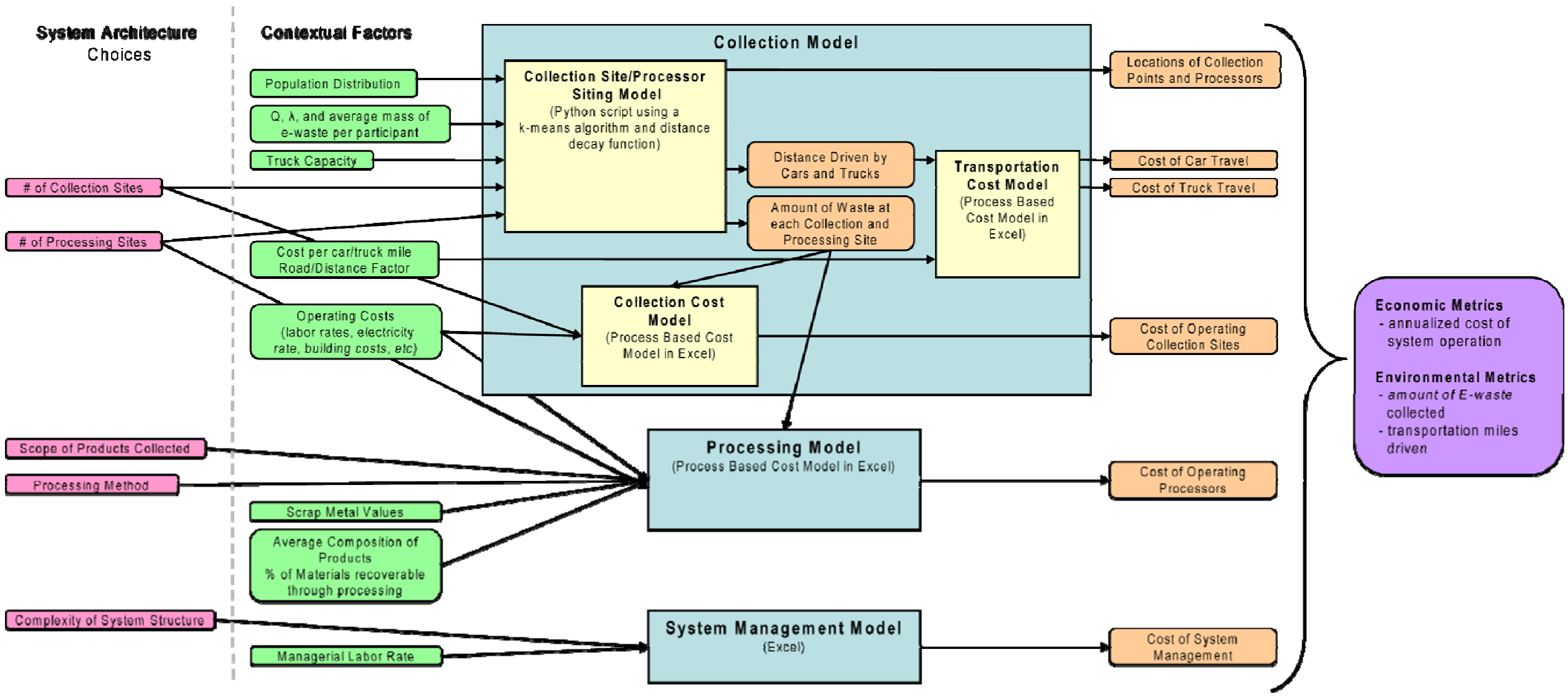


Figure 14: Flow chart of inputs and outputs for the e-waste model

3.2 Collection Model

The collection model presented here predicts the quantities of e-waste collected and associated costs of collection for a chosen number of collection sites within a given population distribution. In doing so, it also calculates the ideal locations for the chosen number of collection and processing sites as a function of the distance e-waste must travel to reach each of these sites. Generally, it would be expected that the more convenient it is for people to place their e-waste into a collection system, the more likely they are to do so. Convenience can be increased by offering more collection points or keeping existing sites open during more hours. Both of these solutions incur additional expenses and thus the system manager must decide which solution is the most optimal. The model therefore attempts to aid in this decision-making process by presenting estimates of the mass of e-waste which will be collected and cost of doing so for different scenarios.

E-waste can be collected through many different types of locations. A truck may drive door-to-door to pick up e-waste, or the owners of the e-waste may be held responsible for the initial transportation of their waste. Owners may drive their waste to a drop-off location, or mail it to a consolidator. Drop-off sites for e-waste are often collocated with existing municipal waste collection sites. Electronic retail stores may also serve as drop-off sites and many locations run special collection events in large parking lots a few times per year. The model presented here currently only models the costs associated with the use of municipal collection sites, or other non-retail permanent sites. Future work is necessary to model systems which use retail stores, special events, and mail programs to collect e-waste.

This subchapter will present how the model 1) incorporates the concept of participation decay with distance, 2) locates collection points, and 3) estimates the costs associated with e-waste collection. Finally, it will also demonstrate an example of how the collection model can be utilized.

3.2.1 Participation Decay with Distance

For a broad range topics ranging including outdoor recreation, shopping, commuting, and tourism, the distance one must travel to reach a location affects their likelihood of participating in activities there. (Fesenmaier and Lieber 1985, and Hurst 1972) The distance one must travel to participate in an e-waste system is therefore likely to affect participation in e-waste recovery systems as well. When recycling requires little to no effort, individuals are much more likely to recycle than when it requires driving a long distance, during specific hours, to a location they would not otherwise visit. Age, education, income, peer pressure, and distance to the nearest collection site have all been cited as potential contributors to an individual's likelihood to recycle. The degree to which each of these factors influence participation is disputed in current literature. (Nixon et al. 2008 and Schultz et al. 1995) However, reports from existing e-waste recycling systems strongly suggest that an individual's distance from a recycling point does affect their participation in that recycling program. (Ohio EPA 2004, and Sepanski et al. 2005) Prior models have shown that it is feasible and useful to incorporate distance decay into recycling siting decisions, but have not examined systems of significant size or the impact on system cost. (Farhan and Murray 2006). When distance is not included as a factor in choosing a number of collection points, the model will tend to suggest very few sites leads to the optimal solution. This is because the operation of additional sites typically constitutes additional costs. Thus, if people are willing to drive long distances to participate in the system, there is no need to operate additional sites. For example, the "robust solution" of an analysis of hypothetical e-waste systems in Georgia without distance decay includes only 5 collection sites. (Realff et al. 2004)

Our model assumes that an individual's likelihood of participation decays with increasing distance to the nearest collection site. Based upon similar demand decay equations in Sheppard (1995) and Fotheringham and O'Kelly (1989), it is assumed that this decay takes the following exponential form.

$$eWaste\_Collected = eWaste\_Per\_Participant \bullet \sum_{population}\left[Max\_Participation \bullet e^{-\lambda * \text{distance}}\right]$$

Or

$$eWaste\_Collected = eWaste\_Per\_Participant \bullet \sum_{town}\left[town\_population \bullet Max\_Participation \bullet e^{\lambda * \text{distance}}\right]$$

eWaste_Per_Participant represents the average mass of e-waste each participant will bring to the collection site.

Max_Participation, or Q, represents the maximum likelihood, as a percentage, that a member of the population will participate in the e-waste program. Among the long list of factors which can influence Q are the individual's age, education, likelihood of having e-waste, convenience of drop-off points, public awareness of the system and other similar factors.

$$Max\_Participation = (\%\text{ with eWaste}) \bullet (\%\text{ participating if distance} = 0)$$

λ (Lambda) determines the strength of the decay in participation as a function of distance

Distance is the length between an individual's home and his or her nearest collection site.

The constants in this equation (eWaste_Per_Participant, Max_Participation, and Lambda) were chosen to be consistent with the empirical data presented in Chapter 2 as well as other published literature. For the model results presented in this thesis, the eWaste_Per_Participant is assumed to be 25 kg, Max_Participation ranges between 5% and 20% and lambda ranges between .02 and 2.0. The rational for choosing these values is described in the following paragraphs, but the model has been developed such that any of these constants can be easily changed to better represent the jurisdiction of interest.

As in Chapter 2, the scope of e-waste collected in this model is limited to EU WEEE Category 3, or IT and telecommunications equipment. Thus, the 25 kg per participant estimate is derived from the assumption that, on average, each individual making a trip to the e-waste drop-off facility brings either a complete computer system (CPU, CRT monitor, and accessories) or a TV. The weights of these objects have been estimated in many different reports; a few examples are shown below in Table 6, Table 7 and Table 8. The 25 kg value additionally falls within the range of mass of e-waste per car estimated from various collection events in section three of the NERC manual for setting up and operating e-waste programs (NERC 2002).

Table 6: Electronic Product Weight Estimations used for Seattle Washington Program Planning (Cascadia Consulting Group Inc. and Sound Resolutions 2003)

The average weight of a computer CPU is 26 pounds. *(11.80 kg)*
The average weight of a cathode ray tube (CRT) monitor is 30 pounds. *(13.61 kg)*
The average weight of a flat-panel monitor is 10 pounds. *(4.54 kg)*
The average weight of a laptop computer is 7 pounds. *(3.18 kg)*
The average weight of a television is 50 pounds. *(22.69 kg)*

Table 7: Electronic Product Weight Estimations from the Staples Inc 2005 Pilot Program (Product Stewardship Institute Inc. 2005)

	lbs/unit	kg/unit
CPUs	23	10.44
Monitors	38	17.24
Large Peripherals (Printers, Fax, etc)	8	3.68
Laptops	15	6.81
Small Peripherals(Keyboards, Mice, Speakers)	15	6.81
Other	10	4.72

Table 8: Electronic Product Weight Estimations from the US Environmental Protection Agency (US EPA 2007a)

	Average Product Mass (kg)
CRT Monitors	18.14
CRT TVs	31.75
CPUs	9.98
LCD Monitors	7.26
LCD TVs	13.15
Laptops	3.63
Peripherals	6.80

The participation rate of e-waste owners in an e-waste recycling system is determined by many factors including an individual's age, education, likelihood of having e-waste, convenience of nearest drop-off point, public awareness of the system and other similar factors. In order to use the aforementioned exponential form of participation decay with distance, the likelihood of an individual who does not have to travel any distance to reach his or her nearest drop-off point must be estimated. The NERC 2002 survey estimated that 1% of US households participated in electronics collection programs where available. (Figure 8 in NERC 2002) Bohr (Bohr 2007 page 63) did not assume any distance decay, but instead assumed a constant 12% of available e-waste lost to illegal dumping and household waste. The US EPA (2007b) estimates that each year, between 10% and 20% of the US population has electronic products which have reached their end of life and could enter an e-waste system. A review of reports on traditional curbside recycling suggests that participation in this situation where there is essentially zero distance to the nearest drop-off point, US participation ranges between 50% and 90% percent depending on the area. (Gamba and Oskamp 1994 and Scott 1999) Multiplying the percentage of people with e-waste by their likelihood of participation at zero distance suggests that in the US, Max_Participation, or Q, could range between 5% and 20%.

$$Max\_Participation \text{ or } Q = (\text{\% with eWaste}) \bullet (\text{\% participating if distance} = 0)$$

Low Estimate	=	(10%)	●	(50%)	=	5%
High Estimate	=	(20%)	●	(100%)	=	20%

The rate at which the participation rate drops with increasing distance from the nearest site is determined by Lambda. To determine an appropriate value for Lambda, given an assumed Q and eWaste_Per_Participant, the distance decay equation was solved for a range of Lambda values within the geographical context of several existing systems. The distance "as the crow flies" that each person would have to travel to participate in the system was measured, using the

Vincenty formula,[1] from their town center to their nearest collection site. Results of this process for 2006 data in the US state of Maine, the Canadian province of Alberta, and Switzerland's SWICO are shown in Figure 15. For maximum participation rates (Q) of 5%, 10%, 15% and 20%, these figures demonstrate the values of lambda which if used with the demand decay function, would predict the same amount of category 3 waste collected in each system as was actually collected in 2006. In all cases, when a smaller Q, or maximum participation rate, is chosen, a smaller Lambda, or less significant decay in participation with respect to increasing distance, is necessary to collect the same amount of material. Interestingly, for the same range of Max_Participation, the range of corresponding Lambdas in each of these systems varies substantially. The range of Lambdas which correspond to the chosen values of Max_Participation appear to be strongly influenced by the population density of each jurisdiction. In Switzerland, where the population density is high, the corresponding values of Lambda are very small. In Maine and Alberta, where the population densities are lower, the corresponding values of lambda for the same Max_Participations are larger. This is shown in Table 9. A rule of thumb used by hazardous waste collection site planners in Massachusetts is that people will travel 15 minutes or 15 miles, whichever is closer, to their nearest collection site. (Dann 2008) It is more likely for people to travel 15 minutes before they have traveled 15 miles in densely populated areas. It is therefore surprising that the empirical data from Maine, Switzerland and Alberta show the reverse trend. Switzerland, with the greatest population density of these three systems appears to have the weakest distance decay function. And Alberta, with the smallest population density, appears to have the strongest decay function. However, population density is only one of many factors which influence participation. The participation rates observed in Maine, Switzerland and Alberta are each also influenced by the amount of e-waste generated, the specific scope of products collected, and the attitude of the people within the system with respect to recycling. For these three current systems, some combination of these other factors appears to influence the shape of the participation distance decay function more strongly than population density.

[1] The Vincenty Distance formula uses an ellipsoidal model of the earth to calculate the distance between two points provided as latitude and longitude. (Vincenty 1975)

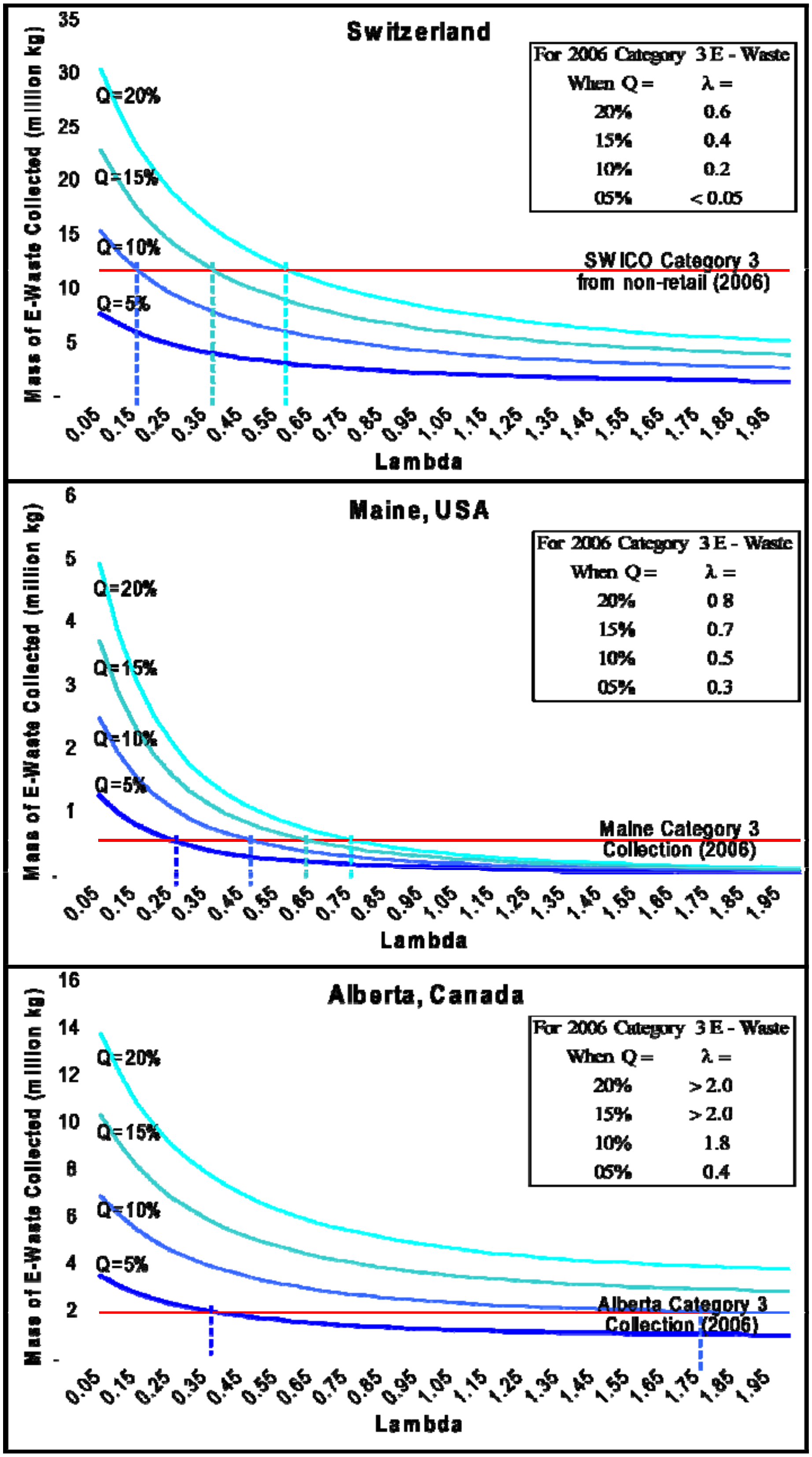


Figure 15: Calibrating lambda to 2006 E-Waste collection amounts in Maine, Switzerland and Alberta for Max_Participation (Q) values of 5%,10%, 15% and 20%.

Table 9: Combinations of Q and Lambda which predict the same amount of category 3 e-waste collection as was actually collected by each system in 2006. It is interesting to note that the corresponding Lambdas are greater in the jurisdictions with lower population densities.

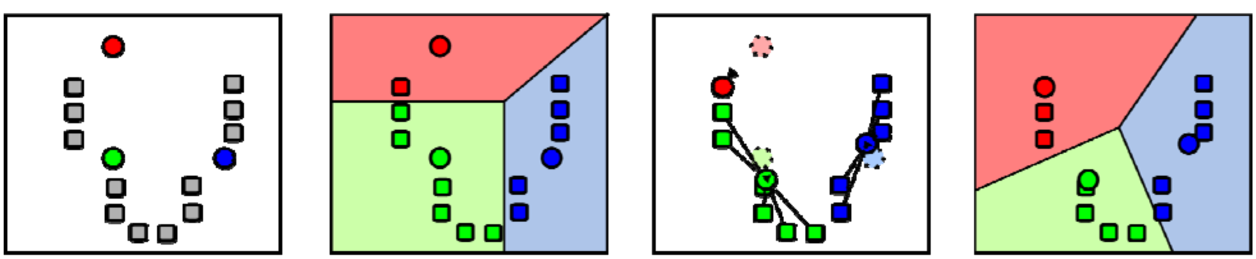
Values of λ which correspond to the mass of Category 3 E-Waste Collected in 2006 in			
	Switzerland (188 ppl/km^2)	Maine (16 ppl/km^2)	Alberta (5 ppl/km^2)
Q = 0.20	0.6	0.8	>2.0
Q = 0.15	0.4	0.7	>2.0
Q = 0.10	0.2	0.5	1.8
Q = 0.05	<0.05	0.3	0.4

3.2.2 Locating Collection Sites

Given the assumption that people's willingness to deposit e-waste into the system is a function of how far they must travel to their nearest collection site, collection sites should be located as close to as many people as possible in order to maximize the amount of e-waste collected. The locations of collection sites are determined in the model by the k-means clustering algorithm. The algorithm is implemented through the use of a computer script (included as Appendix B) written in the Python programming language. When given a list of population values, each at a specific latitude and longitude, and a desired number of collection sites, this program will use a k-means clustering algorithm to return the ideal latitude and longitude locations for each site. It does not, however, account for the fact that the numerically ideal collection site may be on a lake, mountaintop, or other illogical location.

The K-Means Algorithm

The k-means clustering algorithm is a systematic way of grouping data into a desired number of clusters such that the mean value of each cluster is minimized. For example, if you wanted to place 3 collection sites within a population distribution, you would not want to place all 3 in the center of town, but rather spread them out such that each individual's distance to his or her nearest site is minimized. The k-means algorithmic process for determining the optimal locations for multiple sites is explained in Figure 16.



Step 1. Initial sites (circles) are located within the population distribution (squares).

Step 2. Each population group (square) is assigned to its nearest site (circle).

Step 3. Sites (circles) are relocated to the center of their assigned population (squares).

Steps 2 and 3 are repeated until a specified threshold of convergence is reached.

Figure 16: Explanation of the k-means algorithm. Modified from Weston.pace (2008).

The computer code to perform the k-means algorithm was written in C by Roger Zhang (Zhang 2005) and modified by Chris Murphy (Murphy 2008) to run within the Python structure comprising the rest of the collection siting model. As implemented in the presented collection siting model, the k-means algorithm threshold is set at 0.001. This means that the program stops running when the sum of the squared distances, in both the x and y directions, from each data point to its nearest cluster, has changed by less than 0.001 m^2 between the last iteration and the current iteration. In this implementation, the centers of the most populated cities are always chosen as the initial collection site locations. Thus, for any constant definition of a population distribution, the solution to the k-means algorithm is deterministic.

Weighting K-Means by Population

The k-means algorithm can be used in any dimensional space. However, for the purposes of siting collection centers, only two dimensions (latitude and longitude) are relevant. In computing the best average location, the k-means algorithm applies equal weight to each data point input. A list of the latitude and longitude of each household within an e-waste recycling system's jurisdiction would provide a highly accurate data source to work from, but obtaining this information is highly impractical. The most detailed data set which can reasonably be obtained is typically a list of the location of the center of each municipality and its population. As used in this work, municipalities typically refers to cities, towns, or whatever units constitute the largest set of non-overlapping population clusters within a region. In order to weight each municipality location by its population, more data points are attributed to municipalities with larger populations.

The collection model uses the k-means algorithm weighted by population to select locations in 2D (latitude, longitude) space. By default, the k-means algorithm will find solutions in n-dimensional space, where n is the number of parameters it is given. Thus, if given a list of latitudes, longitudes, and populations, the population data would be treated as a third dimension instead of a weighting factor for the latitudes and longitudes. To correct for this, the model converts each municipality's population into many "dots", where each dot represents a population of 100 people. Thus, a town with a population of 2000 will be represented as 20 dots in the same location, a town with 30,000 people will be represented by 300 collocated dots, etc. Furthermore, the dots are scattered slightly using a normal distribution with the town center as their mean. The standard deviation for scattering the dots latitudinally and longitudinally was chosen to match half the standard deviation in distance between the nearest towns in each direction. For Maine, one-half of the standard deviation in latitude between the nearest towns is 0.00680 and in longitude is 0.00463. Therefore, the standard deviation used to scatter the dots latitudinally was 0.006 and longitudinally was 0.004. This scattering step allows for a more accurate estimation of the distance each person must travel to his or her nearest site. More importantly, it also allows the possibility of splitting the e-waste within a town with a large population between multiple collection sites. This division would not happen if all residents of a municipality are assumed to live in the same spot. It is also important to note that because of the randomization used to scatter the population dots, the k-means algorithm will not reach the exact same conclusion with each run of this model. The difference in model results due to this randomization is, however, extremely minimal. For the analyses completed in this thesis, the variation in annual system-wide mass collected due to this randomization was less than 1 kg.

Map Projections

Except at one specific latitude just north and south of the equator, one degree of latitude does not correspond to the same distance as one degree of longitude. In fact, the length of one degree of longitude ranges from 0 meters at the poles to 1855 meters at the equator. Therefore, in order to avoid artificially skewing the position of the collection sites towards people living closer in one direction over the other, all lat/long coordinates are converted to x/y coordinates using a map projection appropriate for the area being evaluated. Any projection of latitude and longitude points onto a two-dimensional map results in some distortion. In order to minimize this distortion, different types of projections are used to create maps of different parts of the world. For example, Alberta which is much longer North to South than East to West is better mapped with a different projection than Switzerland which is longer East to West, and smaller overall. In this thesis, the geographies of Alberta, Maine, and Switzerland are evaluated. The following map projections, chosen locally as a standard for each area, were used for each projection.

Alberta: Transverse Mercator (10 degree width) WGS84
(Alberta Environmental Protection Land and Forest Service 1998)
Maine: Universal Transverse Mercator 19 WGS84
(Maine.gov 2008)
Switzerland: Swiss Oblique Mercator EPSG::2056 aka CH1903+ / LV95
(Remote Sensing 2004)

3.2.3 Collection Cost Model

There are three main components to the costs associated with e-waste collection:

1) the cost of operating collection sites
2) the cost of transporting e-waste from collection sites to processing sites and
3) the cost of transporting e-waste to the collection sites.

The third cost is typically borne by the individual or business owning the e-waste and thus typically not included in calculations of the total system cost. The model presented here predicts this personal cost, but similarly does not include it in the total system cost.

Collection Site Operation

A process-based cost model (PBCM) was created in Microsoft Excel to estimate the costs of operating collection sites. (Field et al. 2007 and Kirchain 2001) Like other PBCMs, this model maps engineering requirements to process descriptions, process descriptions to facility requirements, and finally facility requirements to facility investments. The costs of the collection facility include capital costs, such as buildings, equipment, and other infrastructure, as well as operating costs, such as labor, electricity, and packaging material. All of these costs can vary with context. This model, using a similar framework and methodology to that of Jeremy Gregory in (Gregory et al. 2006), assumes all collection sites are permanent collection sites that collect other types of waste in addition to e-waste. The additional cost of hosting special collection events is not currently included in the model. For the purposes of estimating the collection site costs, each site was assumed to process an equal share of the total waste collected, and operate under the conditions outlined in Table 10. The data in this table came from a variety of sources (noted in the table) including published literature and personal conversations with recycling system managers and collection facility operators. The total amount of waste collected for any given number of collection sites is obtained from the collection siting model described earlier.

Transportation of E-Waste

The transportation of e-waste to collection sites is typically completed by private automobiles whereas the transportation of e-waste from collection sites to processors is typically completed by truck. These two transportation steps, and their associated different vehicle loading factors, will therefore have different economic and environmental impacts per mile driven. The total mileage driven for each of these steps is output by the collection siting model. The mileage values are calculated by using the distance decay function to determine the likelihood that each person in a population center will travel the shortest available distance to a collection point. This likelihood is then multiplied by both the population at that center and twice the distance to the nearest site. This therefore estimates each trip to a collection center as one that is roundtrip, and does not include any other stops along the way. This assumption will tend to overestimate the actual miles driven to transport e-waste. However, the mileage of each trip is underestimated by assuming people can drive in a straight line to their collection site, rather than following the curves of available roads. The sum of these resulting distance values for each population center is then used to approximate the total car miles driven. The cost associated with this activity is estimated at \$0.31 per km (\$0.50 per mile). (Blanco 2008)

For the transport of e-waste from collection centers to processing centers, a truck is assumed to drive roundtrip from a processing center to each of the nearest collection sites for every 5500 kg (~6 tons) of e-waste collected at that site. (Andrews 2008) If a site collects less than 5500 kg of waste in one year, a single roundtrip drive is estimated to be made by a truck at the nearest processing center each year. The cost for driving these trucks is estimated at \$1.55 per km (\$2.50 per mile). (Blanco 2008) Some e-waste systems may transport e-waste from collection sites to consolidation centers prior to processing centers, but this model does not account for this step.

Table 10: Inputs to the collection cost model for the context of Maine, USA in 2006. Items without specific citations were derived from the sources at the top of each section.

Collection Cost Model Inputs for Maine, USA			
Exogenous Variables (Field et al. 2007, Kirchain 2001, and Gregory et al. 2006)			
Average Employee Wage	$16	/hr	(LABORSTA 2008)
Benefits	82%		(Cascadia 2003)
Working days	260	days/yr	
Number of shifts	1	shifts/day	
Paid time	7	hrs/shift	
Financial Rate of Return	15%	%	
Equipment Life	10	Yrs	
Building Life	20	Yrs	
Price of Electricity	$0.12	/kWh	(EIA 2006)
Price of Building Space	$1,000	/sq m	
Investment Maintenance Cost	5%	%	
Overhead Cost	25%	%	
Facility Operations (Cascadia Consulting Group Inc. and Sound Resolutions 2003, Caudill et al 2003, and Gregory et al. 2006)			
Capacity/Actual Processed	100000		
Equipment Cost	$2,000	/station	
Space Requirement	100	m^2/station	
Processing Rate	300	kg/hr/station	
Workers	1	workers/station	
Power consumption	1	kW/station	
Is equipment dedicated?	0	[1=Y 0=N]	
Forklift Cost	$20,000		
Forklifts required per station	0.25	forklifts/station	
Forklift power (electric)	2	kW/forklift	
Forklift dedicated?	0	[1=Y 0=N]	
Packaging (NERC 2002 and Gregory et al. 2006)			
Gaylord cost	$10	/Gaylord	Take it Back Network (2003)
Gaylord capacity	200	Kg	
Pallet cost	$8	/pallet	
Cardboard layer cost	$3	/ea	
Pallet CRT capacity	27	/pallet	(FEC 2006)
Cardboard layers per CRT pallet	2	/pallet	
Pallet CPU capacity	45	/pallet	(FEC 2006)
Cardboard layers per CPU pallet	2	/pallet	
Shrink wrap cost	$0.03	/m	
Shrink wrap amount per pallet	17.48	m/pallet	
E-Waste Product Composition (NERIC 2007b)			
CRT Monitors	29%	of e-waste mass	
CRT TVs	70%	of e-waste mass	
Laptop Computers	1%	of e-waste mass	

3.2.4 Demonstration of the Collection Model

When population distribution, product scope, and the other aforementioned contextual factors are input to the model, the following figures (Figure 17, Figure 18, and Figure 19) can be derived from the output of the collection model. In the cases presented in this subchapter, all contextual variables, with the exception of population distribution, are chosen based upon Maine's electronics recycling system. The Max_Participation rate, Q, is set to 10%, the median value within the range of reasonable Qs derived earlier. The decay rate with distance, λ, is set to 0.4, such that, as shown in Figure 15, the distance decay function used is consistent the observed collection in Maine during 2006. Results obtained from different Q and λ combinations are reviewed in Section 3.5.

Using these values of Max_Participation (10%) and Lambda (0.4) and a population distribution of Maine in the model produces results that indicate that architecture, in the form of number of collection sites, has a profound effect on the expected amount of mass collected. Figure 17 shows that as the number of available collection sites increases, the total mass of e-waste collected also increases. This is a result of the distance decay relationship. With more collection sites in the system, more consumers live closer to a collection facility, thus increasing the total number of participants and the total mass collected. Without this link between convenience and participation, little benefit would ever be expected in a model from increasing the number of collection sites available. As shown in Figure 17, initial increases in the number of collection sites provide the greatest gains in mass collected. With the availability of a larger number of collection sites, fewer new participants will join the system if more collection sites are added. The costs of operating additional collection sites, also shown in Figure 17, increase more linearly. Thus, a cost-benefit analysis must be completed in order to determine the ideal number of collection sites in an area. This is best accomplished after incorporating all costs associated with the e-waste system.

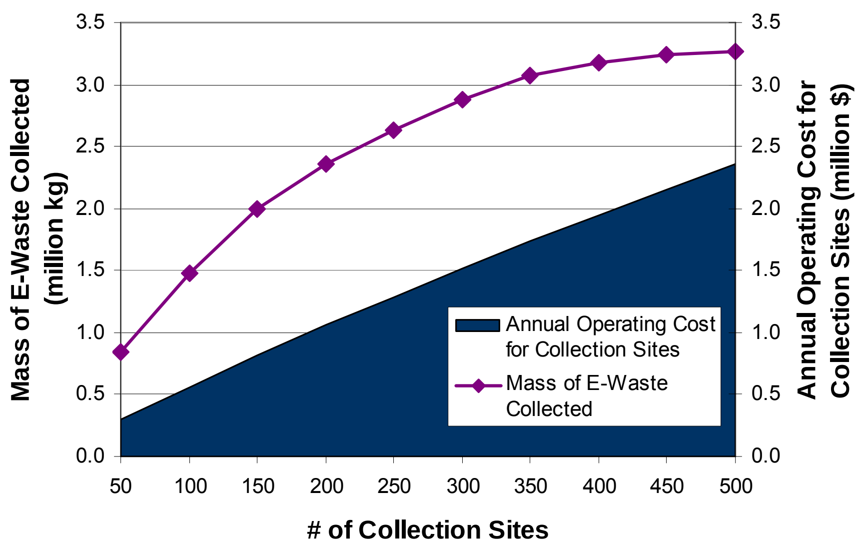


Figure 17: Modeled Mass of E-Waste Collected and Annual Operational Costs of Collection in Maine, USA as a function of the number of collection sites.

One form of output from the collection model is the latitude and longitude coordinates of each collection site as located by the k-means algorithm. The computer program includes an output of these files in a .kml format to facilitate the visualization of these locations using standard mapping programs. Figure 18A shows the center of each municipality within Maine. Figure 18B displays the locations chosen by the model for 150 collection sites in Maine. And Figure 18C, displays the actual locations of the ~150 e-waste collection centers currently operating in Maine. Comparing these three figures, it can be seen that the model's sites and Maine's actual sites are both located in similar regions, and most concentrated nearest Maine's most densely populated areas. It can also been seen that the model does not allocate as many collection sites to the less densely populated areas of Maine as Maine has currently chosen to.

A) Population Centers in Maine B) 150 Modeled Sites in Maine C) 151 Existing Sites in Maine

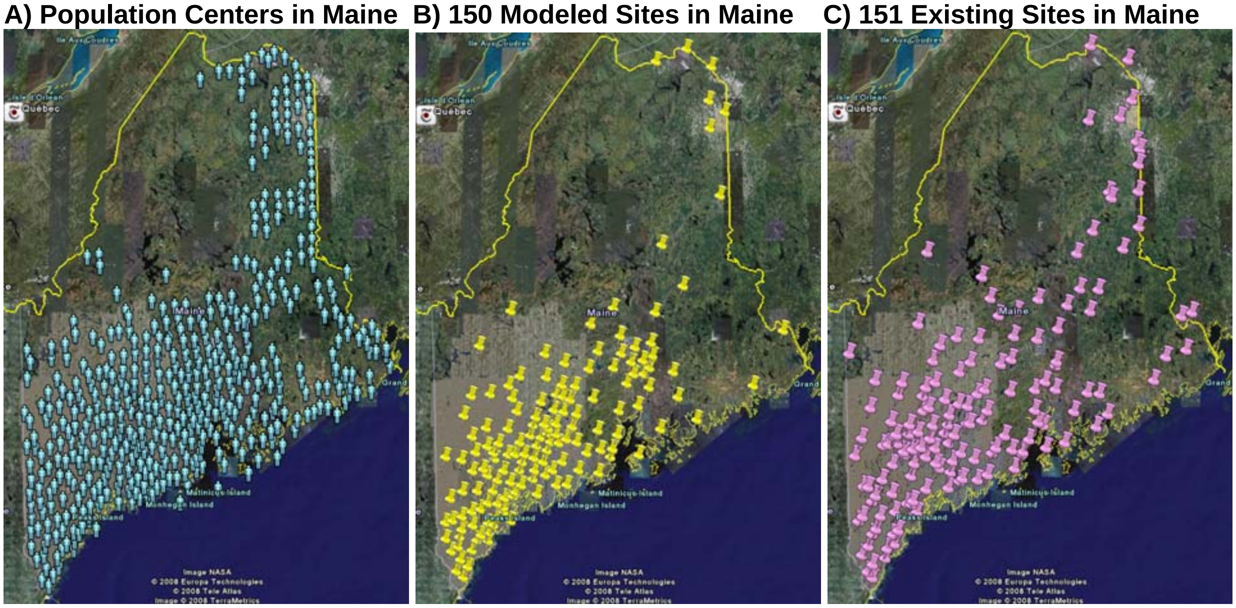


Figure 18: Maps of A) the centers of Maine's municipalities, B) the locations chosen by the e-waste model for 150 collection sites, and C) the locations of the 151 existing waste collection sites in Maine.

<u>Transportation</u>

Another use of the collection model is estimating the economic and environmental impacts associated with the transportation of e-waste. Transportation can be examined both in terms of the distance travelled by the owner to his or her nearest collection facility, typically by automobile, and by a truck from a collection facility to the nearest processing facility.

For the Maine scenario, with only one processing location, Figure 19A shows the total distances travelled by car and by truck over a range of possible number of collection sites. As the number of collection sites increases, the distance travelled by trucks increases both to reach more collection sites, and to accommodate the resultant larger volume of e-waste collected. The distance travelled by cars initially increases with more collection sites, as more constituents find themselves within participation distance, but then begins to decrease as the additional sites allow for shorter commutes. Overall, the total distance travelled by both vehicles generally increases with the addition of more collection points because more collection points lead to more participation. The truck distance driven per amount of e-waste collected also continuously increases with the addition of collection points. The total distance driven (cars plus trucks) per mass of e-waste collected does not, however, always increase. In fact, a minimum value for total distance driven per amount e-waste collected is visible at approximately 350 collection sites.

Thus, a system architect may easily come to a different optimal solution if the transportation of e-waste to the collection sites is included in the analysis of transportation costs than if it is not.

Figure 19B plots the costs associated with e-waste transportation. As described earlier, a cost of \$0.31/km is attributed to car travel and \$1.55/km to truck travel. Here the truck transportation costs clearly dominate the total cost of e-waste transportation, even with low numbers of collection sites where the total cost of car transportation is highest. The truck transportation cost per mass of e-waste collected continuously increases with additional collection sites. However, as with the distances shown in Figure 19A, a minimum value for total cost per mass collected is visible. Whereas the minimum total distance per mass collected occurred with approximately 350 collection sites, the minimum total cost per mass collected occurs with approximately 150 collection sites. These analyses were run for quantities of collection sites in increments of 50 sites. Thus, the actual minimum values may be +/- 50 collection sites of the observed minimum.

As a measure of environmental impact, the energy required to transport e-waste is presented in Figure 19C. Energy data came from the Swiss Ecoinvent life cycle assessment (LCA) database, which has a car travel energy consumption of 3.25 MJ/km (Ecoinvent Transport, passenger car/RER U) and truck travel energy consumption of 6.25 MJ/km (Ecoinvent Transport, lorry 16t/RER U). (The Ecoinvent Centre 2003) The contribution of car travel to the total transportation energy usage is more significant than to total cost, but less than to total distance. As with distance and cost, the energy usage for trucks, and energy usage for trucks per mass collected, increases with collection points. The energy usage of cars follows the same initial increase before decreasing as shown for the distance driven by cars in Figure 19A. As was the case when measuring total distance driven per mass collected, the total energy usage (cars plus trucks) per mass collected also appears to be at its minimum with approximately 350 collection sites.

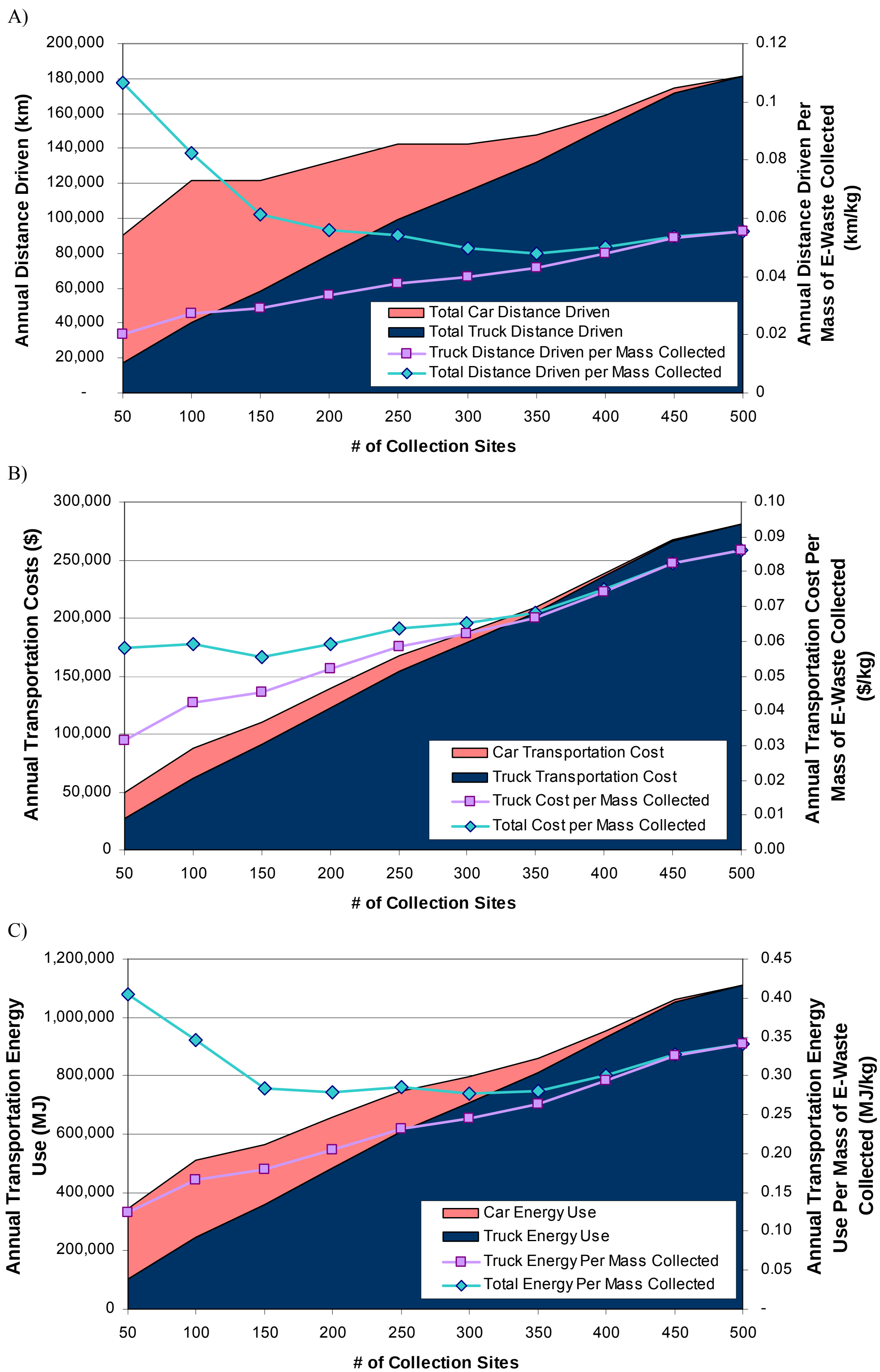


Figure 19: Modeled Transportation Distances (A), Costs (B) and Energy Usages (C) for various numbers of collection sites in Maine's population distribution with Q = 0.10, λ = 0.4 and 1 processing site.

3.3 Processing Model

Once the e-waste has been collected, it must be processed in order to recover materials for reuse and recycling. The processing model has a very similar structure to the collection model. Like the collection model, the processing model both selects ideal locations for processors and estimates the cost of their annual operations.

3.3.1 Locating Processors

In the same manner that the collection model uses the k-means algorithm to site collection centers from a list of municipality locations with associated populations, the processing model sites processors using the list of collection site locations with annual quantities of waste at each. Once the locations of the collection sites have been determined, the distance decay function is used to determine how much e-waste is collected annually at each collection site. With this information, any number of processors can be sited in the same manner that the collection sites were. To site the processors, the k-means algorithm is given a list of mass-weighted collection sites analogous to the population-weighted list of municipalities used to site the collection centers. However, unlike the collection siting process, there is no need to scatter the e-waste source locations around the collection center as all of the e-waste of a collection center truly does reside in the same location.

3.3.2 Processing Cost Model

Like the collection cost model, the processing cost model was developed as a process-based cost model in Microsoft Excel. The cost model comprises all processing within the system post-collection, and thus may include the operation of multiple facilities. It assumes an equal share of the total waste collected is processed by each processing facility. The total amount of waste processed by all facilities is obtained from the collection siting model described earlier. Additional assumptions regarding the operation of the processing facilities are outlined in Table 11. The data in Table 11 were obtained from a variety of sources (listed in the table) including published literature and personal conversations with recycling system managers and collection facility operators.

In developing PBCMs for processing facilities, the revenue streams from the sale of reusable components and recyclable materials must also be accounted for. Thus, the processing model contains an estimation of the recoverable material composition and resale values for several product types. The values used in the model for results shown in this thesis are presented in Table 12. Product composition values were obtained from a variety of sources listed in (Dahmus 2007). Material resale values were obtained from Recycler’s World (2008). The total mass of each product type brought to the processors is determined by the collection model.

Another important aspect of the costs associated with processing e-waste is the percentage of the processor’s operation that is related to the recycling system e-waste. For example, many processing facilities process e-waste from large corporations or other sources separate from a state-wide recycling program. Thus only a fraction of the processor’s total annual costs should be attributed to the recycling system e-waste. In the model presented here, each processing facility is assumed to process a mass of non-recycling-system-e-waste equal to one million kg plus 20% of the mass of recycling system e-waste received. The costs then attributed to the e-waste recycling system are the fraction of the processor’s total cost equal to the fraction of e-waste processed relative to total waste processed.

Table 11: Inputs to the processing cost model for the context of Maine, USA in 2006. Items without specific citations were derived from the sources at the top of each section.

Processing Cost Model Inputs for Maine, USA			
Exogenous Variables (Field et al. 2007, Kirchain 2001 and Gregory et al. 2006)			
Average Employee Wage	$16	/hr	(LABORSTA 2008)
Benefits	54%		(Cascadia 2003)
Working days per week	5		
Working weeks per year	50		
Working days (hourly workers)	250	days/yr	
Working days (supervisors)	250	days/yr	
Number of shifts	1	shifts/day	
Paid time (hourly workers)	7	hrs/shift	
Paid time (supervisors)	8	hrs/shift	
Rate of Return	15%	%	
Equipment Life	10	Yrs	
Building Life	30	Yrs	
Price of Electricity	$0.12	/kWh	(EIA 2006)
Price of Building Space	$1,076	/sq m	
Investment Maintenance Cost	5%	%	
Overhead Cost	15%	%	
Supervisor Pay	$32	/hr	
Second Shift Premium	10%	%	
Facility and Equipment (Gregory et al. 2006, Andrews 2008)			
Total Equipment Cost	500,000	$	
Minimum Equipment Cost	300,000	$	
Cost per Station	16,667	$	
Facility Size	2500	m^2	
Minimum facility size	500	m^2	
Facility Space per Station	166.67	m^2	
Power Consumption while processing e-waste	600	kW	
Power Consumption during idle business hours	100	kW	
Supervisors per hourly worker	0.1	People	
General Supervisors	2	People	
Other e-Waste (base load)	1,000,000	kg/yr	
Other e-Waste (additional % of system e-waste)	20%	%	
Operations (Gregory et al. 2006, Andrews 2008)			
Maximum Capacity (12 stations)	2192	kg/hr	
Maximum Station Capacity	183	kg/hr	
Stations per facility	12		
Hourly Workers per station	1		
Power consumption	500	kW	
Is equipment dedicated?	0	[1=Y 0=N]	
Product Mix			
Monitors (CRT)	Obtained from collection model	Kg	
Televisions (CRT)		Kg	
Laptop Computers		Kg	

Table 12: E-Waste Product Material Compositions and Resale Values
(Dahmus 2007 and Recycler's World 2008)

		Monitor (CRT)	Television (CRT)	Laptop Computer	Cell Phone	Desktop Computer	Fax Machine	% of Material Recovered	Resale Value ($/kg)
	Unit Mass (kg)	15.39	36.74	3.36	0.12	9.04	26.57		
	Component Resale Value ($/unit)	--	--	0.25	0.15	1.25	--		
Product Composition as a Percentage of Total Product Mass	Glass	44%	49%	10%	12%	0%	0%	90%	0.01
	Plastic	23%	20%	38%	28%	5%	35%	95%	0.20
	Steel	18%	11%	20%	0%	67%	0%	95%	0.21
	Copper	5%	3%	12%	17%	7%	0%	90%	1.16
	Lead	4%	0%	0%	1%	0%	0%	85%	2.48
	Iron	3%	1%	2%	4%	0%	41%	95%	0.21
	Aluminum	2%	0%	4%	2%	5%	0%	90%	0.73
	Tin	0%	0%	1%	1%	1%	0%	90%	0.03
	Silver	0%	0%	0%	1%	0%	0%	90%	2.24
	Gold	0%	0%	0%	0%	0%	0%	90%	39.55
	Nickel	0%	0%	1%	2%	0%	0%	85%	11.30
	Paper	0%	0%	0%	0%	0%	0%	80%	0.02
	Other	1%	16%	12%	34%	14%	22%	100%	-0.09

3.3.3 Demonstration of the Processing Model

For a single processor, the additional cost of processing more e-waste is very small until the point of requiring additional employees and other facilities to handle the additional load is reached. However, while increased processing demand increases total processing costs, it also allows economies of scale to be realized. Figure 20 shows the increase in total cost and decrease in cost per unit mass processed as a function of the quantity of e-waste processed. Both functions are stepwise due to the quantized costs associated with adding capacity and hiring additional employees to handle the increased mass. In looking at the net annual processing cost curve (blue) in Figure 20, the points at which the facility must be expanded and new managers hired, is evidenced by the periodic large rises in cost. Between these steps, the additional cost of processing more e-waste is small. These same periodic steps are visible in the net annual processing cost per unit mass curve (green) as well.

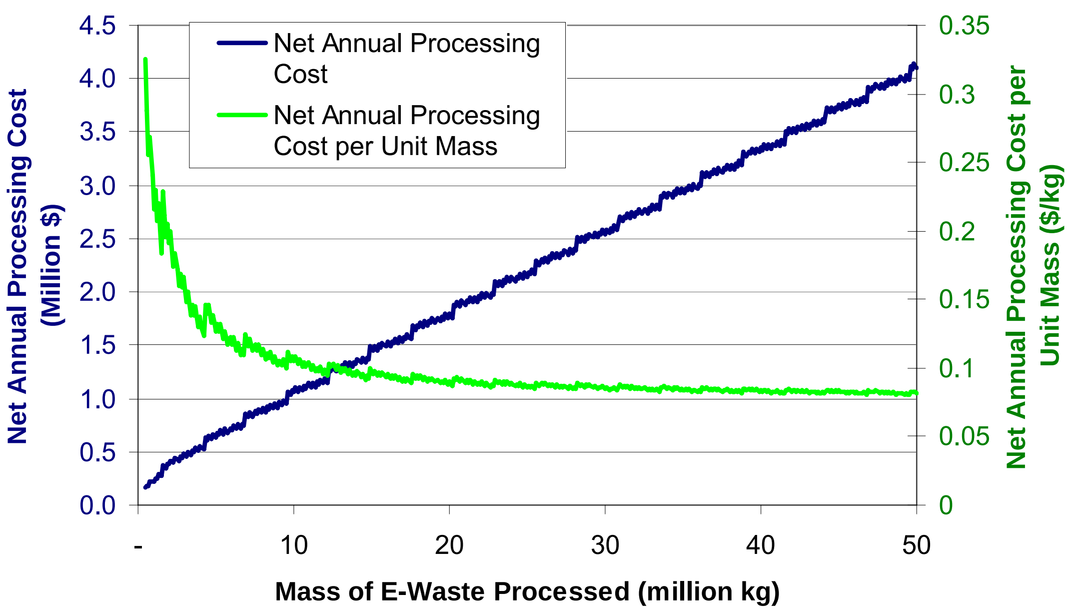


Figure 20: Modeled annual net processing cost and net processing cost per unit mass as a function of the mass of e-waste processed for a single processor.

Figure 21 presents processing cost for all processors as a function of the number of processors used. Each processor is assumed to handle an equal portion of the total mass collected, and the net annual processing cost is the sum of the net costs of all processors. Here it can be observed that the total cost generally increases with the use of additional processors. This is because the operation of additional processors requires payment for additional facilities and employees, costs which may be unnecessary given processors' unused capacity. Figure 21 also demonstrates that the total cost of processing generally increases with additional mass. This is consistent with the observations made for Figure 20. Furthermore, Figure 21 demonstrates that greater quantities of e-waste processed correspond with increasingly jagged lines in. Thus, when processing large quantities of e-waste, there are more opportunities to lower processing costs by operating additional processors, than when processing a small total volume.

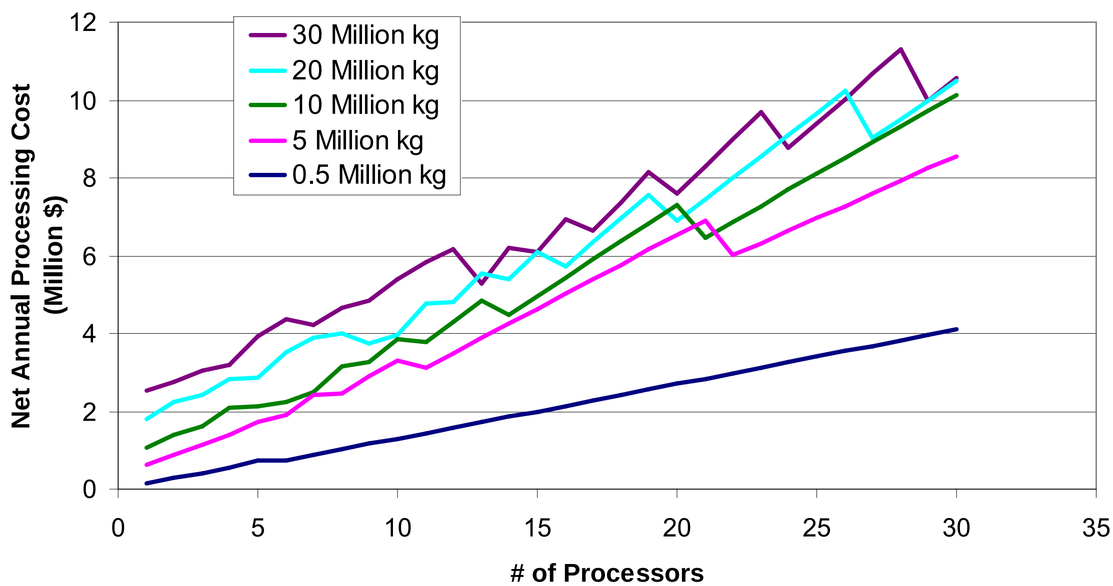


Figure 21: Net annual processing cost for all processors as a function of the number or processors used for several different total quantities of e-waste.

Figure 22 normalizes the costs in Figure 21 by the mass of e-waste being processed. Here it can be seen that, with few exceptions, an increase in the number of processors being used results in an increased cost per unit mass collected, regardless of the scale of the total mass collected. The increase in cost per unit mass with additional processors is most substantial when the quantities of e-waste being processed are small.

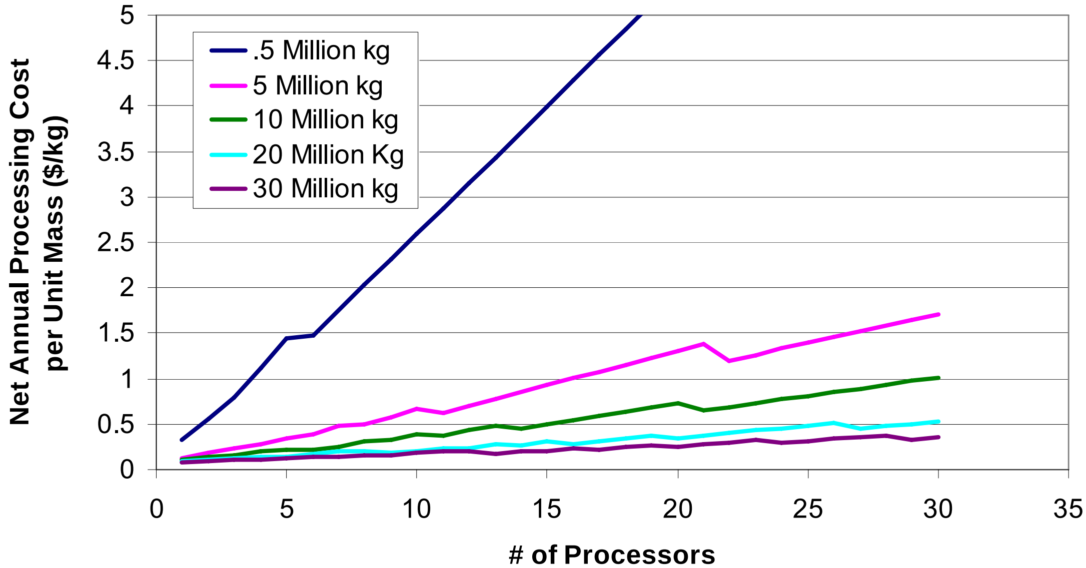


Figure 22: Net annual processing cost per unit mass for all processors as a function of the number or processors used for several different total quantities of e-waste.

3.4 System Management

The system management component of the model accounts for the management and oversight of the entire system. As described in Section 2.1.3, e-waste recycling systems may have many different forms of managerial organization. These costs are largely administrative, and are heavily dependent on the fee structures and oversight mechanisms that are put in place; as fee structures become more complex, and as oversight increases, system management costs increase. In general, these costs can be modeled simply, with labor and related expenses often the dominant costs.

Our model currently estimates the annual system management cost for Maine's context at $200,000. This value is derived from knowledge of the 2006 system management costs for Maine's operation. (Gregory and Kirchain 2007) In comparison, Switzerland which processes a larger scope and quantity of e-waste spent approximately $3 million on administrative costs in 2006. (SWICO Recycling Guarantee 2006) A comparison of the system management costs for Maine and Switzerland are shown in Table 13.

Table 13: Reported 2006 System Management Costs for Maine and Switzerland

	Total Cost	Cost Per kg collected	Cost Per Capita	Cost per Collection Site
Maine	$200,000	$0.11	$0.15	$458
Switzerland	$3,700,000	$0.09	$0.19	$1250

3.5 An Application of the Full E-Waste Model

To test the utility of the full e-waste model, it was run using three different population distributions: Maine, Alberta and Switzerland, each with very different population densities, over the range of constants derived in Section 3.2.1. This example will focus on analyzing the effect of one aspect of system architecture – the number of collection sites – on the overall economic and environmental performance of the system for several demand decay curves.

Continuing the example used to demonstrate the collection model, the calculated annual processing costs and system management costs are added to the aforementioned Maine-based collection system analysis with Max_Participation = 10% and Lambda = 0.4 in Figure 23. Here the collection cost contains the cost of both operating collection sites and transporting e-waste to the processors. The costs associated with transporting e-waste to the collection sites are not included because this cost is typically borne by the e-waste owner, and not financed as part of the e-waste recycling system. As expected, given Maine's flat system management cost structure that is independent of the amount of e-waste collected, the system management cost per mass collected continuously decreases as the amount of e-waste collected increases. While the total cost of processing increases with additional e-waste collection, processors are able to increase their economic efficiency (cost per mass collected) with additional e-waste collected. In total, the minimum e-waste system cost for this scenario is approximately \$0.75/kg and occurs with the operation of 100 collection sites and 1 processor. There is, however, a less than 1 cent per kg predicted rise in total collection costs to collect 35% more e-waste by operating 150 collection sites, or 60% more e-waste with 200 collection sites. The system manager must determine if the environmental benefit associated with operating more collection sites to collect more e-waste is worth the added cost.

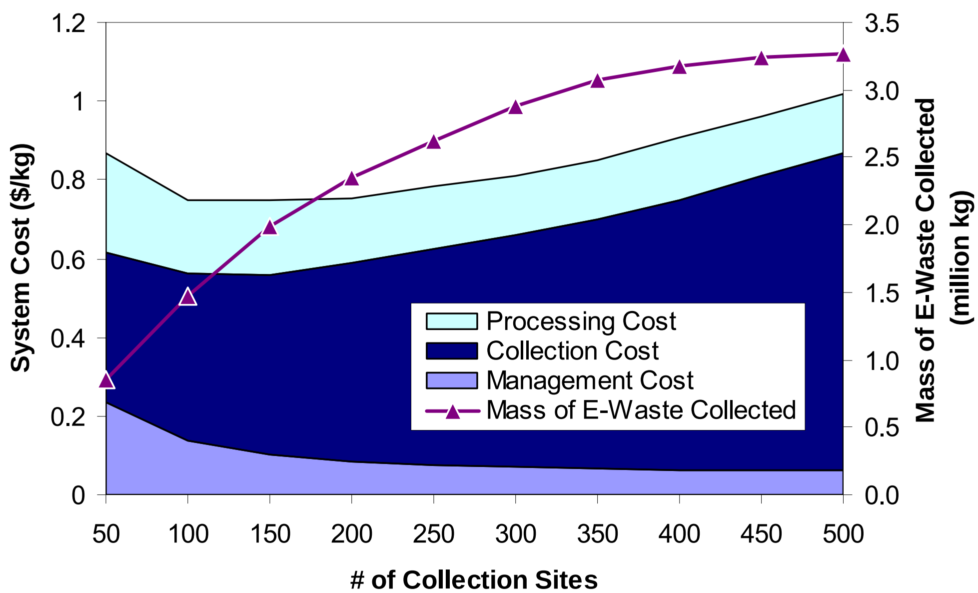


Figure 23. Total mass collected and total recycling system cost per kg collected as a function of the number of collection sites. Model inputs based upon Maine's characteristics with Max_Participation = 10% and λ = 0.4.

The modeled economically-optimal number of collection sites changes as the values of Max_Participation and Lambda used in the distance decay function change. Table 14 presents the Max_Participation (Q) and Lambda combinations derived to fit 2006 collection data in Section 3.2.1. Table 15, Table 16, and Table 17 present the lowest cost modeled solutions for a range of Q and Lambda combinations applied to three different population distributions from

Maine, Switzerland and Alberta. As was the case with the examples presented in Section 3.2.4, all of the contextual values presented for each simulation in Table 15 - Table 17, with the exception of the population distribution, are held constant. Thus, the values presented for the high population density geography (Switzerland) and low population geography (Alberta) are not expected to match the observed performance of the e-waste recycling systems in those regions. Rather, the analyses are included as a test of the model's performance over a range of conditions.

In examining how the lowest cost solution varies with Max_Participation in Table 15, it can be seen that, in all cases, a larger Max_Participation corresponds with a lower minimum cost. A larger Max_Participation is representative of both more e-waste within a population and residents who are more willing to bring their e-waste to a collection site. Thus, larger values of Max_Participation correspond with a greater quantity of e-waste collected per dollar spent.

Examining variations in the lowest cost solution with respect to Lambda, it is visible that a lower Lambda value always corresponds with a lower-cost solution than a larger Lambda. Lambda determines how far e-waste owners are willing to travel in order to bring their e-waste to a collection site; smaller Lambdas are representative of communities where people are willing to travel long distances. Thus, given the fact that the cost of this travel by the e-waste owners is not included in the total system cost, the observed increase in system cost with higher values of Lambda is expected.

Table 16 displays the number of collection sites which correspond with the lowest cost solution for each geography at each Max_Participation and Lambda combination. The possible collection site values range between 50 and 500 in increments of 50. Thus, the optimal number of collection sites for each case may be plus or minus 49 sites of the value shown. It is interesting to note that with only two visible exceptions (Max_Participation=5%, λ=0.2 and Max_Participation=15%, λ=0.2), for any combination of Q and Lambda, the geographies with higher population densities are always assigned a greater or equal number of collection points than those regions with lower population densities. This trend is most visible in systems with high values of Lambda.

The total amount of e-waste collected in the lowest costs solution for each Max_Participation and Lambda combination is presented in Table 17. As was the case looking at costs in Table 15, the most ideal scenario, which in this case is the largest mass of e-waste collected, is that which corresponds with high values of Max_Participation and low values of Lambda. Looking across the different geographies, for the same values of Max_Participation and Lambda, the geographies with the greatest total population are those that collect the greatest total mass.

The current processing model assumptions lead to the selection of a single processor as the most economically efficient solution in all cases. This suggests that most existing e-waste recycling systems could lower their costs by consolidating the multiple processing locations typically used and take advantage of the potential for greater economies of scale within a single facility. Currently, over 90% of the e-waste collected in Maine is processed at the same facility. (Gregory and Kirchain 2008) However, there are still reasons a recycling system may choose not to process all of their waste at the same facility. Multiple processing facilities may already exist within the jurisdiction, thereby eliminating the investments associated with building a new facility. Furthermore, the use of multiple facilities can also create a competitive market for processing e-waste. This competition can potentially create an environment where processing prices remain low with little or no regulation of the market.

Table 14: Combinations of Max_Participation (Q) and Lambda which predict the same amount of category 3 e-waste collection as was actually collected by each system in 2006.

Values of λ which correspond to the mass of Category 3 E-Waste Collected in 2006 in			
	Switzerland (188 ppl/km^2)	Maine (16 ppl/km^2)	Alberta (5 ppl/km^2)
Q = 20%	0.6	0.8	>2.0
Q = 15%	0.4	0.7	>2.0
Q = 10%	0.2	0.5	1.8
Q = 5%	<0.05	0.3	0.4

Table 15: The lowest-cost modeled solutions in 3 geographies for multiple Max_Participation (Q) and λ combinations given choices of 50-500 collection points in increments of 50, and 1, 2, 5, 10, 20, or 30 processors. Highlighted cells correspond to Q and Lambda combinations which represent actual collection amounts in the geography corresponding to their highlighted color.

Lowest Modeled System Cost ($/kg e-waste collected)

In Maine's Geography (Pop=1.3 mil; Pop. Dens. = 16 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	$ 0.66	$ 1.06	$ 1.19	$ 1.25	$ 1.29	$ 1.36
Q = 10%	$ 0.47	$ 0.68	$ 0.75	$ 0.78	$ 0.79	$ 0.83
Q = 15%	$ 0.39	$ 0.53	$ 0.58	$ 0.59	$ 0.61	$ 0.63
Q = 20%	$ 0.36	$ 0.45	$ 0.49	$ 0.51	$ 0.51	$ 0.53

In Alberta's Geography (Pop=3 mil; Pop. Dens. = 5 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	$ 0.48	$ 0.52	$ 0.53	$ 0.54	$ 0.53	$ 0.54
Q = 10%	$ 0.40	$ 0.41	$ 0.41	$ 0.42	$ 0.41	$ 0.42
Q = 15%	$ 0.36	$ 0.37	$ 0.37	$ 0.38	$ 0.37	$ 0.37
Q = 20%	$ 0.34	$ 0.35	$ 0.35	$ 0.35	$ 0.35	$ 0.35

In Switzerland's Geography (Pop=7.5 mil; Pop. Dens. = 188 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	$ 0.33	$ 0.44	$ 0.52	$ 0.59	$ 0.65	$ 0.84
Q = 10%	$ 0.28	$ 0.34	$ 0.39	$ 0.42	$ 0.44	$ 0.54
Q = 15%	$ 0.27	$ 0.30	$ 0.34	$ 0.35	$ 0.38	$ 0.44
Q = 20%	$ 0.26	$ 0.28	$ 0.31	$ 0.32	$ 0.34	$ 0.38

Table 16: The number of collection sites corresponding to the lowest-cost modeled solutions in 3 geographies for multiple Max_Participation (Q) and λ combinations given choices of 50-500 collection points in increments of 50, and 1, 2, 5, 10, 20, or 30 processors. Highlighted cells correspond to Q and Lambda combinations which represent actual collection amounts in the geography corresponding to their highlighted color.

# of Collection Sites for Lowest Cost Solution

In Maine's Geography
(Pop=1.3 mil; Pop. Dens. = 16 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	50	100	150	150	150	150
Q = 10%	50	100	100	200	150	150
Q = 15%	50	150	150	150	200	150
Q = 20%	50	100	150	150	150	150

In Alberta's Geography
(Pop=3 mil; Pop. Dens. = 5 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	50	50	50	50	50	50
Q = 10%	50	50	50	100	50	50
Q = 15%	50	50	50	50	50	50
Q = 20%	50	50	50	50	50	100

In Switzerland's Geography
(Pop=7.5 mil; Pop. Dens. = 188 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	50	50	150	200	200	500
Q = 10%	50	100	200	250	250	500
Q = 15%	50	100	150	150	300	450
Q = 20%	50	100	150	150	200	450

Table 17: The total quantity of e-waste collected at the lowest-cost modeled solutions in 3 geographies for multiple Max_Participation (Q) and λ combinations given choices of 50-500 collection points in increments of 50, and 1, 2, 5, 10, 20, or 30 processors. Highlighted cells correspond to Q and Lambda combinations which represent actual collection amounts in the geography corresponding to their highlighted color.

Total Quantity of E-Waste Collected at Lowest Cost Solution (million kg)

In Maine's Geography
(Pop=1.3 mil; Pop. Dens. = 16 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	1.37	0.91	1.00	0.94	0.91	0.86
Q = 10%	2.75	1.82	1.47	2.26	1.82	1.72
Q = 15%	4.12	3.38	2.99	2.82	3.31	2.58
Q = 20%	5.50	3.64	3.98	3.76	3.64	3.44

In Alberta's Geography
(Pop=3 mil; Pop. Dens. = 5 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	3.71	2.93	2.75	2.67	2.62	2.54
Q = 10%	7.43	5.87	5.50	6.60	5.24	5.09
Q = 15%	11.14	8.80	8.25	7.99	7.86	7.63
Q = 20%	14.85	11.73	11.00	10.66	10.47	12.22

In Switzerland's Geography
(Pop=7.5 mil; Pop. Dens. = 188 people/km^2)

25 kg/trip	λ = 0.02	λ = 0.2	λ = 0.4	λ = 0.6	λ = 0.8	λ = 2.0
Q = 5%	7.75	3.21	3.63	3.50	3.02	4.08
Q = 10%	15.49	8.56	8.53	7.89	6.89	8.16
Q = 15%	23.24	12.85	10.90	8.75	11.64	11.15
Q = 20%	30.99	17.13	14.54	11.66	12.08	14.87

3.6 Conclusions from E-waste Recycling System Modeling

The e-waste model, comprised of sub-models for collection, processing and system management, can be used to estimate costs and environmental impacts associated with various system architectures within a specified geo-economic context. The modeling framework is both broad, in order to address all components of recycling systems, and general, such that many different systems, both real and hypothetical, can be analyzed. Varying the system architecture in terms of number of collection and processing sites, the model can predict

- the most economically efficient number of collection sites and their locations based on a given population distribution,
- the most economically efficient number of processor sites and their locations based on modeled collection data, and
- the environmental impact associated with e-waste transportation from an energy consumption standpoint.

Social and political conditions may lead policymakers to implement architectures other than those deemed economically or environmentally optimal. The model allows the economic and environmental performance of these options to be quantified and compared as well.

The utility of the model in understanding e-waste systems was demonstrated using a theoretical context based upon the operating conditions of Maine's current e-waste system. Results of varying the population distribution, likelihood of residents to participate in the program, number of collection sites and number of processors within this example application suggest the following:

<u>E-waste collection</u>

- Increasing the availability of collection sites leads to growth in the mass of e-waste collected, at a decaying rate.
- The costs associated with operating additional collection sites and processors increase in an approximately linear fashion.
- The constants used to define how participation decays with increasing distance to collection sites have significant influence on the projected e-system operation.
    - A larger Max_Participation, or Q, corresponds with a lower minimum system cost
    - Larger decay rates, or Lambdas, representing communities less likely to drive long distances to participate, correspond with higher-cost solutions.
- The most economically efficient number of collection sites for a region is typically higher in regions with greater population density.

<u>Transportation</u>

- For low collection site densities, the inclusion of the costs associated with personal transportation of e-waste to collection sites may alter which architectural scenario appears most economically efficient
- The addition of collection sites generally decreases the mileage driven by individuals and increases that driven by trucks carrying consolidated e-waste to processors.
- The contribution of car travel to overall transportation impact is more significant when analyzing energy usage than cost.
- The locations chosen by the model for collection sites are similar to those actually chosen by Maine. The model, however, does not allocate as many collection sites to the less densely populated areas of Maine as Maine has currently chosen to.

Processing

- Due to high fixed costs, a large quantity of e-waste collected over a large geographic area is necessary to economically support use of multiple processing sites. In the scenarios presented here, one processor was always the most economically efficient solution.

4 CONCLUSIONS & RECOMMENDATIONS

As our society continues to consume more electronic products every year, the amount of e-waste produced, and its associated hazards continue to increase. Several electronic waste recycling systems now exist worldwide in many different forms, and the amount of related legislation continues to increase. Numerous approaches have been proposed including landfill bans, extended producer responsibility (EPR) and advance recovery fee (ARF) funded recycling systems. In fact, the breadth of combinations of e-waste recycling system architectures currently in operation is so large that there is no obvious correlation between architectural choices and observed performance. There are more differences between most existing systems than there are similarities. In order for policymakers and system architects to establish the optimal recycling system for their location, they need to know how to evaluate the performance of existing systems, and furthermore, how to use this information to design new systems. A review of the current literature regarding e-waste recycling systems demonstrated a need to better understand what mechanisms can increase collection rates. This thesis therefore attempted to address the question: How does the physical system architecture of e-waste systems influence system performance? and specifically, How does the physical system architecture of collection site density and distribution influence system performance?

The work presented here began with the presentation of a systematic methodology developed with the Materials Systems Laboratory for characterizing recycling systems. Case studies of existing e-waste systems operating in Switzerland, Sweden, the Netherlands, Norway, Belgium, the Canadian province of Alberta and the US States of California, Maine and Maryland were examined for correlations between the environmental and financial performance of existing systems with respect to both the context and the architectural options of those systems. The case study analysis furthermore informed the construction of a model of e-waste systems. This model, which enables examination of architectural choices in collection, processing and system management of e-waste, can be used to predict the environmental and financial performance of hypothetical e-waste systems in both real and theoretical locations. The analysis and resulting conclusions and recommendations focus upon the influence of collection site availability on system performance, and demonstrated that this architectural characteristic does significantly impact e-waste recycling system performance. The frameworks developed to complete this analysis are additionally applicable to other forms of system architecture as well as other types of waste. The ability of the model to enable exploration of changes in system parameters makes it possible to rapidly explore a number of different scenarios. Such explorations can reveal interesting and non-intuitive insights. Given the complex interaction between the many factors influencing any system's performance, the economic and environmental ramifications of such any one change can be difficult, if not impossible, to decipher through intuition. Such problems are well served by modeling. This final chapter presents a summary of the conclusions drawn for these combined analyses and then recommendations for the e-waste recycling system policymakers. Future work with this model will focus on exploring additional contexts and architectures, both to evaluate and improve the performance of existing systems and to aid in the design and implementation of new systems.

4.1 Summary of Conclusions

System performance is influenced by both system architecture and system context

Existing e-waste recycling systems vary significantly not only in system architecture, but in their operating context. The density of population distributions, quantities of e-waste generated, attitudes towards recycling, local labor costs and energy costs, are all characteristics of contextual factors which influence the performance of e-waste recycling systems. Comparing the performance of systems without also acknowledging the differences in the system's context can lead to recommendations ill-suited to the context at hand. For example, Chapter 2 conclusions noted that when comparing systems in countries with very different population densities, the number of collection points available per capita appears to be a more relevant metric than collection points available per area as a predictor of mass of e-waste collected per capita. This is because jurisdictions such Norway and Alberta have very large areas of uninhabited land. Thus, comparing these jurisdictions with those that are more fully settled on a per land area basis suggests that the density of people in the inhabited parts of Norway and Alberta is much lower than it actually is.

An increase in the mass of e-waste collected per capita might be a result of consumers buying more electronics, and not an improvement in system performance.

Performance data for the oldest European e-waste systems shows that each system has been able to continuously increase the amount of e-waste collected per year. However, given that the quantity of electronic items owned per person has also been increasing with time, the amount of e-waste generated per person has likely been increasing over time as well. Therefore, the collection of more e-waste per capita may simply be an artifact of increased e-waste generated and not a representation of an increase in the percentage of e-waste recovered. As shown in Section 2.3, examining the amount of e-waste collected per electronic item in use suggests that in fact, the oldest e-waste systems may have reached a plateau with respect to this metric of system performance.

Generally speaking, the increasing availability of collection points correlates with increasing quantities of e-waste collected, up to a limit.

Analysis of the performance of several existing e-waste collection systems (in Switzerland, Sweden, the Netherlands, Belgium, Norway, California, Maine, Maryland, and Alberta) showed that the systems offering the greatest number of collection sites were also the systems which collected the greatest mass of e-waste. The amount of e-waste collected per system is, however, not solely determined by the number of collection sites offered. For example, the analysis presented in Section 2.3 demonstrates that over time Norway has increased the quantity of e-waste collected while decreasing the number of collection points offered.

Furthermore, if it is assumed that an individual's likelihood to participate in the e-waste recycling system is a function of her distance to the nearest collection site, then increasing the availability of collection sites leads to a growth in the mass of e-waste collected up to a limit. In other words, adding collection sites to a system with very few sites enables more people to participate and thus has a substantial effect on the amount of e-waste collected. Conversely, adding more collection sites to a system in which all citizens already live close to existing sites will have little effect on participation. (See Section 3.2.1 and Section 3.2.4 for more detail on this effect.)

The system collecting the most total e-waste is not necessarily the same one collecting the most e-waste in all product categories

With 149.9 million kg, or 16.5 kg per capita, of e-waste collected in 2006, Sweden's El-Kretsen is often noted as the e-waste recycling system recovering the largest quantities of e-waste. However, looking only at IT and telecommunications equipment, Category 3 of the EU's WEEE Directive, Switzerland's SWICO has consistently collected both a larger total mass and mass per capita than Sweden each year. Thus, it should not be assumed that the e-waste systems with the best overall performance are also the best in each sub-category.

European e-waste recycling systems are currently collecting significantly more IT and telecommunications e-waste than current North American systems.

Current European e-waste systems are not only collecting a total mass of IT and telecommunications (WEEE category 3) e-waste which surpasses that collected in North American systems, but the quantities of mass collected per inhabitant are greater in Europe as well. This discrepancy is in part a result of North American systems collecting a more limited scope of products than the European systems. It is also likely because the European systems examined have been operating longer than the North American systems. Furthermore, North America lacks the equivalent of the European Union's WEEE directive, a piece of legislation enacted in 2003 which mandates EU-wide e-waste collection and processing for a broad definition of e-waste. (See Section 2.3 for more details.)

Individual willingness to participate in an e-waste recycling system significantly impacts the amount of e-waste collected.

Section 3.2.1 demonstrated that the constants used to define an individual's likelihood of participation in a recycling system have significant influence on the projected e-waste system performance. The modeled example suggests that the e-waste systems operating at the lowest cost per kg collected are those that operate in regions with large quantities of e-waste generated and citizens likely to participate, even when they must travel long distances to do so.

Consideration of personal transportation of e-waste to collection sites can be significant with respect to energy usage

To minimize the environmental impact associated with e-waste transportation, it is important to consider the transportation of e-waste to collection centers. The analysis of e-waste systems typically does not include this step because the costs associated with it are borne by the owner of the e-waste and are not considered within the scope of system managers. As modeled in Section 3.2.4, the costs associated with the personal transportation of e-waste are most significant in areas with low collection site densities per area and individuals willing to drive long distances to participate. The addition of collection sites generally decreases the mileage driven by (and associated costs to) individuals and increases mileage and costs for trucks carrying consolidated e-waste to processors. For the numbers of collection sites operated in existing e-waste systems, the total cost of car travel is small compared to that of truck transportation. However, the relative energy inefficiency of car transport compared to truck transport suggests that the contribution of car travel with respect to the overall environmental impact is more significant in terms of energy than cost.

Regions with high population densities and people unwilling to travel long distances benefit most from additional collection points

Modeling several distance decay functions in multiple geographies revealed that in regions with greater population densities, the lowest-cost solution required the use of more collection sites than in regions with lower population densities. Furthermore, it was revealed that this trend is most pronounced in the regions where people are only willing to participate if there is a collection site within a short distance of their residence. The rate at which participation drops as a function of one's distance to one's nearest collection site is represented by Lambda (λ) in the distance decay function used in this thesis.

4.2 Recommendations

The recommendations drawn from the conclusions of this work have been organized as they apply to three categories of people: e-waste recycling system managers, manufacturers of electronics and legislators. While each recommendation has been categorized with the group of people most likely to utilize it, each recommendation may be applicable to all groups.

4.2.1 For E-Waste Recycling System Operators

Share performance data and allow the industry to learn from best practices

The scope of analysis presented in Chapter 2 was limited by the data made available by each existing system. In order to gain a better understanding of how different system architectures influence system performance, more data describing the operation of current systems must be made available. The WEEE Forum is comprised of many representatives of European e-waste recycling systems sharing limited data and best practices. However, the majority of e-waste recycling systems have still not made as much data publically accessible as is needed to fully utilize the comparison framework presented in this thesis. If more e-waste recycling systems, many of which have government-sanctioned monopolies managing their region's e-waste, revealed more of their performance data, more insight could be gained with respect to how to evaluate and construct effective e-waste systems.

Consider the environmental impact of consumer transport of e-waste to collection sites

E-waste systems attempting to minimize the environmental impact associated with e-waste should remember to consider the impact of consumer transport of e-waste to collection sites. As shown in this thesis, the environmental impact associated with the energy usage from this transportation step can be significant, particularly when the system offers few collection sites at great distance to residents.

Consider increasing the availability of collection sites in order to increase collection

The e-waste systems currently collecting the most e-waste are also those that are offering the most collection sites. This correlation is not so direct as to suggest that every additional collection site will increase collection and vice versa; however, the availability of collection sites is an important characteristic of e-waste system architecture. When determining the number of collection sites to offer it is important to estimate how far residents will be willing to travel in order to participate. If this likelihood to travel is overestimated, too few sites may be funded, and many people with e-waste may choose not to participate.

Encourage consumer participation in the e-waste system

While consumer participation is influenced by the distance to collection sites, participation is also influenced by other factors including age, education, income, and peer pressure. The degree to which each of these factors influence participation is disputed in current literature. However, increasing public awareness of the program and its benefits can increase participation without the addition of new collection sites. In fact, as observed in Norway, it is possible for a system to increase the amount of e-waste collected while lowering the number of collection sites offered.

4.2.2 For Electronics Manufacturers

Encourage E-Waste Operators to Share Performance Data

As stated by Benjamin Wu, former Assistant Secretary for Technology Policy to the U.S. Department of Commerce, with regards to electronics recycling, "Industry believes a national solution is required because conflicting state legislation would lead to uncertainties, inefficiencies, and high compliance costs that will impede their ability to be competitive and innovative. Industry is focusing on efforts to create a national system that will achieve the goal of increasing recycling while not hindering interstate commerce." (Wu 2005) The industry's beliefs on this issue are well founded and likely correct. However, in order for the US to arrive at a national policy, or for any other group of jurisdictions to agree upon a unified approach to e-waste, the performance of existing systems should be better understood. In order for such a common understanding to be reached, current system operators must be more willing to disclose details regarding their current operation.

Design products for easy disassembly and material separation

The costs associated with processing e-waste are significant to the overall e-waste system recycling costs. When products are manufactured such that at end-of-life they can be easily dismantled, a greater percentage of material can be recovered, with less energy, and at a lower net cost to the system. Therefore, in order to aid both environmental and economic goals of e-waste systems, manufacturers should attempt to design products which can be easily disassembled. Many manufacturers rightly argue that such a design goal is not always achievable without additional cost to the manufacturing firm. Thus, manufacturers should also consider encouraging e-waste system designers to promote such behavior via the design of the system's financial structure.

4.2.3 For Legislators

Measure mass collection performance by the amount of e-waste available rather than by population

A common metric, and that included in the European Union's WEEE Directive, for e-waste system performance is the annual mass of e-waste collected per capita. Likewise, the US Department of Commerce summarized the consensus of a stakeholder meeting it held with the statement that e-waste legislation should "Set performance goals such as targets for percent or weight per capita for collection and recycling." (Wu 2005) Both because the average mass of e-waste generated per person is not the same in all jurisdictions and because the mass of e-waste generated in most jurisdictions is increasing every year, comparing different systems, or even the same system in different years, on a mass per capita basis is not a useful measure of performance when comparing systems. A better metric for comparison over time and various jurisdictions is the amount of e-waste collected compared to the amount of e-waste available. Estimating the actual amount of e-waste generated in any given year is challenging, yet possible using sales records from prior years and lifetime estimates.

Encourage participation in the e-waste system

The performance of most e-waste systems can still be improved by simply collecting a greater percentage of the e-waste generated. Whether done via the system's financial structure, a mandated maximum distance between collection sites, advertising, or other creative approaches, changing the shape of the distance decay function for participation in a region can substantially alter the amounts of e-waste collected and costs of operating the recycling system.

Encourage electronics manufacturers to design products for reuse and easy material recovery

The costs of processing e-waste are lower for products which are easily dismantled. Furthermore, a larger percentage of material can be reused from products which facilitate material separation, thus lowering the environmental impact of the product's lifecycle. Thus, legislators should consider the use of financial or other structures tied to the e-waste recycling system to encourage electronics manufacturers to produce products which can be easily broken-down at end-of-life to recover their material value.

4.3 Future Work

This thesis has presented a framework for comparing existing e-waste recycling systems, a model for predicting the performance of future e-waste systems, and provided examples of the utility of both. The limited availability of data, in particular with respect to system operating costs, has constrained the set of conclusions that can currently be drawn via applications of the comparison framework. As more e-waste recycling systems begin operation and release their performance data, additional observations and conclusions can be drawn from the use of this framework. Further insight can also likely be gained through using more detailed population distribution data with the model, and using the model to simulate additional combinations of system architecture and system context. The model itself could also better represent actual e-waste systems with the following enhancements:

- Integrate the participation distance decay function into the k-means algorithm. This will prevent sites from being located based upon the location of people who live further away than the decay function dictates will participate in collection at a given site. It should therefore result in a different set of locations than without the decay function, and will likely more strongly favor population-dense regions than the current implementation. This change may however also decrease the stability of the model.
- Limit the set of points where the model can choose to locate a collection site or processor to prevent the choice of lakes, mountain tops, or other inappropriate locals.
- When analyzing real geographies, integrate the distance calculator with a mapping program such that the distances calculated are based upon actual road lengths.
- Add retail and special event collection type events to the collection model
- Further develop the system management model into a full process-based cost model.
- Add a sub-model for the financial flows through the e-waste system to the model

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6 APPENDICES

Appendix A: WEEE Directive ANNEX IB

(The European Parliament and the Council of the European Union 2003)

List of products which shall be taken into account for the purpose of this Directive and which fall under the categories of Annex IA

1. Large household appliances

Large cooling appliances
Refrigerators
Freezers
Other large appliances used for refrigeration, conservation and storage of food
Washing machines
Clothes dryers
Dish washing machines
Cooking
Electric stoves
Electric hot plates
Microwaves
Other large appliances used for cooking and other processing of food
Electric heating appliances
Electric radiators
Other large appliances for heating rooms, beds, seating furniture
Electric fans
Air conditioner appliances
Other fanning, exhaust ventilation and conditioning equipment

2. Small household appliances

Vacuum cleaners
Carpet sweepers
Other appliances for cleaning
Appliances used for sewing, knitting, weaving and other processing for textiles
Irons and other appliances for ironing, mangling and other care of clothing
Toasters
Fryers
Grinders, coffee machines and equipment for opening or sealing containers or packages
Electric knives
Appliances for hair-cutting, hair drying, tooth brushing, shaving, massage and other body care appliances
Clocks, watches and equipment for the purpose of measuring, indicating or registering time
Scales

3. IT and telecommunications equipment

Centralised data processing:
Mainframes
Minicomputers
Printer units
Personal computing:
Personal computers (CPU, mouse, screen and keyboard included)
Laptop computers (CPU, mouse, screen and keyboard included)
Notebook computers
Notepad computers
Printers
Copying equipment
Electrical and electronic typewriters
Pocket and desk calculators and other products and equipment for the collection, storage, processing, presentation or communication of information by electronic means
User terminals and systems
Facsimile
Telex
Telephones
Pay telephones
Cordless telephones
Cellular telephones

Answering systems and other products or equipment of transmitting sound, images or other information by telecommunications

4. Consumer equipment

- Radio sets
- Television sets
- Videocameras
- Video recorders
- Hi-fi recorders
- Audio amplifiers
- Musical instruments
- And other products or equipment for the purpose of recording or reproducing sound or images, including signals or other technologies for the distribution of sound and image than by telecommunications

5. Lighting equipment

- Luminaires for fluorescent lamps with the exception of luminaires in households
- Straight fluorescent lamps
- Compact fluorescent lamps
- High intensity discharge lamps, including pressure sodium lamps and metal halide lamps
- Low pressure sodium lamps
- Other lighting or equipment for the purpose of spreading or controlling light with the exception of filament bulbs

6. Electrical and electronic tools (with the exception of large-scale stationary industrial tools)

- Drills
- Saws
- Sewing machines
- Equipment for turning, milling, sanding, grinding, sawing, cutting, shearing, drilling, making holes, punching, folding, bending or similar processing of wood, metal and other materials
- Tools for riveting, nailing or screwing or removing rivets, nails, screws or similar uses
- Tools for welding, soldering or similar use
- Equipment for spraying, spreading, dispersing or other treatment of liquid or gaseous substances by other means
- Tools for mowing or other gardening activities

7. Toys, leisure and sports equipment

- Electric trains or car racing sets
- Hand-held video game consoles
- Video games
- Computers for biking, diving, running, rowing, etc.
- Sports equipment with electric or electronic components
- Coin slot machines

8. Medical devices (with the exception of all implanted and infected products)

- Radiotherapy equipment
- Cardiology
- Dialysis
- Pulmonary ventilators
- Nuclear medicine
- Laboratory equipment for in-vitro diagnosis
- Analysers
- Freezers
- Fertilization tests
- Other appliances for detecting, preventing, monitoring, treating, alleviating illness, injury or disability

9. Monitoring and control instruments

- Smoke detector
- Heating regulators
- Thermostats
- Measuring, weighing or adjusting appliances for household or as laboratory equipment
- Other monitoring and control instruments used in industrial installations (e.g. in control panels)

10. Automatic dispensers

- Automatic dispensers for hot drinks
- Automatic dispensers for hot or cold bottles or cans
- Automatic dispensers for solid products
- Automatic dispensers for money
- All appliances which deliver automatically all kind of products

Appendix B: Python Code for Collection Siting Model

E-Waste Model.py

```
#(c)2008 Susan Fredholm (fredholm@alum.mit.edu)
# With contributions by Edgar Blanco, Chris Murphy and Elsa Olivetti
#Released under MIT License: http://www.opensource.org/licenses/mit-license.php
'''E-Waste Recycling Model for Siting Collection and Processing Sites'''

from scipy import *
import pylab
import os
import sys
import MakeKml
from NearestSiteDist import sites2dist, assignedsites2dist
import cluster
from LatLong2XY import LL2XY, XY2LL

def loadCSV(filename):
    """imports data from a CSV file with a header row into an array of floating
    point values"""
    data = array(pylab.load(filename, delimiter=",", skiprows=1), dtype=float64)
    return data

def makeCSV(array,NewFileName):
    """make a CSV from an array - NewFileName needs to be in quotes such as
    'newfile.csv'"""
    pylab.save(NewFileName, array, fmt='%.8f', delimiter=',')

def npopdots(pop,n=100.0):
    """make additional data points at each location in order to weight for
    population
    note: only works when pop/n < 65536"""
    dots_per_location = (pop[:,2]/n).round()
    if (dots_per_location >= 65536).any():
        raise Exception('Too many dots created.  Quantity per dot must'
                        ' be larger.')
    stackedxydots = pop[:,0:2].repeat(uint16(dots_per_location),axis=0)
    return stackedxydots

def npopdots_wscat(pop,n=100.0):
    """make additional data points at each location in order to weight for
    population, scatter the dots slightly so that they're not all directly
    on top of each other,
    note: only works when pop/n < 65536"""
    stackedxydots = npopdots(pop,n)
    # Now randomly shift the locations a little bit to spread out each stack and
    # help kmeans in below, stackedxydots is used as the mean, with the 2nd
    #input as the standard deviation
    xydots = zeros(stackedxydots.shape,dtype=float64)
    xydots[:,0] = random.normal(stackedxydots[:,0], 4e-3)  #lat
    xydots[:,1] = random.normal(stackedxydots[:,1], 6e-3)  #long
    return xydots

def add3rdcolumn(array2,value):
    """takes an array of width 2, and adds a 3rd column with a constant value"""
    array3 = zeros((array2.shape[0],3),dtype=float64)
    array3[:,0] = array2[:,0]
    array3[:,1] = array2[:,1]
    array3[:,2] = value
    return array3
```

```python
def create_collection_points(CC,pop,k_coll,ave_waste_per_participant,recycling_Q,
                             recycling_lambda,pop_dot_size):
    #convert lat/long values into x y values using a standard projection
    popXY=LL2XY(pop,CC)

    #split pop into more dots each with a pop of pop_dot_size
    popXY100dots = npopdots_wscat(popXY,pop_dot_size)

    #order pop array by population
    rows = argsort(popXY[:,2], kind='mergesort')
    rows = rows[-k_coll:]

    #use the k_coll number of towns with the highest pop as the initial sites
    init_clusters = popXY[rows, 0:2]

    #cluster sites!
    clustered_sites, assignments = cluster.kmeans(popXY100dots,init_clusters)

    #convert location units back into lat long
    clustered_sites=XY2LL(clustered_sites,CC)
    pop100dots = XY2LL(popXY100dots,CC)

    #add a 3rd row to pop100dots designating the 3rd row as population
    #of each dot (pop_dot_size)
    pop100dots3 = add3rdcolumn(pop100dots,pop_dot_size)
    #calculate distances people live from their nearest collection sites
    #people_dist = [pop,dist-to-nearest-site for each town, sitelat, sitelong]
    people_dist = assignedsites2dist(pop100dots3,clustered_sites,assignments)

    #calculate how much waste from each town will be brought to the nearest
    #site given how far away that site is from the town
    #waste from each dot per town =[sitelat,sitelong,waste,car-km]
    waste_from_each_town = zeros((people_dist.shape[0],4),dtype=float64)
    waste_from_each_town[:,0]= people_dist[:,2] #site lat
    waste_from_each_town[:,1]= people_dist[:,3] #site long
    #reminder: people_dist[:,0] = town population;
    # people_dist[:,1]=distance to site
    participation_likelihood = recycling_Q*exp(-1*recycling_lambda
                                               *people_dist[:,1])
    waste_from_each_town[:,2]= people_dist[:,0]*ave_waste_per_participant
                                *participation_likelihood
    waste_from_each_town[:,3]= people_dist[:,0]*participation_likelihood
                                *people_dist[:,1]

    #sum the amount of waste brought to each collection site
    #goal is for waste_at_cpoints to contain [sitelat,sitelong,amount of waste,
    #                                                  car-km]
    waste_at_cpoints = zeros((clustered_sites.shape[0],4),dtype=float64)
    waste_at_cpoints[:,0]= clustered_sites[:,0]
    waste_at_cpoints[:,1]= clustered_sites[:,1]
    for i,site in enumerate(clustered_sites):
        sitelat = site[0]
        sitelong = site[1]
        sitewaste = 0
        car_dist = 0
        for town in waste_from_each_town:
            if town[0]==sitelat and town[1]==sitelong:
                sitewaste += town[2]
                car_dist += town[3]
        waste_at_cpoints[i,2]= sitewaste
        waste_at_cpoints[i,3]= car_dist
```

```
    total_waste = waste_at_cpoints[:,2].sum()
    #sum the total number of car km driven (round-trip) to collection sites
    total_car_dist = 2*waste_at_cpoints[:,3].sum()

    #Print Results to Screen
    print ('Number of collection sites located = ' + str(k_coll))
    print ('Total E-Waste Collected = ' + str(total_waste) + 'kg')
    print ('Total Car Distance = ' + str(total_car_dist) + 'km')

    #Create output files
    makeCSV(people_dist,(str(k_coll)+'people_dist.csv'))
    makeCSV(waste_at_cpoints,(str(k_coll)+'cpoint_waste_dist.csv'))
    #makeCSV(people_dist,(str(k_coll)+'people_dist.csv'))
    KMLfilename = str(k_coll)+'clusters.kml'
        #another way to write the line above: KMLfilename ='%dclusters.kml' %k
    KMLtitle = str(k_coll)+'clusters'
    MakeKml.array2kml(clustered_sites,KMLfilename,KMLtitle)

    return waste_at_cpoints, total_waste, total_car_dist


def create_processor_points(CC,waste_at_cpoints,k_coll,k_proc,truck_capacity,
                            waste_dot_size):
    '''Determine where the processors should be placed'''
    #order waste_at_cpoints array by mass of waste collected
    rows = argsort(waste_at_cpoints[:,2], kind='mergesort')
    rows = rows[-k_proc:]  #takes the last k_proc number of collection sites
    #                       as initial processor sites
    #use the k_proc number of processors with the lowest masses
    #as the initial sites
    init_procs = waste_at_cpoints[rows, 0:2]

    #divide each collection point into several with smaller waste quantities
    coll_dots = npopdots(waste_at_cpoints[:,0:3],waste_dot_size)
    print "colldots shape: %s" % str(coll_dots.shape)
    #convert lat/long values into x y values using a standard projection
    coll_dotsXY=LL2XY(coll_dots,CC)
    init_procsXY=LL2XY(init_procs,CC)

    #Use the k-means algorithm to determine ideal processor locations
    #print "data shape: %s" % str(coll_dotsXY.shape)
    #print "cluster shape: %s" % str(init_procsXY.shape)
    proc_sitesXY, wpoint2proc_assignments = cluster.kmeans(coll_dotsXY,
                                                        init_procsXY)

    #convert XY values back to lat long values using standard projection
    proc_sites = XY2LL(proc_sitesXY,CC)

    '''Determine the truck miles driven to transport waste at cpoints
    to processors'''
    #condense the list of waste-dot assignments into cpoint2proc_assignments
    #waste_at_cpoints is [sitelat,sitelong,amount of waste,car-km]*k_coll length
    #coll_dots=[sitelat,sitelong,amount of waste,car-km] with extra long length
    #wpoint2proc_assignments [processor#] with extra long length

    cpoint2proc_assignments = zeros(k_coll, dtype=int32)
    for i,cpoint in enumerate(waste_at_cpoints):
        sitelat = cpoint[0]
        sitelong = cpoint[1]
        for j,wpoint in enumerate(coll_dots):
            if wpoint[0]==sitelat and wpoint[1]==sitelong:
                cpoint2proc_assignments[i] = wpoint2proc_assignments[j]
                break #go to next i,cpoint instead of next j,wpoint
```

```
    cpoint2proc_assignments = cpoint2proc_assignments.T

    #calculate distances from collection sites to their nearest processor
    coll2proc_dist = assignedsites2dist(waste_at_cpoints[:,0:3],proc_sites,
                                        cpoint2proc_assignments)
    """coll2proc_dist = [waste-per-collection-site,dist-to-nearest-processor
    for each site, desinationlat, destinationlong]"""

    #sum the amount of waste brought to each processor
    #goal is for waste_at_ppoints to contain [sitelat,sitelong,
    #                                         amount of waste,truck-km]
    waste_at_ppoints = zeros((proc_sites.shape[0],4),dtype=float64)
    waste_at_ppoints[:,0]= proc_sites[:,0]
    waste_at_ppoints[:,1]= proc_sites[:,1]
    for i,site in enumerate(proc_sites):
        sitelat = site[0]
        sitelong = site[1]
        proc_waste = 0
        truck_dist = 0
        for cpoint in coll2proc_dist:
            if cpoint[2]==sitelat and cpoint[3]==sitelong:
                proc_waste += cpoint[0]
                truck_dist += ceil(cpoint[0]/truck_capacity)*2*cpoint[1]
        waste_at_ppoints[i,2]= proc_waste
        waste_at_ppoints[i,3]= truck_dist
    total_truck_waste = waste_at_ppoints[:,2].sum()
    #sum the total number of truck km driven (round-trip) to processors
    total_truck_dist = waste_at_ppoints[:,3].sum()

    #Print Results to Screen
    print (str(k_coll) + ' collection points with ' + str(k_proc)+
           ' processors:')
    print ('Total Truck Distance = ' + str(total_truck_dist) + 'km')

    #Create output files
    makeCSV(waste_at_ppoints,(str(k_coll)+'c'+str(k_proc)+
                              'ppoint_waste_dist.csv'))
    #makeCSV(truck_dist,(str(k_proc)+'truck_dist.csv'))
    KMLfilename = str(k_coll)+'c'+str(k_proc)+'processors.kml'
    #another way to write the line above: KMLfilename ='%dclusters.kml' % k
    KMLtitle = str(k_coll)+'c'+str(k_proc)+'processors'
    MakeKml.array2kml(proc_sites,KMLfilename,KMLtitle)

    return waste_at_ppoints, total_truck_waste, total_truck_dist

def calculate_coll_cost(k_coll,total_waste):
    #This part of the code is not currently active.  The Process-Based
    #Cost Model in Excel is instead used to determine the collection costs.
    collection_cost = 0.
    return collection_cost

def calculate_trans_cost(total_dist,cost_per_km):
    transportation_cost = total_dist*cost_per_km
    return transportation_cost

def calculate_proc_cost(k_proc,total_waste):
    #This part of the code is not currently active.  The Process-Based
    #Cost Model in Excel is instead used to determine the processing costs.
    fixed_proc_cost_per_site = 0. #$/site
    variable_proc_cost_per_kg = 0. #$/kg
    processing_cost = fixed_proc_cost_per_site*k_proc
                    + variable_proc_cost_per_kg*total_waste
    return processing_cost
```

```python
def calculate_mgmt_cost():
    management_cost = 200000
    return management_cost

def create_points_and_proc(CC,pop,k_coll_list,k_proc_list, output_log_filename,
                           ave_waste_per_participant,recycling_Q,
                           recycling_lambda,truck_capacity, pop_dot_size=100.0,
                           waste_dot_size = 500.0):
    #k_coll = the number of collection sites you want to create
    #k_proc = the number of processing sites you want to create

    fields =['k_coll','k_proc','total_waste','total_car_dist','total_truck_dist',
             'management_cost','collection_cost','truck_transportation_cost',
             'car_transportation_cost','processing_cost','total_cost_per_kg']

    f = file(output_log_filename,'w')
        #a=append (Adds), r=read, w=write (overwrites)
    f.write("Results for: \n")
    f.write("Average Waste(kg) Per Person:,"+str(ave_waste_per_participant)+"\n")
    f.write("Q:,"+str(recycling_Q)+"\n")
    f.write("Lambda:,"+str(recycling_lambda)+"\n")
    f.write(",".join(fields)+"\n") #write the list of field names across
    #the top of the csv file

    for k_coll in k_coll_list:
        waste_at_cpoints, total_waste,
        total_car_dist = create_collection_points(CC,pop,k_coll,
                                                  ave_waste_per_participant,
                                                  recycling_Q,
                                                  recycling_lambda,
                                                  pop_dot_size)
        collection_cost = calculate_coll_cost(k_coll,total_waste)
        management_cost = calculate_mgmt_cost()
        car_transportation_cost = calculate_trans_cost(total_car_dist,.31)
        #$0.31/km ~ $0.50/mile

        print "Last Waste Dot Size:", waste_dot_size
        waste_dot_size = total_waste/10000
        if waste_dot_size < 25.0:
            waste_dot_size = 25.0
        print "New Waste Dot Size:", waste_dot_size

        for k_proc in k_proc_list:
            waste_at_ppoints,total_truck_waste,
            total_truck_dist= create_processor_points(CC,waste_at_cpoints,
                                                      k_coll,k_proc,
                                                      truck_capacity,
                                                      waste_dot_size)
            #$1.55/km ~ $2.50/mile
            truck_transportation_cost = calculate_trans_cost(total_truck_dist,
                                                             1.55)
            #$0.31/km ~ $0.50/mile
            car_transportation_cost = calculate_trans_cost(total_car_dist,.31)
            processing_cost = calculate_proc_cost(k_proc,total_truck_waste)
            total_cost_per_kg = (management_cost+collection_cost+
                                 truck_transportation_cost+processing_cost)
                                /total_waste

            #get value for each field name, convert values to strings,
            #and join with commas
            f.write(",".join([str(locals()[field]) for field in fields])+"\n")
            f.flush() #really write to the file (not buffer) now
```

```
    f.close()
    return


def run_multiple_simulations(popdata, CountryCode, output_folder):
    for rec_Q,rec_lambda in array([[1.25,.4],[1.25,.28],[2.5,.18],
                                   [2.5,.5],[4.5,.72],[4.5,.53]]):
            dirname = "%s-Q%.02f-L%.02f" % (CountryCode, rec_Q, rec_lambda)
            sim_dir = os.path.join(output_folder, dirname)
            os.mkdir(sim_dir)
            os.chdir(sim_dir)
            sim_log_filename="Results-log.csv"

            #specify which numbers of collection sites and processor sites
            #you want to evaluate
            #range(start(incl),stop(not included),stepsize)
            k_coll_list = arange(50,501,50)
            k_proc_list = [1,2,5,10,20,30,40]

            ave_waste_per_participant = 25 #kg

            #Assign variables associated with transportation
            truck_capacity = 5500 #in kg

            mini_rec_Q = rec_Q/ave_waste_per_participant

            #Determine Collection Points, Processor Points, and create lots
            #of output files in the above directory
            create_points_and_proc(CountryCode, popdata, k_coll_list,
                                   k_proc_list, sim_log_filename,
                                   ave_waste_per_participant,mini_rec_Q,
                                   rec_lambda, truck_capacity)


#the main function that runs when you run this python script
if __name__ == '__main__':
    # Get the name of the folder this python file is in.
    base_folder = os.path.dirname(os.path.abspath(sys.argv[0]))
    output_folder = os.path.join(base_folder, "Model-Outputs")
    os.mkdir(output_folder)

    print "=====================Starting on Switzerland==============="
    popdata = loadCSV(os.path.join(base_folder, 'CH-Pop.csv'))
    run_multiple_simulations(popdata, 'CH', output_folder)
    print "=====================Starting on Maine======================"
    popdata = loadCSV(os.path.join(base_folder, 'Maine-Pop.csv'))
    run_multiple_simulations(popdata, 'ME', output_folder)
    print "=====================Starting on Alberta==================="
    popdata = loadCSV(os.path.join(base_folder, 'Alberta-Pop.csv'))
    run_multiple_simulations(popdata, 'AB', output_folder)
```

NearestSiteDist.py

```python
#(c)2008 Susan Fredholm (fredholm@alum.mit.edu)
# With Contributions by Chris Murphy
#Released under MIT License: http://www.opensource.org/licenses/mit-license.php

from scipy import *
import pylab
import os
import sys
from geopy import distance

def load_data():
        """imports population and existing site data into arrays"""
        pop = array(pylab.load('CH-Pop.csv', delimiter=",", skiprows=1),
                                dtype=float64)
        clusters = array(pylab.load('CH-Sites.csv', delimiter=",",skiprows=1),
                                         dtype=float64)
        return pop, clusters

def sites2dist(pop,clustered_sites):
        #takes 2 arrays pop = [poplat,poplong,pop]
        #and clustered_sites = [sitelat,sitelong]
        #and creates output array = pop,dist-to-nearest-site for each town,
        #                                                         sitelat, sitelong]

        #create an array the length of pop, and width 2
        car_dist= zeros((pop.shape[0],4),dtype=float64)
        #fill the first column with city population data
        car_dist[:,0]= pop[:,2]

        #fill the second column with the distance from each town to the nearest site
        for i,city in enumerate(pop):
                #create a big min distance to be overwritten
                min_dist = 9999999999
                poplat = city[0]
                poplong = city[1]
                for site in clustered_sites:
                        sitelat = site[0]
                        sitelong = site[1]
                        #calculate distance between the city and each collection site
                        try:
                                dist = distance.VincentyDistance((poplat,poplong),
                                                         (sitelat,sitelong)).km
                        except:
                                #there's a bug in Vincenty Distance such that it
                                #doesn't work if the site and destination are the
                                #same, this fixes that by defining the distance as
                                #zero in these cases
                                if (poplat == sitelat) and (poplong == sitelong):
                                        dist = 0
                                else:
                                        raise Exception('unknown problem - fix me!')

                        #if the current distance calculated is smaller than the last,
                        #       update min_dist
                        if dist < min_dist:
                                min_dist = dist
                                bestsitelat = sitelat
                                bestsitelong = sitelong
                        #write the min distance calculated and location of collection
                        #site for each city to the car_dist array
                car_dist[i,1]= min_dist
```

```
            car_dist[i,2]= bestsitelat
            car_dist[i,3]= bestsitelong

        return car_dist

def assignedsites2dist(pop, clustered_sites, assignments):
        #takes 2 arrays pop = [poplat,poplong,pop]
        #and clustered_sites = [sitelat,sitelong]
        #and creates output array = pop,dist-to-nearest-site for each town,
        #                                                   sitelat, sitelong]

        #create an array the length of pop, and width 4
        car_dist= zeros((pop.shape[0],4),dtype=float64)
        #fill the first column with city population data
        car_dist[:,0]= pop[:,2]

        #fill the second column with the distance from each town to the nearest site
        for i,city in enumerate(pop):
                #create a big min distance to be overwritten
                poplat = city[0]
                poplong = city[1]
                site = clustered_sites[assignments[i],:]
                bestsitelat = site[0]
                bestsitelong = site[1]
                #calculate distance between the city and each collection site
                try:
                        dist = distance.VincentyDistance((poplat,poplong),
                                         (bestsitelat,bestsitelong)).km
                except Exception, e:
                        #there's a bug in Vincenty Distance such that it doesn't work
                        # if the site and destination are the same, this fixes that
                        #by defining the distance as zero in these cases
                        #if (poplat == bestsitelat) and (poplong == bestsitelong):
                        if all([(abs(poplat-bestsitelat)<1e-8),
                                         (abs(poplong -bestsitelong)<1e-8)]):
                                dist = 0
                        else:
                                print "Something failed in calculating distances"
                                print "pop shape : ", pop.shape
                                print "clustered sites shape : ",
                                                         clustered_sites.shape
                                print "assignments shape : ", assignments.shape
                                print "poplat : ", poplat
                                print "poplong : ", poplong
                                print "bestsitelat : ", bestsitelat
                                print "bestsitelong : ", bestsitelong
                                print "latdiff = ", poplat - bestsitelat
                                print "longdiff = ", poplong - bestsitelong
                                raise e #prints original error message that
                                        #led to being in this "else" instruction

                #write the minimum distance calculated and location of collection
                #site for each city to the car_dist array
                car_dist[i,1]= dist
                car_dist[i,2]= bestsitelat
                car_dist[i,3]= bestsitelong

        return car_dist

#if this file is run by itself it will use CH-pop.csv and clusters.csv
if __name__ == '__main__':
        os.chdir(os.path.dirname(os.path.abspath(sys.argv[0])))
        pop, clusters = load_data()
```

```
        car_dist = sites2dist(pop,clusters)
        print 'Success!'
```

MakeKML.py

```
#(c)2008 Susan Fredholm (fredholm@alum.mit.edu) and Chris Murphy
#Released under MIT License: http://www.opensource.org/licenses/mit-license.php

from scipy import *
import pylab
import os
import sys

def load_data():
        sites = array(pylab.load('Maine-Sites.csv', delimiter=",", skiprows=1),
                                 dtype=float64)
        pop = array(pylab.load('Maine-Pop.csv', delimiter=",", skiprows=1),
                               dtype=float64)
        return sites, pop

def array2kml(csv,NewFileName,NewTitle,color='ff00ccff'):
        #NewFileName needs to be in single quotes
        f = file(NewFileName,'w')
        output = ""
        output += """<?xml version='1.0' encoding='UTF-8'?>
        <kml xmlns='http://earth.google.com/kml/2.2'>
                <Document>
                        <name>%s</name>
                """% NewTitle

        for row in csv:
                output += """<Placemark>
        <Point><altitudeMode>clampToGround</altitudeMode>
        <coordinates>%.9f,%.9f,0</coordinates></Point>
        </Placemark>""" % (row[1], row[0])

        output += """</Document>
        </kml>"""

        f.write(output)
        f.close()
        return

def WriteKML(collect, proc, title, filename, color='ff00ccff'):
        #NewFileName needs to be in single quotes
        f = file(filename,'w')
        output = """<?xml version='1.0' encoding='UTF-8'?>
        <kml xmlns='http://earth.google.com/kml/2.2'>
                <Document>
                        <name>%s</name>
                """% title

        output += "<Folder><name>Collection Sites</name>"
        for row in collect:
                output += """<Placemark>
        <Point><altitudeMode>clampToGround</altitudeMode>
        <coordinates>%.9f,%.9f,0</coordinates></Point>
        </Placemark>""" % (row[1], row[0])
        output += "</Folder>"
```

```
        output += "<Folder><name>Processors</name>"
        for row in proc:
                output += """<Placemark>
        <Point><altitudeMode>clampToGround</altitudeMode>
        <coordinates>%.9f,%.9f,0</coordinates></Point>
        </Placemark>""" % (row[1], row[0])
        output += "</Folder>"

        output += """</Document>
        </kml>"""

        f.write(output)
        f.close()
        return


if __name__ == '__main__':
        os.chdir(os.path.dirname(os.path.abspath(sys.argv[0])))
        sites, pop = load_data()
        #sites, pop, clusters = load_data()
        orange = 'ff00ccff'
        array2kml(sites,'MaineSites.kml','MaineSites',orange)
```

LatLong2XY.py

```
#(c)2008 Susan Fredholm (fredholm@alum.mit.edu) and Chris Murphy
#Released under MIT License: http://www.opensource.org/licenses/mit-license.php

'''Converts lat/long coordinates into x/y coordinates in meters'''

import osgeo.osr as osr
import scipy

##to check the units of the projected data,
##use OGRSpatialReference::GetLinearUnitsName()
##and for a conversion to meters (if not already in meters) GetLinearUnits()


#### Map Projection for Switzerland ####
CH1903_WKT = """PROJCS["CH1903+ / LV95",
    GEOGCS["CH1903+",
        DATUM["CH1903",
            SPHEROID["Bessel 1841",6377397.155,299.1528128],
            TOWGS84[674.374,15.056,405.346,0,0,0,0]],
        PRIMEM["Greenwich",0],
        UNIT["degree",0.01745329251994328]],
    PROJECTION["Hotine_Oblique_Mercator"],
    PARAMETER["latitude_of_center",46.95240555555556],
    PARAMETER["longitude_of_center",7.439583333333333],
    PARAMETER["azimuth",90],
    PARAMETER["rectified_grid_angle",90],
    PARAMETER["scale_factor",1],
    PARAMETER["false_easting",2600000],
    PARAMETER["false_northing",1200000],
    UNIT["metre",1]]"""

srSwiss = osr.SpatialReference()
srSwiss.ImportFromWkt(CH1903_WKT)
```

```
#### Map Projection for Maine ####
srMaine = osr.SpatialReference()
srMaine.SetProjCS("UTM 19 (WGS84)")
srMaine.SetWellKnownGeogCS("WGS84")
srMaine.SetUTM(19, True)

#### Map Projection for Alberta ####
srAlberta = osr.SpatialReference()
srAlberta.SetProjCS("Transverse Mercator 10deg width (10TM)")
srAlberta.SetWellKnownGeogCS("WGS84")
#SetTM(centerlat, centerlong, scale, false easting, false northing)
''' false easting and northing are shifts in north and south to make
compatible with UTM - their values won't change anything I'm doing since I'm
only looking at differences, not absolute positions'''
'''Center lat shouldn't matter either since TM is based on longitude,
not latitude '''
'''Center long does matter'''
'''Scale also matters a lot.  This is what makes the map valid over 10 deg
instead of 6 like UTM does (with scale = .9996)'''
#values from Alberta Environmental Protection Land and Forest Service
srAlberta.SetTM(0,-115,.9992,500000,0)


#### Transformation Functions ####
srLatLong = osr.SpatialReference()
srLatLong.SetWellKnownGeogCS("WGS84")

xformMaine2LL = osr.CoordinateTransformation(srMaine, srLatLong)
xformSwiss2LL = osr.CoordinateTransformation(srSwiss, srLatLong)
xformAlberta2LL = osr.CoordinateTransformation(srAlberta, srLatLong)

xformLL2Maine = osr.CoordinateTransformation(srLatLong, srMaine)
xformLL2Swiss = osr.CoordinateTransformation(srLatLong, srSwiss)
xformLL2Alberta = osr.CoordinateTransformation(srLatLong, srAlberta)

def XY2LL(XYpts,CC):
  """XYpts = an array with x values in the first column, and
  y values in the second column.  CC = country (or state) code.
  This function converts the x values in the first column of the array
  into latitudes, and the y values in the second column into longitudes.
  Any data in additional columns of the input array will be passed back
  in the output array as well."""
  LL = XYpts.copy()
  if(CC=="CH"):
    for i,point in enumerate(XYpts):
      LL[i,0:2] = xformSwiss2LL.TransformPoint(point[0], point[1], 0.0)[1::-1]
    return LL
  if(CC=="ME"):
    for i,point in enumerate(XYpts):
      LL[i,0:2] = xformMaine2LL.TransformPoint(point[0], point[1], 0.0)[1::-1]
    return LL
  if(CC=="AB"):
    for i,point in enumerate(XYpts):
      LL[i,0:2] = xformAlberta2LL.TransformPoint(point[0], point[1], 0.0)[1::-1]
    return LL
  else:
    print "No projection available for this location"
    return


def LL2XY(LL,CC):
```

```
  """LL = an array with latitude values in the first column, and
  longitude values in the second column.  CC = country (or state) code.
  This function converts the latitude values in the first column of the array
  into x values, and the longitude values in the second column into y values.
  Any data in additional columns of the input array will be passed back
  in the output array as well."""
  XYpts = LL.copy()
  if(CC=="CH"):
    for i,point in enumerate(LL):
      XYpts[i,0:2] = xformLL2Swiss.TransformPoint(point[1], point[0], 0.0)[0:2]
    return XYpts
  if(CC=="ME"):
    for i,point in enumerate(LL):
      XYpts[i,0:2] = xformLL2Maine.TransformPoint(point[1], point[0], 0.0)[0:2]
    return XYpts
  if(CC=="AB"):
    for i,point in enumerate(LL):
      XYpts[i,0:2] = xformLL2Alberta.TransformPoint(point[1], point[0], 0.0)[0:2]
    return XYpts
  else:
    print "No projection available for this location"
    return


#the main function that runs when you run this python script
if __name__ == '__main__':
  swissXYpts = scipy.array([(2617300.62300,1268506.59600,3),
  (2776668.24900,1265376.04600,3),
  (2722590.15600,1087792.04700,3),
  (2612759.68800,1178654.25700,3)])
  print swissXYpts

  swissLL = XY2LL(swissXYpts,"CH")
  print "Swiss LL:"
  print swissLL
  swissXY = LL2XY(swissLL,"CH")
  print "Swiss XY:"
  print swissXY
  swissLL2 = XY2LL(swissXYpts,"CH")
  print "Swiss LL2:"
  print swissLL2
  print

  maineLLs = scipy.array([(45.27361, -69.48972),(46.61556,-68.17361)])
  print maineLLs
  maineXY = LL2XY(maineLLs,"ME")
  print "Maine XY:"
  print maineXY
  maineLL = XY2LL(maineXY,"ME")
  print "Maine LL:"
  print maineLL
```

Appendix C: C Code for K-Means Algorithm with Python Wrapper

kmeans.c

```c
/* (c) 2008 Roger Zhang, Chris Murphy and Susan Fredholm
 * Released under MIT License: http://www.opensource.org/licenses/mit-license.php
 * Contact Chris Murphy (cmurphy@whoi.edu) with questions / bugfixes / comments.
 *
 * Derived from code created on 2005-04-12 by Roger Zhang (rogerz@cs.dal.ca)
 * Modified by Chris Murphy to facilitate python bindings (cmurphy@whoi.edu)
 *
 * kmeans.c -- a simple k-means clustering routine
 * - returns 1 on success, 0 on failure.
 *
 * Parameters
 * - array of data points (double *data)
 * - number of data points (int n)
 * - dimension (int m)
 * - desired number of clusters (int k)
 * - error tolerance (double t)
 *   - used as the stopping criterion, i.e. when the sum of
 *     squared euclidean distance (standard error for k-means)
 *     of an iteration is within the tolerable range from that
 *     of the previous iteration, the clusters are considered
 *     "stable", and the function returns
 *   - a suggested value would be 0.0001
 * - output address for the final labels (int *labels)
 *   - user must make sure the memory is properly allocated
 * - output address for the final centroids (double *centroids)
 *   - user must make sure the memory is properly allocated
 * References
 * - J. MacQueen, "Some methods for classification and analysis
 *   of multivariate observations", Fifth Berkeley Symposium on
 *   Math Statistics and Probability, 281-297, 1967.
 * - I.S. Dhillon and D.S. Modha, "A data-clustering algorithm
 *   on distributed memory multiprocessors",
 *   Large-Scale Parallel Data Mining, 245-260, 1999.
 */

#include <stdlib.h>
#include <assert.h>
#include <float.h>
#include <math.h>

int kmeans(double *data, int n, int m, int k, double t, int *labels,
           double *centroids) {

   int h, i, j; /* loop counters, of course :) */
   int *counts; /* size of each cluster */
   double old_error, error = DBL_MAX; /* sum of squared euclidean distance */
   double *c = centroids; /* temp centroids */
   double **c1;

   if (!(data && k > 0 && k <= n && m > 0 && t >= 0)) {
     return 0;
   }

   // Allocate some memory.
   counts = (int*)calloc(k, sizeof(int));
   c1 = (double**)calloc(k, sizeof(double*));
```

```c
   /****
   ** initialization */

   for (i=0; i < k; i++) {
      c1[i] = (double*)calloc(m, sizeof(double));
   }
   /* Points are now preselected.
   for (h = i = 0; i < k; h += n / k, i++) {
      c1[i] = (double*)calloc(m, sizeof(double));
      // pick k points as initial centroids
      for (j = m; j-- > 0; c[i*m + j] = data[h*m + j]);
   }*/

   /****
   ** main loop */

   do {
      /* save error from last step */
      old_error = error, error = 0;

      /* clear old counts and temp centroids */
      for (i = 0; i < k; counts[i++] = 0) {
         for (j = 0; j < m; c1[i][j++] = 0);
      }

      for (h = 0; h < n; h++) {
         /* identify the closest cluster */
         double min_distance = DBL_MAX;
         for (i = 0; i < k; i++) {
            double distance = 0;
            for (j = m; j-- > 0; distance += pow(data[h*m + j] - c[i*m + j], 2));
            if (distance < min_distance) {
               labels[h] = i;
               min_distance = distance;
            }
         }
         /* update size and temp centroid of the destination cluster */
         for (j = m; j-- > 0; c1[labels[h]][j] += data[h*m + j]);
         counts[labels[h]]++;
         /* update standard error */
         error += min_distance;
      }

      for (i = 0; i < k; i++) { /* update all centroids */
         for (j = 0; j < m; j++) {
            c[i*m + j] = counts[i] ? c1[i][j] / counts[i] : c1[i][j];
         }
      }
   } while (fabs(error - old_error) > t);

   /** housekeeping */

   for (i = 0; i < k; i++) {
      free(c1[i]);
   }

   free(c1);
   free(counts);
   return 1;
}
```

Cluster.c (Wrapper to allow k-means.c to be used in Python)

```
/* (c) 2008 Chris Murphy
 * With contributions from Susan Fredholm
 * Released under MIT License:http://www.opensource.org/licenses/mit-license.php
 * Contact Chris Murphy (cmurphy@whoi.edu) with questions / bugfixes / comments.
 */

#include "Python.h"
#include "arrayobject.h"
#include <stdlib.h>
#include <stdio.h>

extern int kmeans(double *data, int n, int m, int k, double t, int *labels,
                  double *centroids);

PyDoc_STRVAR(kmeans__doc__,
  "kmeans(data, initial_centroids, thresh=0.0001) ==> (centroids, labels)\n\n"
  "Perform kmeans clustering on `data', and return a 2-tuple of the centroid\n"
  "locations (`centroids') and data assignments to clusters (`labels').\n"
  "Each row of `data' is an item to cluster, `initial_centroids' is an initial\n"
  "guess at the cluster locations, and `thresh' is the acceptable error\n"
  "threshold for stopping.");
static PyObject * kmeans_wrapper(PyObject *self, PyObject *args) {
  PyArrayObject *data         = NULL;
  PyArrayObject *contig_data  = NULL;
  PyArrayObject *clust        = NULL;
  PyArrayObject *centroids    = NULL;
  PyArrayObject *labels       = NULL;
  PyObject *ret = NULL;
  double thresh = 0.001;
  int lbl_dims[1];
  int success;

  /* data array and initial guess array are inputs, threshold optional. */
  if (!PyArg_ParseTuple(args, "O!O!|d", &PyArray_Type, &data, &PyArray_Type,
                                        &clust, &thresh)) {
    return NULL;
  }
  /* Get simple 2D arrays for data and initial centroid guesses */
  contig_data = (PyArrayObject *)PyArray_ContiguousFromObject(
                                     (PyObject*)data, PyArray_DOUBLE, 2, 2);
  centroids = (PyArrayObject *)PyArray_ContiguousFromObject(
                                     (PyObject*)clust, PyArray_DOUBLE, 2, 2);
  if (!contig_data || !centroids) {
    PyErr_SetString(PyExc_TypeError, "Couldn't get contiguous 2D Double array "
                                     "for either centroids or data.");
    return NULL;
  }

  // The centroids should be the same size as the data!
  if(centroids->dimensions[1] != contig_data->dimensions[1]) {
    PyErr_SetString(PyExc_IndexError, "The number of rows of data must be the "
    "same as the number of initial centroids provided.");
    return NULL;
  }

  // Setup array to store the returned data labels
  lbl_dims[0] = contig_data->dimensions[0];
  labels      = (PyArrayObject*)PyArray_FromDims(1, lbl_dims,  PyArray_INT);

  success = kmeans((double *)contig_data->data, contig_data->dimensions[0],
                   contig_data->dimensions[1], centroids->dimensions[0], thresh,
```

```
                    (int *)labels->data, (double *)centroids->data);

  if (!success) {
    PyErr_SetString(PyExc_Exception, "You messed up.  Either:\n"
    "* You have no data,\n* Number of clusters > number of rows\n"
    "* Your data is zero-width\n* Your threshold is < 0, or\n"
    "* You passed in no initial clusters. (probably.)");
    return NULL;
  }

  ret = PyTuple_Pack(2, centroids, labels);
  Py_DECREF(centroids); //Maybe? I think?
  Py_DECREF(labels);    //Maybe? I think?
  return ret;
}

static PyMethodDef ClusterMethods[] = {
    {"kmeans", kmeans_wrapper, METH_VARARGS, kmeans__doc__},
    {NULL, NULL, 0, NULL} /* Sentinel */
};

/* Module Documentation and Initialization */
PyDoc_STRVAR(cluster__doc__, "Miscellaneous Clustering Utilities.");
PyMODINIT_FUNC initcluster(void) {
  Py_InitModule3("cluster", ClusterMethods, cluster__doc__);
  import_array();
}
```