Development of Metrics for Streamlined Life Cycle Assessments: A Case Study on Tablets

by

María de Lourdes Alcaraz Ochoa

S.B., Chemical Engineering
Massachusetts Institute of Technology, 2012

Submitted to the Institute for Data, Systems, and Society
in Partial Fulfillment of the Requirements for the

Masters of Science in Technology and Policy

at the

Massachusetts Institute of Technology

June 2016

Signature redacted

Signature of Author ....
Technology and Policy Program
May 6, 2016

Signature redacted

Certified by ....
Elsa Olivetti
Thomas Lord Assistant Professor, Department of Materials Science & Engineering
Thesis Supervisor

Signature redacted

Accepted by ....
Munther Dahleh
William A. Coolidge Professor of Electrical Engineering and Computer Science
Acting Director, Technology and Policy Program
Director, Institute for Data, Systems, and Society

Development of Metrics for Streamlined Life Cycle Assessments:
A Case Study on Tablets
by
María de Lourdes Alcaraz Ochoa

Submitted to the Institute for Data, Systems, and Society
On May 6, 2016 in Partial Fulfillment of the Requirements for the
Degree of Masters of Science in Technology and Policy
at the Massachusetts Institute of Technology

Abstract

Growing concern about climate change and human impact on the environment have resulted in an increase in interest for evaluating the environmental impact of products and services we consume. Life cycle assessment (LCA) has become the most prominent method for environmental evaluation. Life cycle assessment is the quantification of the environmental impacts of a product or service through its whole life cycle, from the extraction of materials to manufacturing and end of life. A carbon footprint is a subset of an LCA. LCAs are required as part of government regulations, used by companies to identify high resource use in their supply chain or to choose between product designs and by consumers to choose between alternative product choices. LCAs provide valuable information; however, they are resource intensive, time consuming and uncertain. Therefore, a methodology that addresses all these issues is needed.

This study addresses the following question: Can LCAs be streamlined while still providing useful information? To answer this, an under-specification, probabilistic screening methodology is employed. The screening methodology uses a high level assessment of the footprint, incorporates uncertainty in the inputs, and refines data around the primary drivers of impact. The streamlined LCA procedure is extended to include a Sobol based sensitivity analysis methodology for identifying high impact activities. The effects of partial perfect information in subsequent data acquisition activities on the streamlining methodology are examined. Metrics to determine sufficiency in the data gathering procedure and to determine whether decision makers can sufficiently distinguish between two products or design alternatives are developed. A procedure to quantify the cost of additional information is developed. Finally, an exploration of the scenario space of the impacts is analyzed. The extended streamlined methodology is applied to a case study on tablets, with a focus on integrated circuits.

This thesis finds that the streamlined, probabilistic methodology can be used to cost-effectively evaluate the environmental impact of products while still taking uncertainty into account. Metrics to determine sufficiency can be effectively used, and the presence of partial information does not limit the usefulness of the metrics. Furthermore, quantifying the cost of additional information can help determine sufficiency in data collection efforts and can help understand the challenges that companies face when performing an LCA.

Thesis Supervisor:
Elsa Olivetti, Thomas Lord Assistant Professor, Materials Science & Engineering

~ Acknowledgements ~

The journey of writing this thesis has been challenging and very rewarding. I am grateful for having had the opportunity to participate in the Technology and Policy Program at MIT. This work would not have been possible without the help of many amazing individuals.

First of all, I would like to thank Elsa Olivetti for her guidance since day 1. I have learned a lot from her and I'm still impressed by her passion and commitment to her work and her interest in the well-being of her students. Thank you, Elsa! I would also like to thank Arash Noshadravan for spending many afternoons sharing his knowledge and answering many e-mails with my questions. Next, I would like to thank Randy Kirchain, Josh Hester and Reed Miller from the Materials Systems Laboratory for meeting with me to brainstorm ideas. Similarly, I would like to thank Eddie Kim for helping me with the code and Xinkai Fu for spending his own time translating the surveys. I would also like to thank Pamela Silva, from the Writing Center, for helping me edit this thesis.

I would like to thank the Olivetti group for making my time in the office and at group meetings enjoyable, and for celebrating my birthday in random dates. Also, thank you Pat, for being available in the office to talk about life, sustainability, and our future career paths. I would also like to thank all of my friends at TPP and at MIT who made my experience unforgettable, and all the amazing TPP staff. Special thanks to all of my friends, near and far, who encouraged me along the way.

Finally, I would like to thank my dear family for all their love and support, and Enrique, for encouraging me to pursue my dreams.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1. Motivation

Life cycle assessment is the quantification of the environmental impacts of a product or service through its whole life cycle, from the extraction of materials to manufacturing and end of life. Life cycle assessment (LCA) has become the most prominent method for environmental evaluation as evident in its adoption in governmental policies in Europe, such as in renewable energy directives (Ahlgren & Röös, 2013), battery recycling, chemicals regulation, and electrical and electronic policies, as well as in the United States in initiatives such as the Energy Independence and Security Act of 2007 (Reed, 2012). Practitioners use LCAs to support business strategy and research and development (Cooper & Fava, 2006), and increasingly, for labeling and corporate environmental reporting (Masanet & Chang, 2014). LCA has gained popularity because of its multidisciplinary approach (Andrae & Andersen, 2010) and its extensive reach. A subset of an LCA is a carbon footprint, which aims to quantify all the greenhouse gas emissions, in units of kilogram CO_2 equivalents, that occur during a product's life cycle (De Koning, Schowanek, Dewaele, Weisbrod, & Guinée, 2010; Henriksson et al., 2015). LCAs and carbon footprints provide guidance to consumers when making environmentally friendly decisions and help industries target areas for environmental improvements of their products.

Several standards have emerged that specify in more detail how a life cycle assessment should be carried out. The International Organization for Standardization's (ISO) 1404X describes the principles and framework, specifies requirements, and provides guidelines and examples of LCAs (*ISO 14040*, 2006, *ISO 14044*, n.d., *ISO 14047*, 2012, *ISO 14049*, 2012). The International Reference Life Cycle Data System (ILCD) Handbook details the steps to perform an LCA for LCA practitioners (Wolf, Pant, Chomkhamsri, Sala, & Pennington, 2012). The British Standards Institute's (BSI) PAS 2050 describes the assessment methodology for quantifying life cycle greenhouse gas emissions (*BSI PAS 2050:2011 Specification for the assessment of the life cycle greenhouse gas emissions of goods and services*, 2011). Despite the vast amount of efforts to standardize life cycle assessment, subjective decisions are still present in LCAs, resulting in a lack of a consistent approach to LCAs.

LCA's and carbon footprints provide valuable information; however, they are resource intensive, time consuming and fraught with uncertainty. They are resource intensive because they require detailed environmental information on the product from the material extraction phase to manufacturing until the end of life (EOL) (Lee, Yang, & Blanco, 2012). Due to the complex nature of supply chains, these data acquisition and analysis efforts can take months to complete (Zgola, 2011). Many times data is unavailable or incomplete, and surrogate data or estimates are used to fill in these data gaps, resulting in estimation bias that can be represented as uncertainty. Increasing the efficiency and robustness of decision-making regarding the alternative choices or improvement options requires a methodology that sufficiently accounts for uncertainty. Thus, fast, reliable life cycle assessment analyses are needed.

Several streamlining methodologies that attempt to address the issues with LCAs have already been developed. Graedel, Allenby, and Comrie (1995) developed a semi-quantitative, matrix type assessment that ranks the impact of each life cycle inventory parameter by using a predefined impact scoring list. Similarly, Chen and Chow (2003) developed a patterned based methodology, which groups products according to predefined parameters, and then the desired product's environmental impact is mapped to the different groups. These methods provide a rapid evaluation of the environmental impact of a product or process but they are highly uncertain. A more quantitative streamlining methodology identified in the SETAC North America Streamlined LCA Workgroup is scope limiting, in which the upstream and/or downstream stages are limited or eliminated (Todd et al., 1999). All streamlining methodologies already use scope limiting to a certain extent (Olivetti, Patanavanich, & Kirchain, 2013), but limiting the scope can end up ignoring a high impact process or material, yielding an incorrect result. Another quantitative streamlining methodology is screening LCA, which only uses readily available data (Wenzel, 1998), and excludes processes and materials that are known to have a minimal impact (Moberg, Johansson, Finnveden, & Jonsson, 2010). However, the exclusion of certain processes can ignore interaction effects present between different processes and parameters. Other methods that have been developed to reduce the resource intensity, time and cost of LCAs include the development of carbon footprint tools (Huang, Hu, Yin, & Wang, 2016) and data mining techniques (Sundaravaradan, Marwah, Shah, & Ramakrishnan, 2011) .

Olivetti and colleagues developed an under-specification, probabilistic screening methodology to perform quantitative evaluation of the footprint at a reduced cost (Olivetti et al., 2013). The methodology involves using a high level assessment of the footprint that incorporates uncertainty in the inputs based on, for example, publicly available studies and industry expert input, to screen for high impact elements that contribute to a high degree of uncertainty in the assessment. Data are refined around these primary drivers of impact until uncertainty is reduced to a specified target level, while the rest of the analysis remains at the high level of assessment. In their work, they focus only on the materials impact and do not explore how this methodology extends to the impact of a product, including manufacturing. Zgola (2011) does explore this aspect and employs the methodology on a case study of liquid crystal displays but does not explore the whole scenario space.

This thesis builds upon the work of Olivetti and Zgola to expand the probabilistic triage streamlining methodology. In this thesis, we propose a methodology for performing the sensitivity analysis used to screen high impact elements that contribute to a high degree of uncertainty in the assessment. We explore alternative scenarios and propose metrics that can be used by decision makers to determine whether they can sufficiently distinguish between two products or design alternatives or whether more refined data needs to be gathered. Finally, we develop a methodology to quantify the cost savings from employing the streamlining methodology.

The refined probabilistic triage streamlining methodology is applied to a case study of tablets. Tablets, and electronics in general, are of interest because of the need to quantify their environmental impact, which involves the use of high purity chemicals, electricity consumption and emissions during their manufacturing. Electronics have complex high tech, manufacturing processes (Koomey, Matthews, & Williams, 2013), rapid product profile changes (Andrae & Andersen, 2010; Mueller et al., 2004), worldwide supply chains (Koomey et al., 2013; Mueller et al., 2004), complexity in their material composition, and use of highly specific purity levels in their chemical use (Mueller et al., 2004). All of these factors make tablets an ideal candidate for streamlined life cycle assessment. The goal of this thesis is to develop a robust streamlining methodology that takes into account uncertainty.

1.2. Literature Review

Life Cycle Assessments are plagued by uncertainties. In order to learn how to treat uncertainties in LCAs and carbon footprints, it is necessary to have a thorough understanding of the types of uncertainties present. This section will review the literature describing the types of uncertainties found in environmental assessments, particularly dealing with electronics, and efforts to quantify it. As this thesis focuses on the methodology employed to perform the sensitivity analysis to screen high impact elements, a summary of sensitivity analysis techniques will be described as they relate to environmental assessments.

1.2.1. Uncertainty

This section will review the types of uncertainty present in life cycle assessments and it will describe the most common types of uncertainty present in the LCAs of electronics. This section will also discuss methods used to propagate uncertainty.

1.2.1.1. Uncertainty in Life Cycle Assessments

Many times, life cycle assessments and other environmental assessments are carried out for product or design improvement comparisons. However, practitioners of LCAs usually report results as point values, failing to capture the variability and uncertainty present in an LCA (Henriksson et al., 2015; Lloyd & Ries, 2007). Decision makers might not fully endorse LCAs because many times the uncertainty associated with them is ignored (Herrmann, Hauschild, Sohn, & McKone, 2014). It is important to know the amount of uncertainty associated with the outcome of an LCA to be able to judge the significance of the outcome of product comparisons, product design improvements or the use of ecolabels (M. A. J. Huijbregts et al., 2001). Recent efforts have been directed at understanding the types of uncertainties present in an LCA and in developing methods to quantify and incorporate uncertainty in an LCA. However, a clear standard for the quantification and incorporation of uncertainty in an LCA is still needed.

The data within a life cycle inventory and impact assessment method used in an LCA contains both uncertainty and variability. Based on Heijungs and Huijbregts (2004), uncertainty differs from variability in that uncertainty deals with a lack of knowledge (epistemic uncertainty) or with measurement errors, while variability has to do with inherent differences that arise from the heterogeneous nature of the process in question. We will refer to both uncertainty and variability as uncertainty.

In 1992, the USEPA classified uncertainty into three different types: parameter, scenario, and model uncertainty (USEPA, 1992). Parameter uncertainty refers to uncertainty in the input values to the model that results from incomplete knowledge of the true value, inaccurate measurements or from estimates or assumptions. Parameter uncertainty is the type of uncertainty most incorporated into LCA studies. All of the studies incorporating uncertainty surveyed by Lloyd and Ries (2007) incorporated parameter uncertainty, while only 38% and 33% incorporated scenario and model uncertainty, respectively. Scenario uncertainties arise from normative choices that exist in an LCA, such as the system boundary chosen, the time horizon observed, the allocation of environmental impacts for processes with multiple outputs and geographical choices. These choices can result in different outcomes for an LCA. Model uncertainty has to do with the uncertainty associated with the chosen model and with how well it describes the real world. Many simplifications are done when choosing a model. Types of models commonly employed for an LCA are process-based models, economic input-output (EIO) LCA and hybrid LCAs. Huijbregts, Gilijamse, Ragas, & Reijnders (2003) found that it is important to quantify the three types of uncertainty as all of them can be significant.

Huijbregts et al. (2001) categorized the uncertainty present in an LCA into two: a lack of data and of representative data, and data inaccuracy. Data gaps can occur because of a lack of resources (both time and monetary resources) needed to obtain the information or because of confidentiality issues in the production chain. The lack of representative data is further split into three components: temporal, geographical, and technological correlation. Uncertainty from temporal correlation occurs when the year that the data was collected differs from the year of the study. Thus, older data is used as a proxy of newer data. Geographical correlation uncertainty arises when the data obtained is for a particular geographical location and differs from the geographical area covered in the study. Uncertainty from technological correlation includes all other aspects uncertainty due to the correlation between the data obtained and the study. Huijbregts et al. (2001) explains data inaccuracy as uncertainty that arises from sources such as imprecise measurements and expert estimations and assumptions.

The next section will describe the most pertinent types of uncertainty present in the LCA's of electronics.

1.2.1.2. Uncertainty in LCA's of electronics

All sources of uncertainty are significant in the carbon footprints and LCAs of electronics (Lloyd & Ries, 2007). LCAs of electronics have parameter, scenario, and model uncertainty. Large data gaps are common in the LCAs of electronics. Particularly noticeable sources of uncertainty are temporal and geographical variability, lack of inventory and impact factor data, and differences in impact characterization schemes (Teehan & Kandlikar, 2012).

Temporal variation in electronics arises when data gaps exist and individual data values are assumed independent and are substituted for older data. Data gaps in the electronics industry are common because the products evolve approximately every two years (Murphy, Kenig, Allen, Laurent, & Dyer, 2003), and because data acquisition is burdensome because of the complex manufacturing process, industry secrets (Koomey et al., 2013; Krishnan et al., n.d.; Murphy et al., 2003), and rapid changes in the supply chains (Deng, Babbitt, & Williams, 2011). Thus, by the time the data acquisition task is complete, the product profile has changed. LCA practitioners end up using the older data in the study of a newer product, and this results in uncertainty of the assessment result.

Geographical variation occurs when the data collected is for a specific geographical area, but it is used as a substitute when studying a different geographical area. In electronics, geographical variation is mainly caused by differences in the electricity generation mix from country to country. Manufacturing mostly happens in Southeast Asia but product use occurs everywhere (Teehan & Kandlikar, 2012). Thus, it is difficult to specify the global warming impact of the use phase, as this will depend on the use location, and normative choices have to be made. Teehan and Kandlikar (2012) found that global warming impacts due to use phase will be 30 times higher in China than in Norway because of differences in electricity sources. Further geographical variation occurs because of differences from location to location in the energy consumption in the materials, manufacturing, and assembly process (Deng et al., 2011).

Other uncertainties in the LCAs of electronics arise because of the difficulty in obtaining a value for product lifetimes, the availability of different choices for the functional unit (Teehan & Kandlikar, 2012), and from cutoff and aggregation errors (Deng et al., 2011). In addition, many data gaps exist because of intellectual property issues, which prevents manufacturers from sharing information on their production process, and because they cannot measure emissions since it is time consuming and requires specialized equipment and methods. Furthermore, the global warming potential (GWP) allows comparison of the global warming impact of different gases. However, the GWP changes depending on the time period used, resulting in further variation in the assessment.

1.2.1.3. Uncertainty Characterization and Methods for Propagating Uncertainty

In order to calculate the uncertainty of the output of a model with respect to parameter uncertainty, the uncertainties of the input parameters need to be specified. Input uncertainties are usually specified with probability density functions and sometimes with possibility functions. Clavreul, Guyonnet, Tonini, and Christensen (2013) argue that a combination of probability and possibility functions should be used when dealing with both epistemic uncertainty and variability. Even though a clear methodology on the incorporation of uncertainty in LCAs is still missing (Groen, Heijungs, Bokkers, & de Boer, 2014), efforts should be directed towards incorporating uncertainty into LCAs to prevent misleading decision makers and users of the assessment.

Common distributions used in the uncertainty characterization of an LCA are the normal, lognormal, uniform, beta, trapezoidal and triangular distributions (Heijungs & Huijbregts, 2004; Lloyd & Ries, 2007). In general, available data and expert estimates are used to choose the type of distribution and the parameters of the distribution. Lognormal distributions are widely used for LCAs because they only allow positive values and skewed distributions, which have been found to be representative of LCA data, while uniform and trapezoidal distributions are used for less understood parameters (Lloyd & Ries, 2007). Ecoinvent's modification of Weidema and colleagues' pedigree matrix and their data quality indicators can be used to quantify the uncertainty of a parameter when enough information is not available (Weidema et al., 2013)

Several efforts have been made in the LCA literature to propagate uncertainty in LCAs. Some of these approaches have included fuzzy data sets, interval calculations, analytical uncertainty propagation, Bayesian statistics and stochastic modeling (M. Huijbregts, 1998; Lloyd & Ries, 2007). All of the methods have advantages and disadvantages.

Analytical uncertainty propagation incorporating a Taylor series expansion was first introduced by Morgan and Henrion (1990). In analytical uncertainty propagation, mathematical expressions are used to quantify the uncertainty of the output based on the input parameters. Analytical uncertainty propagation does not require specifying a distribution for the input parameters, thus decreasing the additional uncertainty from choosing a distribution. However, it requires complex mathematical expressions that are many times not feasible for an LCA study (Lloyd & Ries, 2007).

Fuzzy data sets, which use possibility functions, are used for epistemic uncertainty. LCA practitioners use fuzzy data sets to deal with the lack of LCI data that makes it difficult to perform goodness-of-fit tests to derive the probability function (Lloyd & Ries, 2007). Possibility functions assign degrees of likelihood to intervals of input values rather than exact values, resulting in fuzzy intervals (Clavreul et al., 2013). These intervals are propagated throughout the model, resulting in a family of distributions for the characterization of the output uncertainty. Fuzzy data sets account for missing information, but they do not take correlation of parameters into account.

The most widely used method for uncertainty propagation in LCAs is stochastic modeling. Stochastic modeling samples from the input distributions. The most common stochastic method is Monte Carlo simulations. In Monte Carlo simulations, numbers are randomly sampled from the distribution of the input variables to obtain the sample distribution of the output. Monte Carlo simulations allow for the use of different parameter distributions for the various inputs and they allow for correlations between the input parameters (M. Huijbregts, 1998). Another similar method used is Latin hypercube sampling. Just as in Monte Carlo simulations, numbers are randomly sampled from the input distributions, but the distributions are divided into equally probable strata. Stochastic modeling has become easier with the increasing computing power; however, it has also been found to require more data than is usually available.

The method chosen to quantify and propagate uncertainty will depend on the availability of data. Efforts should be directed towards developing a common standard for the incorporation of uncertainty in LCAs.

1.2.2. Sensitivity analysis

Due to the presence of uncertainty in environmental models used in decision making, sensitivity analysis can help determine the changes in the output of the model caused by changes in the input variables, and it can also determine the contribution of the input parameters to the uncertainty of the output. The EPA recommends carrying out a sensitivity analysis in environmental models in order to understand the confidence that can be placed in model results (EPA, 2009). Several methods exist to conduct a sensitivity analysis, and the method chosen depends on the goal of the sensitivity analysis, on the model, and on the resources available.

Cariboni, Gatelli, Liska, and Saltelli (2007) describe four possible goals for a sensitivity analysis. First, a sensitivity analysis can be carried out to identify the parameters that contribute the most to the output variance, and which by fixing them, could lead to the greatest reduction in uncertainty. It can also be used to simplify a model by screening for the non-influential parameters or to reduce the uncertainty of the output to a specified threshold by fixing the value of the smallest number of input factors. Finally, the goal of a sensitivity analysis can also be to determine at what values the input parameters can be fixed to obtain a given range of the output. Sensitivity analysis in LCAs is usually carried out to identify the parameters which, if fixed to their true values, would reduce the uncertainty of the output of a model.

Several different sensitivity analysis methods have been used in LCAs. Sensitivity analysis techniques can be divided into local and global techniques. Local techniques involve One-At-a-Time (OAT) sampling, in which each input parameter is varied at a time while the rest of the parameters remain fixed at a value. Local techniques are usually fixed to a specific point in the space of parameters and do not account for interactions between parameters, but are computationally inexpensive. On the other hand, global techniques tend to be model independent and they determine the effect of an input parameter on the output while varying all the parameters at the same time. However, global techniques require a large number of model evaluations and are therefore computationally expensive. Local sensitivity techniques are usually derivative based, while global techniques include the Morris method, standardized regression coefficients and Sobol indices.

For local, derivative based sensitivity analysis, the sensitivity of output Y to a change in input x_i is determined by evaluating the partial derivative of Y at a given value of x_i:

$$S_{x_i} = \left.\frac{\delta Y}{\delta x_i}\right|_{x_i = x_i^*} \quad (1\text{-}1)$$

This technique only works if the model is linear and as it is evaluated at a specific value, it only gives the sensitivity of the output to the input parameters around a specific region in the space of parameters. Kucherenko, Rodriguez-Fernandez, Pantelides, and Shah (2009) proposed a method that averages local derivatives using Monte Carlo and quasi-Monte Carlo sampling methods. They argue that the method is comparable to Sobol' global sensitivity indices and with less computational intensity.

Another widely used screening sensitivity analysis technique is the Morris method, proposed by Morris in 1991 (Campolongo, Cariboni, & Saltelli, 2007). The Morris method averages local measures using sampling of points at a delta increment. Thus, it cannot account for effects with characteristic dimensions lower than delta and it cannot provide information about the contribution of individual variables to uncertainty (Kucherenko et al., 2009). Campolongo and Saltelli (1997) compared the Morris screening method to the Sobol' indices technique and suggested that the Morris method be used to screen parameters followed by the Sobol index on the subset of selected inputs for a more efficient procedure.

The standardized regression coefficient technique is based on regression analysis and Monte Carlo simulations. A linear relationship is built between the input parameters and the model output:

$$Y = b_0 + \sum_{i=1}^{n} b_i x_i \tag{1-2}$$

Regression analysis is used to determine the regression coefficients b_i. The standardized regressions coefficients, which are used as the sensitivity measure, are then calculated as:

$$SRC(y, x_i) = b_i \frac{\sigma_{x_i}}{\sigma_Y} \tag{1-3}$$

where σ_{x_i} and σ_Y are the standard deviations of parameters x_i and of the output Y, respectively. This method allows for the estimation of the model coefficient of determination, R^2. If R^2 is low, the model is non-linear and another method needs to be used.

Another technique for determining the sensitivity of the output to input parameters is the method of Sobol' (Sobol', 1990). This method was shown to be the correct technique to use for identifying the most significant input parameters (Andrea Saltelli & Tarantola, 2002). The output variance is decomposed into the amount of variance explained by each parameter V_i:

$$V(Y) = V_1 + \cdots + V_n + \in \tag{1-4}$$

where $\in$ is the residual. The first order sensitivity indices are then defined as:

$$S_i = \frac{V_i}{V(Y)} \tag{1-5}$$

The total sensitivity index or total effect takes into account interactions between parameters. This method is model independent, captures interaction effects as well as the full range of variation of each parameter, but it is very computationally intensive, and as the number of input parameters increases, it becomes more challenging to calculate.

A similar methodology to determine where efforts for acquiring more data should be directed to is value of information. Value of information belongs to decision analysis methods and it explores how a decision might change based on acquiring new information. Value of information has been used to determine where research efforts should be directed at, with limited information available (Bates, Sparrevik, de Lichy, & Linkov, 2014; Linkov, Bates, Canis, Seager, & Keisler, 2011). This is similar to a sensitivity analysis as it determines which parameters, or research efforts, can have the most leverage in reducing the uncertainty of the system. Future efforts should be directed at comparing the methodologies, both in terms of accuracy and computational effort.

1.2.3. Cost of Additional Information

A literature search on life cycle assessment will quickly yield results that mention the resource intensity of performing an LCA and the need to reduce data collection efforts. As shown in section 1.1, several streamlining efforts have been developed that aim to reduce the time and resource intensity of performing an LCA. However, to the best of our knowledge, there has been no prior work on quantifying the cost, both effort and monetary cost, of performing an LCA. A search on cost and LCA might yield results on Life Cycle Costing (LCC), however, this is a different methodology as it deals with the economic effects of products and/or services and with comparing the cost amongst alternatives, not with the cost of making an LCA (Bierer, Götze, Meynerts, & Sygulla, 2014; Gluch & Baumann, 2004; Norris, 2001).

Quantifying the cost of acquiring additional information on an LCA can help evaluate the efficiency (hereto referred as the monetary and effort saved) of the streamlining methodology. Olivetti, Patanavanich, & Kirchain (2013) defined efficiency in their streamlining procedure as the percentage of the parameters they had to specify further to reach a predetermined uncertainty threshold to the total number of parameters in the life cycle assessment. However, specifying each activity might differ significantly in the amount of cost (or effort) required and thus, information on the cost of acquiring information on each parameter is more exact. Furthermore, determining the cost of acquiring additional information provides more information that can be used as a metric to determine when sufficient information about the life cycle assessment has been gathered. Therefore, there is a need to develop a methodology for quantifying the cost of acquiring additional information.

Bates et al. (2015) used Value of Information (VOI) analysis to determine the best way to allocate resources to a set of research activities and research portfolios. They complemented the VOI analysis with information on the cost of reducing the uncertainty for each research activity. They estimated the cost by sending a survey to experts and asked them to rank a series of activities. This type of methodology could be applied in the LCA field to gather knowledge on the cost of acquiring additional information.

1.3. Gap Analysis

As seen in the literature review, a need for quantifying the uncertainty of LCAs of electronics in an efficient manner has been identified in several studies. Several streamlining methodologies exist, and in particular, Olivetti and colleagues' probabilistic streamlining methodology is a promising method because it quantifies uncertainty. However, a deeper understanding of the method to identify the parameters of the footprint that should be specified further is needed as well as a more thorough exploration of the scenario space. This thesis will bridge the lack of knowledge and will focus on developing a clear methodology and understanding of the identification of high impact activities under different conditions.

Furthermore, the literature review identified a gap in the knowledge of the cost of gathering additional information on the parameters in an LCA. The work in this thesis aims to eliminate this gap and develop a methodology for gathering information on the cost of the parameters in an LCA, based off of the methodology developed by Bates et al. (2015) in the VOI space. Finally, this thesis will develop metrics, some which incorporate cost, to determine when sufficient information has been gathered in a streamlined LCA.

1.4. Central Questions

Due to the growing interest in LCAs and the inherent uncertainty associated with them, this research aims to develop a more robust LCA streamlining methodology by exploring the identification of high impact activities in more detail. This research addresses the question of how the additional information obtained and the presence of partial perfect information affect the subsequent identification of high impact activities. Does the fact that the additional information is still uncertain limit the ability to streamline the assessment? This research has the goal of developing a clear methodology for performing the identification of high impact activities.

This research also takes into account that the acquisition of more data requires additional effort and resources. Thus, this research also addresses the question: how can the cost of gathering additional information be used to prioritize data acquisition efforts and to inform practitioners when sufficient information has been obtained? Since the acquisition of additional information is assumed to be resource intensive but also lowers the uncertainty of the result, we address the question: how can the value of additional information be quantified?

This research also has the goal of understanding how an exploration of the scenario space can be used to make an environmentally sound decision between different products. Finally, this research aims to answer how much cost savings can be obtained by streamlining while still obtaining an assessment with sufficient resolution and how do these cost savings vary by company?

1.5. Thesis Outline

In this thesis, we extend the probabilistic, streamlining methodology to clearly carry out the sensitivity analysis and to include cost.

- Chapter 2 describes the methodology developed to perform the streamlined life cycle assessment, to gather information on the cost of additional information, and to explore the scenario space of the product in question.
- Chapter 3 tests the methodology on a case study of tablets.
- Chapter 4 discusses the results found, as well as the limitations, challenges and areas of future work.
- Chapter 5 summarizes the key points from the thesis.

Chapter 2: Methodology

The goal of the research was to create a robust, streamlined, life cycle assessment methodology. This research gathered high level data on the environmental impact of a product, along with uncertainty data, and prioritized data acquisition efforts. A methodology was developed to quantify the cost of additional information. The analysis explored the scenario space of environmental impacts of the product to derive insights from it. This analysis was performed for two products, tablets and integrated circuits.

The general approach to footprint streamlining (Figure 2-1) begins with data sets collected from a bill of materials and from life cycle inventory data gathered from publicly available studies and from industry expert input. All this data is collected into a bill of activities, which is the bill of materials plus additional information such as process or transportation information. Each component in the bill of activities is referred to as an "activity". Each data set represents samples of different input parameters required to quantify the environmental impact. The uncertainty in these input parameters can then be characterized using the collected data. Depending upon the availability and quality of data, the uncertainty characterization can be performed by fitting appropriate distributions to the available data, or by an expert estimate if sufficient data is not available. Once the underlying uncertainty in each input parameter is characterized and represented as a proper distribution, a probabilistic analysis based on the Monte Carlo simulation is carried out to propagate uncertainty into the global warming potential (GWP) associated with each individual activity and collectively, that of the product, using of Equation (2-1).

$$Emissions = \sum_{i=1}^{Number\ of\ activities} Quantity_i \times Intensity_i \times Impact\ Factor_i \quad (2\text{-}1)$$

A subsequent sensitivity analysis of the data is performed to identify the high impact activities. Data is refined to a narrower distribution for these high-impact activities and the simulation is executed again because the relative importance of the high impact activities in the resulting uncertainty changes after the data is specified in more detail (M. A. J. Huijbregts et al., 2003). This process is repeated until uncertainty has decreased to a previously specified level or to a point where alternative products can be clearly distinguished, as will be discussed in Section 2.3. Metrics, which incorporate cost, are used to determine when sufficient specification has been obtained.

Scenario uncertainty is assessed by creating different scenarios and analyzing each of the scenario's impact. When an activity is specified further, it is specified to a narrower distribution. At this level of resolution, there are different clusters of data to which the activity could be resolved. These different clusters are combined to form the different scenarios.

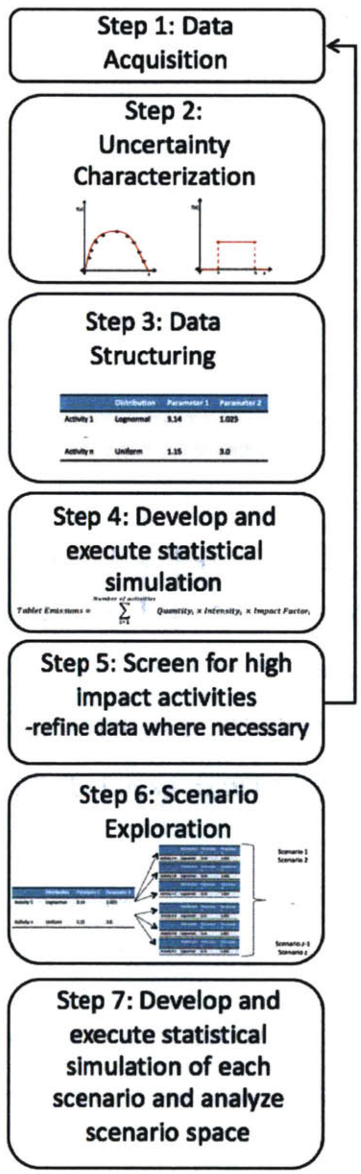


Figure 2-1: Schematic of the under-specification, probabilistic, streamlining methodology.

2.1. Data Acquisition

2.1.1. Environmental Impact Data Acquisition

The first step in the probabilistic screening methodology is gathering information to determine the life cycle phases of the product in question, followed by the acquisition of data on the impacts in each life cycle phase. To accomplish this, previous published studies, individual industry work and input, industry association data, life cycle inventory databases and teardowns were used. End of life (EOL) was left outside the scope of this study. Data obtained is of varying quality, age, source and number of points; however, low fidelity data is acceptable at the high level assessment.

2.1.2. Acquisition of Cost Information

Once information on the life cycle phases to be included in the study was determined, a survey was devised to gather information on the cost of acquiring more specific data on each activity. The cost asked for was the relative cost between the different activities present in the footprint. Here, cost included both monetary costs and effort. Effort was defined as the time spent tracking down individuals in a company or supply chain for input, hiring outside consultants to gather data or other potential ways of gathering data. The question that was asked in the survey was: "What would be the relative cost of reducing the uncertainty of the ______________ from [X] to [Y]." For example, what would be the relative cost of reducing the uncertainty of the scope 1 and the scope 2 emissions for integrated circuits packaging from an industry average to the specific fab emissions?

In the survey, similar activities were grouped together to simplify the process of filling it out. For example, instead of asking for the cost of acquiring additional information on the quantity of ferrous metal and on the quantity of plastic in the product, both activities were combined and the question was modified to ask for the cost of acquiring more information on all the materials present.

The respondents were first asked to identify the most expensive data gathering task on the questionnaire (in other words, the task requiring the most effort) across all parameter uncertainties and assign it a score of 1.0. Next, they were asked to score the cost of reducing uncertainties for the other parameters relative to the cost for the most expensive parameter. If they consulted colleagues to fill out the questionnaire, they were asked to specify for which activities they received outside input and how many colleagues they consulted.

The survey was sent to various industry collaborators who work in gathering data for life cycle assessments. For activities in which our collaborators had to obtain outside input to answer the questionnaire, additional cost was added to the score. The scores for each activity from the various surveys were then averaged and analyzed. The scores were also analyzed individually.

2.1.3. Data Structure

The data was categorized into three hierarchical levels, with level 1 being the most general level and level 3 being the most specified level. For example, level 1 refers to the emissions resulting from electricity usage during the fabrication of integrated circuits in Asia, level 2 refers to the same emissions but in a specific country, such as China, Taiwan or Korea, and level 3 refers to the same emissions but in a specific region of the country. The three levels were created to quickly test the methodology. The analysis starts with all the parameters specified at level 1. Once a parameter was identified as a high-impact activity in the contribution to variance analysis, the information in the next level was used to specify the activity in more detail.

2.2. Uncertainty

2.2.1. Uncertainty Characterization

Characterization of the uncertainty of each activity was done via several methods. For those parameters that have sufficient data points, such as for the material breakdown of the tablet, the values were fit to a distribution using the statistical software JMP®. The tests used to measure the goodness of fit were Empirical Distribution Function (EDF) tests, including the Shapiro-Wilk test and the Kolmogorov-Smirnov test. For activities for which only a couple of data points were available, they were treated as uniform distributions between the available data points. For activities that were single point values, ecoinvent's modification of the

Weidema et al. (2013) pedigree matrix and relevant data quality indicators were used to quantify the uncertainty. The distribution for single values was modeled as lognormal because it only allows positive values and skewed distributions, which have been found to be representative of LCA data (Lloyd & Ries, 2007). Scenario uncertainty was addressed by creating different normative scenarios.

The data was structured in different levels of uncertainty, with the first level being highly unspecific. The first level aggregated all possible values for the activity, while the second level used a subset of those values and the third level used the specific value for the product. Thus, as the information became more specific, the uncertainty diminished. However, even at the third level, uncertainty was present because of measurement error and inherent variability associated with certain activities.

2.2.2. Uncertainty Propagation

Uncertainty was propagated throughout the model using stochastic modeling. The uncertainty propagation was carried out using Monte Carlo simulations, which is widely used in the LCA literature for uncertainty analysis. The Monte Carlo procedure was implemented in MATLAB® by Arash Noshadravan, postdoctorate associate at the Material Systems Laboratory and now Research Assistant Professor at Texas A&M. To carry out this procedure, samples from the distributions of each activity were generated. The distributions encountered in the model were discrete, uniform, normal, and lognormal. To sample from the distributions, random numbers were generated using the built-in function *copularnd*, which takes into account correlations (previously specified) between parameters. When the distribution was discrete, the specified value was returned. When the distribution was uniform, equation (2-3) was used:

$$x_k^i = \min + (\max - \min) * rnd \qquad (2\text{-}2)$$

where x is the sample number i for parameter k, *min* is the minimum value of the specified uniform distribution, *max* is the maximum value of the uniform distribution, and *rnd* is the random number generated. For the normal and the lognormal distributions, the built in MATLAB® functions *norminv* and *logninv* were used. The function *logninv* takes in the mean and standard deviation of the associated normal distribution, so careful consideration was given to ensure consistency.

The number of samples for each activity was set to 300,000 to obtain consistent and replicable results. These samples were in turn used to calculate the realizations of modeled global warming potential using Equation (2-1). This resulted in a sufficiently sized sample for the modeled global warming potential from which the probabilistic description was inferred.

2.3. Sensitivity Analysis/ Contribution to Variance

A variance-based sensitivity analysis was carried out using Sobol's method (Sobol', 1990). This method was chosen because of its ability to decompose the output variance into the variance of the input parameters and to account for the higher order effects associated with the nonlinear interactions of model input parameters. This method was shown to be the correct technique to use for identifying the most significant input parameters (Andrea Saltelli & Tarantola, 2002), which is the goal of the sensitivity analysis in this probabilistic streamlined methodology. The main drawback of this approach is that it is computationally expensive.

A numerical algorithm based on Monte Carlo simulations to estimate the first-order Sobol indices was implemented as described by Saltelli et al. (2008). The first step in this procedure is to generate two distinct matrices, A and B, each sized (N,k) were N is the number of samples (which in our case was 300,000) and k is the number of parameters, or activities in our model, as seen in equations (2-3) and (2-4), drawn from Saltelli et al. (2008). Each matrix has an independent set of samples from the distributions of the activities. The samples were obtained using the Monte Carlo algorithm as described in section 2.2.2.

$$\mathrm{A} = \begin{bmatrix} x_1^{(1)} & \dots & x_k^{(1)} \\ \dots & \dots & \dots \\ x_1^{N} & \dots & x_k^{(N)} \end{bmatrix} \tag{2-3}$$

$$\mathrm{B} = \begin{bmatrix} x_{k+1}^{(1)} & \dots & x_{2k}^{(1)} \\ \dots & \dots & \dots \\ x_{k+1}^{N} & \dots & x_{2k}^{(N)} \end{bmatrix} \tag{2-4}$$

The next step is to form a matrix C, which contains all columns of matrix B except the *ith* column, which is taken from matrix A.

$$\mathrm{C}_i = \begin{bmatrix} x_{k+1}^{(1)} & \dots & x_i^{(1)} & \dots & x_{2k}^{(1)} \\ \dots & \dots & \dots & \dots & \dots \\ x_{k+1}^{(N)} & \dots & x_i^{(N)} & \dots & x_{2k}^{(N)} \end{bmatrix} \tag{2-5}$$

The model outputs for each sample matrix are computed, using equation (2-1) and resulting in three vectors of dimensions (N,1):

$$y_{\mathrm{A}} = f(\mathrm{A}) \qquad y_{\mathrm{B}} = f(\mathrm{B}) \qquad y_{\mathrm{C}} = f(\mathrm{C}_i) \tag{2-6}$$

The estimate of the first order indices can then be computed as:

$$S_i = \frac{\mathrm{V}[E(\mathrm{Y}|\mathrm{X}_i)]}{\mathrm{V}(\mathrm{Y})} = \frac{y_{\mathrm{A}} \cdot y_{\mathrm{C}_i} - f_0^2}{y_{\mathrm{A}} \cdot y_{\mathrm{A}} - f_0^2} = \frac{(\frac{1}{N}) \sum_{j=1}^{N} y_{\mathrm{A}}^{(j)} y_{\mathrm{C}_i}^{(j)} - f_0^2}{(\frac{1}{N}) \sum_{j=1}^{N} (y_{\mathrm{A}}^{(j)})^2 - f_0^2} \tag{2-7}$$

where f_0^2 is the mean and is defined as:

$$f_0^2 = \left((\frac{1}{N}) \sum_{j=1}^{N} y_{\mathrm{A}}^{(j)} \right)^2 \tag{2-8}$$

The activity with the highest sensitivity index was identified as the one with the highest effect on the output. A more in-depth explanation of the procedure can be found in Saltelli et al. (2008). The results of the sensitivity analysis allows us to identify those key activities that had the most leverage to reduce uncertainty either because they contributed the most to the total value and/or because they were highly uncertain. The sensitivity analysis procedure was carried out for the three different kinds of tablets in order to understand how the sensitivity analysis differs based on the values specified.

2.4. Metrics for Determining Sufficiency

The uncertainty in the input parameters that propagates throughout the assessment using a Monte Carlo simulation results in a probabilistic description of the product carbon footprint, which can be represented by a probability density function (pdf). When performing a comparative LCA, the two product carbon footprints to compare have a probability distribution. The product class is the level of categorization of a product we are comparing, for example, a

14" screen to 15" screen (Zgola, 2011). One product class might, on average, have a lower impact than the other product class, but because they are both described by probability density functions, there can be some scenarios in which the environmentally preferable product class is incorrectly classified as the least favored product class. Zgola (Zgola, 2011) defines this error as the false signal rate and describes it as the percentage of scenarios that incorrectly classify an environmentally favored solution as less favored. The false signal rate can be determined from the Monte Carlo simulations by counting the number of scenario pairs for which *product class B* < *product class A*, where B is the less environmentally friendly product class and $\mu_A < \mu_B$.

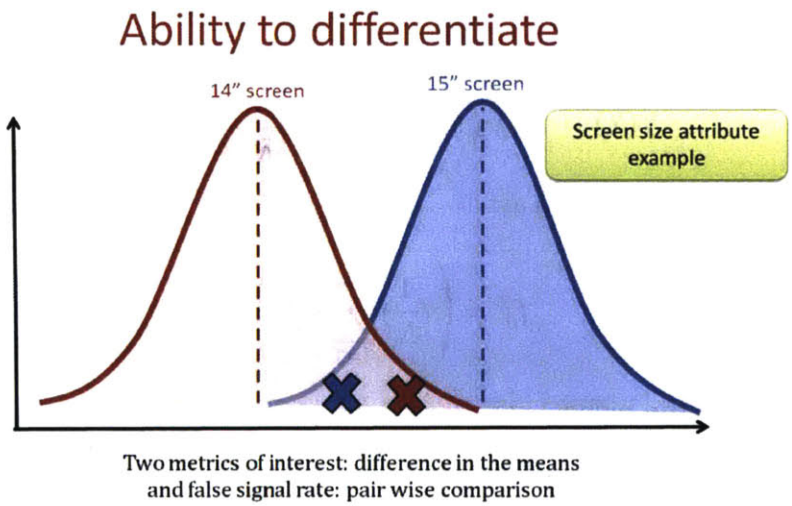


Figure 2-2: The false signal rate is the fraction of scenario pairs for which the impact of product class B (here, the 15" screen) is less than the product class A (14" screen) (reproduced from (Zgola, 2011))

This false signal rate can be seen as a measure of uncertainty. The higher the false signal rate, the higher the uncertainty and the lower the degree of confidence that the two product classes are distinct. The amount of specification in the carbon footprint depends on a balance between the tolerance of error and on the resources available. A lower tolerance of error requires more specification, and therefore, more resources. The acceptable level of error, or of the false signal rate, needs to be specified by the practitioner and the decision maker at the start of the study.

2.4.1. Self-test as a Measure of Sufficiency

When carrying out the under-specification, probabilistic streamlining methodology, only one product is being studied, but the false signal rate, which is used as a measure of uncertainty, requires two distributions. Zgola defined a metric, called the self-test, to evaluate the false signal rate when performing the streamlining methodology (Zgola, 2011). In the self-test, the distribution is shifted by a pre-specified amount and the false signal rate corresponds to the level of overlap between the shifted and the original distribution. The displacement of the distribution is specified as a percentage of the mean. In our study, a 10% displacement was used. As more information is specified, the associated distribution narrows and consequently the self-test false signal rate decreases, but it does so at a decreasing marginal return rate, as seen in Figure 2-3. In this case, the false signal rate corresponds to the number of scenario pairs for which B < A, where B is the displaced distribution and $\mu_A < \mu_B$.

In the case study, the self-test false signal rate is used to inform the sufficiency in the level of specification of input parameters. The metric depends on the pre-specified percentage for shifting the distribution. As the distribution narrows, the overlap between the shifted and the original distribution decreases. When a target false signal rate is not specified *a priori,* the sufficiency can then be defined by prescribing a threshold where the curve starts to plateau and the value of additional information diminishes.

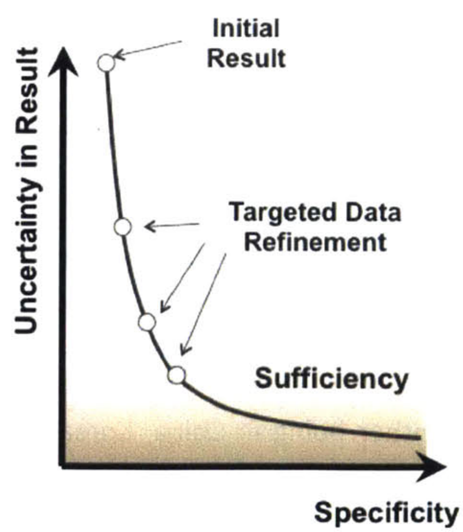


Figure 2-3: Decrease in uncertainty as more activities are specified (reproduced from (Materials Systems Laboratory, n.d.))

2.4.2. Self-test and Cost of Additional Information as a Measure of Sufficiency

As previously mentioned, the amount of specification depends on the tolerance for error and on the resources available to gather additional data. In order to take cost or effort into consideration, the cumulative cost of the study versus the level of separation gained can be plotted. Here, separation is specified as the degree of separation between the distribution and the displaced distribution. The degree of separation is calculated as:

$$Separation = 1 - Self\ Test\ False\ Signal\ Rate \qquad (2\text{-}9)$$

Using a plot of cost versus separation, the LCA practitioner can determine how many parameters to specify depending on the resources available and the required separation. Sufficiency can also be specified as the point where the graph curves upward and additional cost of acquiring data per the amount of separation gained increases exponentially.

The cost of additional information is also used to estimate the amount saved from performing the under-specification streamlined methodology. A plot of cumulative cost versus the number of parameters specified is used to determine the percentage cost spent out of the total cost of an LCA until reaching sufficiency.

2.5. Scenario Uncertainty

2.5.1. Scenario Exploration

Scenario uncertainty was accounted for by creating different scenarios and observing their carbon footprint. Three different "clusters" were created in the second level of the data structure matrix. Each "cluster" consists of a range of possible values for each activity and they consist of a narrower distribution than that of the first level. The clusters were created in different ways. For parameters that relate to the material quantities of the tablet, each cluster corresponds to values for a specific tablet. For quantities such as the grid mix emissions factor, the fab location was specified as either being in China, Korea or Taiwan. A similar procedure was carried out for the other parameters.

The parameters in each cluster were combined in all the possible combinatorial ways based on the results of the probabilistic screening from the first part. For example, only those parameters that were specified further before reaching "sufficiency" were specified at the second level for the scenario formation. Each combination of parameters represents a specific scenario. The carbon footprint realization associated with each scenario combination was calculated using equation (2-1) and the uncertainty propagation procedure.

2.5.2. Scenario Analysis

The different scenarios from Section 2.5.1 Scenario Exploration were compared to each other. First, the difference in the means of two scenario pairs was determined as:

$$\Delta\mu = \frac{|\mu_A - \mu_B|}{\min(\mu_A, \mu_B)} \tag{2-10}$$

where $\Delta\mu$ is the difference in means, μ_A is the average impact of scenario A, and μ_B is the average impact of scenario B. Then, for each scenario pair, their associated false signal rate was computed. A plot of the false signal rate for all of the scenario pairs versus the difference in means was then used to draw insights on all the possible scenarios. Each plot on the graph represents a different product. This sort of graph can then be used to determine how large the difference in means of two products' carbon footprint have to be in order to obtain an error rate lower than a specified value.

Chapter 3: Application of Methodology – A Case Study on Tablets

The number of global shipments of tablets has increased from 19 million in 2010 to a forecasted amount of 269.4 million tablets in 2019 (*Global tablet shipments projection 2010-2019*, 2016). Their growth, coupled with increasing environmental concerns, made them an ideal candidate for a case study of the streamlining, probabilistic methodology. Electronics and semiconductors have been targeted for environmental evaluation because of their use of high purity chemicals, electricity consumption and emissions during their manufacturing stage. However, life cycle assessments of electronics are plagued by uncertainty and are very resource intensive.

Evaluation of electronics is challenging because they have complex high tech, manufacturing processes (Koomey et al., 2013) and worldwide supply chains (Koomey et al., 2013; Mueller et al., 2004). This makes it difficult to obtain precise information on the emissions at each stage of the process and to gather data on the emissions across all of the supply chains. Additionally, suppliers do not want to share information on their production processes because of trade secrets, creating data gaps in the life cycle assessment. The complexity of electronics in their material composition, and use of highly specific purity levels in their chemicals (Mueller et al., 2004) makes it even more difficult to quantify their environmental impacts. Electronics also have rapid product profile changes (Andrae & Andersen, 2010; Mueller et al., 2004), and by the time the life cycle assessment has been completed for a product, the product profile has changed.

Not a lot of literature or information exists on the environmental impact of tablets. Moberg *et al.* performed a comparative screening LCA of a tablet e-paper device (iRex Illiad) but acknowledged the difficulty of performing an LCA due to limited access to data regarding the production and composition of the device (Moberg, Johansson, Finnveden, & Jonsson, 2007). Crane, Ecola, Hassell, and Nataraj (2012) estimated the environmental impact of tablet computers and e-readers, noting that the two differed significantly because the display in tablets requires more energy. Both studies mentioned that the design and composition of the tablet was likely to change very rapidly, making the results of the assessment outdated very quickly.

Companies are also working on quantifying the environmental impact of their products. Dell published a study on the carbon footprint of their Dell Streak tablet in which they found their product emitted 45 $KgCO_2e$ throughout its lifecycle (Stutz, 2011). The life cycle stages that they included were material extraction, manufacturing, transport, use and recycling. Apple has been a leader in releasing the environmental reports for their products. They estimated the emissions of their iPad Pro and iPad Air 2 to be at 270 $KgCO_2e$ and 170 $KgCO_2e$, respectively (Apple, 2014, 2015). Their emissions included production, transport, use and recycling, although they were not clear about what each stage encompasses. Teehan *et al.* estimated the emissions of various electronic products, including the Apple iPad 8gb Wi-Fi first gen (2009) tablet and the Amazon Kindle Wi-Fi third gen (2010) e-reader (Teehan & Kandlikar, 2013). They found that their estimates were lower than other published studies.

The lack of data, rapid profile changes and large variation amongst published studies pinpoint the environmental evaluation of tablets as an ideal target for the streamlined, probabilistic methodology. One of the most significant components of tablets are integrated circuits (ICs). Thus, the goal of this chapter is to demonstrate the streamlining methodology on tablets and ICs.

3.1. Tablet Data Acquisition

3.1.1. Tablet Environmental Impact Data Acquisition

The first step in evaluating the global warming potential of tablets using the streamlined methodology is gathering information about all the life cycle stages that should be accounted for in the carbon footprint. This was done via industry expert input, and publicly available studies, such as the study by Teehan & Kandlikar (2013) and by Moberg et al. (2010). The life cycle stages identified were those found in Table 3-1: Life Cycle Stages for a Tablet.

Table 3-1: Life Cycle Stages for a Tablet

Tablet Life Cycle Stages
Materials Extraction
Manufacturing
Product Assembly
Transport
Retail
Use Phase
End-of-Life

The retail and end-of-life stages were left outside the scope of the study as they were shown to be insignificant in previous carbon footprint studies (Apple, 2014, 2015; Stutz, 2011). Within manufacturing, the major components accounted for were the integrated circuits (ICs), the printed wiring board (PWB), the liquid crystal display (LCD), the battery, and other electronics (e.g. capacitors, diodes, and resistors).

The data in the case study comes from published studies, individual industry work and input, industry association data, life cycle inventory databases and the teardowns of 25 tablets released between 2010 and 2013, obtained from IHS (*Teardown - Tablets, eReaders & Notebooks Intelligence Service*, n.d.).

The teardown analysis was performed by Reed Miller, a research specialist at the Material Systems Laboratory at MIT. The teardown of the 25 tablets provided information on the mass of components and materials. The standard mass and dimensions of many form factors for ceramic and tantalum capacitors, transistors, diodes and resistors were provided by a confidential industry source. For aluminum capacitors, their mass and dimensions were obtained from the product datasheets and assigned to those in the BOM with the same type, material and form factor. For other materials and components, if the mass was available then that was used directly and if it was not, then the density of the component was found via credible websites. The rectangular dimensions were multiplied to find the volume and then multiplied by the density to find the component mass. If the component was hollow, the thickness and the area of the walls were estimated to determine the volume.

The tablet teardown also provided an area estimate for the PWB area and the IC die area. PWBs with any number of layers were included. The area of the PWBs was determined using Google Sketchup. The images of each of the tablets' PWB components were imported into the software and the edges of each component were traced to measure their relative area (based on the size of the image). A bounding rectangle was superimposed on the component to determine the rectangle's relative area. The relative area was multiplied by the ratio of the rectangle's known actual area to its relative area to obtain the irregular shape's actual area. To estimate the IC die area, four categories of ICs were distinguished: flash NAND, DRAM, processor and chipset, and other. Industry data was used to estimate Flash NAND and DRAM area while BOM data was used to estimate processor, chipset, and other IC data. The teardown also provided information on the number of ICs, battery weight and the LCD area. Material emission factors ($KgCO_2e$-/Kg) were obtained from the ecoinvent database, by forming broad categories of materials, as shown in (Olivetti et al., 2013).

The manufacturing data was obtained from industry work and input and industry association data. The data provided included scope 1, scope 2, and scope 3 emissions. Scope 1 refers to all direct greenhouse gas emissions, scope 2 included indirect greenhouse gas emissions from consumption of purchased electricity, gas or steam and scope 3 refers to other indirect emissions not covered in scope 2 (e.g. extraction and production of purchased materials). The grid mix emissions factors ($KgCO_2e$-/KWh) were obtained from various sources, including the literature (Weber, Jaramillo, Marriott, & Samaras, 2010), Industry Statistics (*China Electric Power Industry Statistics Analysis*, n.d.), and other reliable Internet sources.

The use phase data was obtained from EPA's Energy Star slates/tablets category (EPA, n.d.). Upstream transportation, transportation from assembly to retail and from retail to consumer were accounted for. Realistic minimum and maximum distances were calculated for each transportation segment. The emissions ($KgCO_2e$-/tkm) from the transportation phase were based on the modes of transportation, which included air, ship, rail and road transportation.

As can be seen, the data is of varying quality, age, source and number of points; however, uncertainty is associated with the data and thus it proves to be sufficient to demonstrate the methodology.

3.1.2. Acquisition of Cost Information for Electronics

The survey designed and sent to gather information on the cost of additional data acquisition can be seen in Appendix B: Survey for Cost of Additional Information. The survey was sent to industry collaborators and 8 responses were obtained. Each question asks for the relative cost of the research activity mentioned in the question. To use the data from the surveys, the data was aggregated by averaging the responses for each question. The data was also analyzed per response to observe how the cost of data acquisition might vary by company. Section 3.3.3 describes the robustness of the data.

3.2. Uncertainty in the Tablet Footprint

The uncertainty for the activities in the tablet footprint was obtaining using the data from Section 3.1.1 Tablet Environmental Impact Data Acquisition. At the high level assessment, all the possible values for a particular category were aggregated. For example, the material quantities for each tablet present in the data were averaged across all the tablets. Depending on the number of data points for each activity, the data was fitted to a distribution using goodness-of-fit tests. If not enough data was available, the distribution was modelled as uniform distribution between the lowest and highest value. If insufficient data was present to establish a highest and lowest value, the distribution was modelled as lognormal, using the value available as the mean, and the standard deviation was obtained using Weidema's Data Quality Indicators (DQIs) and expert input. The data for the activities can be seen in Appendix A: Data and Uncertainty of Modeled Parameters in the Carbon Footprint of a Tablet.

In order to show the methodology and perform the iterations quickly, the values to which the activities were specified to after they were identified as high impact activities were determined *a priori* and their associated uncertainty was included. The activities were specified to the values of three different hypothetical tablets, termed tablet A, B and C. The tablets were chosen to demonstrate a wide range of possible impacts. In this case, the streamlining methodology consisted of two levels, the "unspecified" level and the "fully specified" level. The only activity that consisted of three levels, and could therefore be identified twice in the sensitivity analysis, was the grid mix. The unspecified level was the value for the average continent (or world) grid mix, the next level was the value for the country grid mix, and the final level was the grid mix at a specific region in the country.

3.3. Probabilistic Streamlined Tablet Footprint

Using the data set described above, the uncertainty was propagated throughout the model through simulation and the output was broken down by life cycle stage for the high level assessment in a box plot (Figure 3-1).

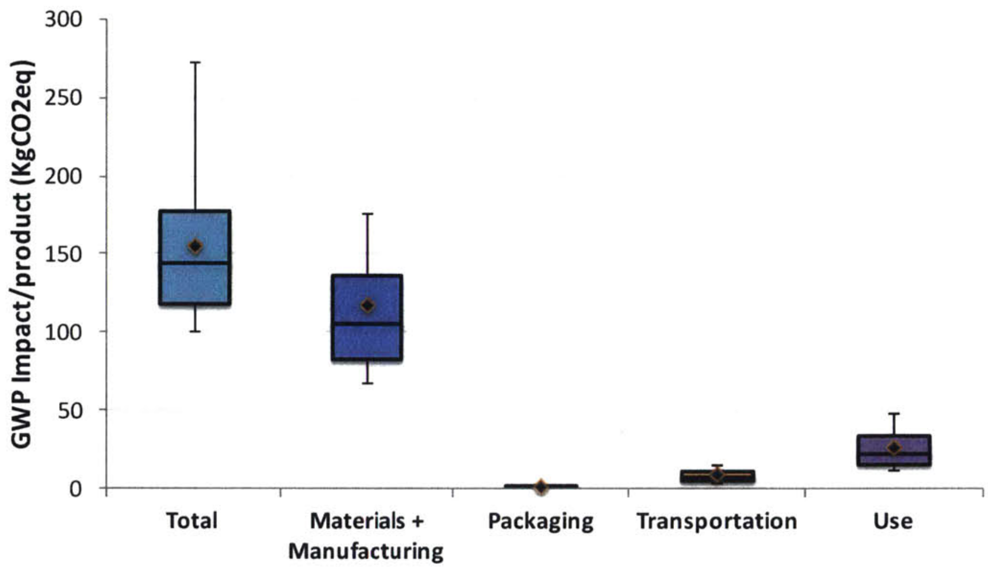


Figure 3-1: Breakdown of tablet footprint by life cycle stage at the high level assessment. The median-derived coefficient of variation is 0.48.

The median-derived coefficient of variation, which was calculated by dividing the standard deviation by the median of the total impact, was 0.48. Thus, the uncertainty at the unspecified level is very high. Approximately 95% of trials indicated that more than 85% of the impact is attributed to the material, manufacturing, and use phase stages. In particular, a breakdown of the materials and manufacturing stage (Figure 3-2) shows that approximately 20% of the impact is attributed to the ICs and the PWB. This agrees closely with the findings in the literature that demonstrate that integrated circuits have high impacts, despite their small size, due primarily to the silicon dies (Teehan & Kandlikar, 2013).

As ICs contribute significantly to the carbon footprint of tablets and the industry has worked hard to address this impact, ICs were examined in further detail to determine which part of their manufacturing process contributes the most. This analysis was also done at the high level assessment, thus, there is a lot of uncertainty. Figure 3-3 shows that the majority of the impacts are caused by the scope 2 emissions in its manufacturing process, followed closely by the scope 1 emissions. Despite the high uncertainty in the underspecified impact assessment, calculating the output by propagating the uncertainty throughout the model serves as a quick exploratory analysis of the data and the model.

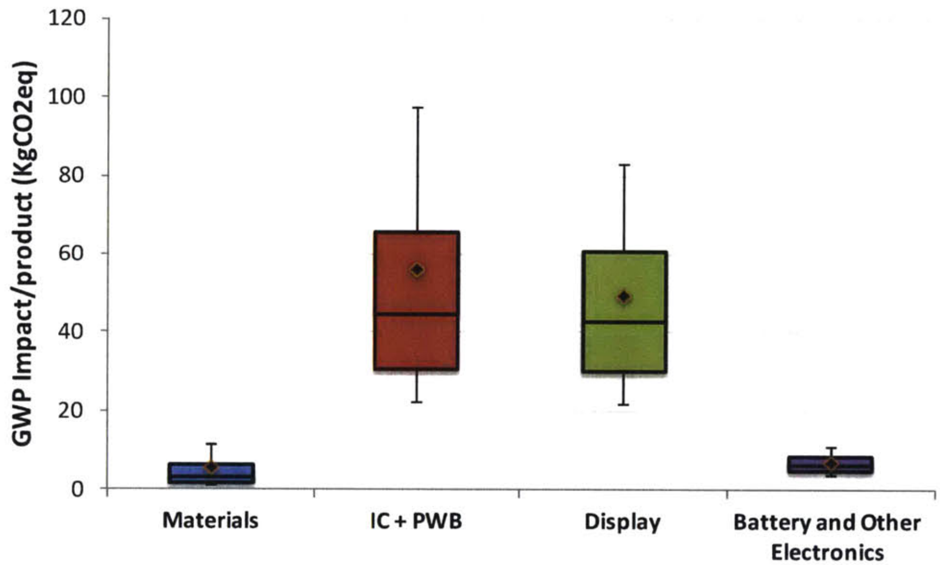


Figure 3-2: Breakdown of the footprint impacts for the material and manufacturing stage within the representative tablet.

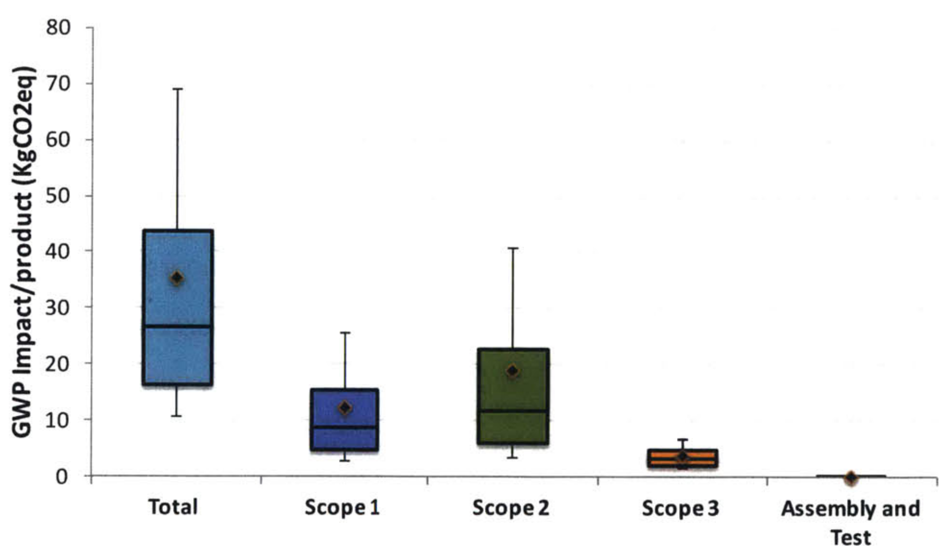


Figure 3-3: Breakdown of the carbon footprint of integrated circuits contained within a representative tablet at the high level assessment.

The next stage in the probabilistic streamlined assessment was identifying the input activities that have high leverage to reduce the uncertainty of the output. This is performed by a contribution to variance analysis. Here, the numerical algorithm to estimate the Sobol indices as described by Saltelli was used (A. Saltelli et al., 2008). The results for the top 10 activities for the first sensitivity analysis can be seen in Table 3-2. Only the first activity, the integrated circuit assembly and test scope 2 emissions, was specified further in the first iteration. Iteration is carried out to identify the top contributors instead of specifying the top 10 activities further because the relative importance of the high impact activities in the resulting uncertainty changes after the data is specified in more detail (M. A. J. Huijbregts et al., 2003).

Table 3-2: Top 10 parameters with the largest Sobol indices for the tablet at the high level assessment.

Activity	Sobol Index
Integrated Circuit Assembly and Test Scope 2 (KWh/package)	0.891
LCD Fabrication Chemicals Impact Factor (KgCO_2e-/m^2)	0.021
IC Fabrication (KWh/cm^2)	0.016
Total Integrated Circuit Die Size (cm^2)	0.014
Use Phase Yearly Tec (KWh/year)	0.011
LCD Area (m^2)	0.007
LCD Perfluorocarbons Emissions (KgCO_2e-/m^2)	0.007
LCD Fabrication (KWh/m2)	0.003
Integrated Circuit Perfluorocarbons Emissions (KgCO_2e-/cm^2)	0.002
10. LCD Fabrication grid mix (KgCO2e-/m2)	0.001

Table 3-3: Top 10 Contributors to uncertainty for Tablet A, based on the iterative sensitivity analysis procedure

Major Contributors to Uncertainty for Tablet A
1. Integrated Circuit Assembly and Test Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor (KgCO_2e-/m^2)
3. IC Fabrication (KWh/cm^2)
4. Use Phase Yearly Tec (KWh/year)
5. Total Integrated Circuit Die Size (cm^2)
6. LCD Perfluorocarbons Emissions (KgCO_2e-/m^2)
7. Integrated Circuit Perfluorocarbons Impact Factor (KgCO_2e-/cm^2)
8. LCD Area (m^2)
9. Integrated Circuit Fabrication Grid Mix (KgCO_2e-/KWh)
10. Printed Wiring Board Area (m^2)

The top 10 contributors, after performing the iterative sensitivity analysis, can be seen in Table 3-3 for tablet A. A comparison of Table 3-2 with Table 3-3 shows that the order of the parameters differ as a result of the change in the relative importance of high impact activities that occurs by specifying activities. However, 9 out of 10 parameters that were identified as the major contributors to uncertainty using the iterative procedure are present in Table 3-2. This is dependent on the data and the model; however, it might be useful to specify activities in groups instead of one by one before iterating the procedure to simplify the process.

The major contributors to uncertainty for tablet B and tablet C can be seen in Table 3-4 and Table 3-5, respectively. In this case, there is less overlap in the activities identified and it is more clear how the relative importance of high impact activities changes depending on the value that the previous parameter was specified to.

Table 3-4: Top 10 Contributors to uncertainty for Tablet B, based on the iterative sensitivity analysis procedure

Major Contributors to Uncertainty for Tablet B
1. Integrated Circuit Assembly and Test Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor ($KgCO_2e$-/m^2)
3. Total Integrated Circuit Die Size (cm^2)
4. IC Fabrication (KWh/cm^2)
5. Use Phase Yearly Tec (KWh/year)
6. LCD Perfluorocarbons Impact Factor ($KgCO_2e$-/m^2)
7. LCD Area (m^2)
8. LCD Fabrication (KWh/m2)
9. Integrated Circuit Perfluorocarbons Impact Factor ($KgCO_2e$-/cm^2)
10. LCD Fabrication grid mix (KgCO2e-/m2)

Table 3-5: Top 10 Contributors to uncertainty for Tablet C, based on the iterative sensitivity analysis procedure

Major Contributors to Uncertainty for Tablet C
1. Integrated Circuit Assembly and Test Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor ($KgCO_2e$-/m^2)
3. Total Integrated Circuit Die Size (cm^2)
4. Use Phase Yearly Tec (KWh/year)
5. LCD Perfluorocarbons Impact Factor ($KgCO_2e$-/m^2)
6. LCD Area (m^2)
7. PWB Area (m^2)
8. Integrated Circuit Assembly and Test grid mix (KgCO2e-/m2)
9. Nonferrous metal Impact Factor ($KgCO_2e$-/Kg)
10. IC Fabrication (KWh/cm^2)

The major contributors for integrated circuits are those found in Table 3-6. The list includes a mixture of contextual information and product attributes (ex. Die size).

Table 3-6: Top 10 Contributors to uncertainty in the footprint of integrated circuits

Major Contributors to Uncertainty for Integrated Circuit A
1. IC Manufacturing Scope 2 emissions (KWh/cm^2)
2. Die size (cm^2)
3. IC Manufacturing Scope 1 emissions ($KgCO_2e$-/cm^2)
4. IC Manufacturing Scope 2 grid mix ($KgCO_2e$-/KWh)
5. Assembly and Test Scope 2 emissions (KWh/cm^2)
6. Wafer yield factor
7. Wafer Emissions Factor ($KgCO_2e$/Kg)
8. H2O2 Amount (Kg/cm^2)
9. O2 Amount (Kg/cm^2)
10. Wafer Usage (Kg/cm^2)

3.3.1. Self-test as a measure of sufficiency

The next step in the streamlining procedure is determining how many parameters to specify in more detail. The metric used to determine sufficiency is the self-test false signal rate. For our case study, a 10% displacement of the mean of the distribution was used to calculate the false signal rate. Figure 3-4 shows the self-test false signal rate as a function of specificity for the three kinds of tablets and Figure 3-6 shows the self-test false signal rate for integrated circuits in particular. This analysis was run until all parameters were specified to observe how the false signal rate changes as a function of specificity. Even after fully specifying the parameters, the false signal rate of the tablets remained at around 0.2 and the false signal rate of the integrated circuit remained at 0.1. This happens because even a fully specified assessment has uncertainty associated with it as a result of inherent variability and measurement error. The curve labeled "Product A with Perfect Information" in Figure 3-4 describes how the false signal rate would change as a function of specificity if perfect information were available and the fully specified assessment had no uncertainty.

As seen in Figure 3-4, the decrease in uncertainty occurs at a diminishing marginal return. For this tablet study, the curves start plateauing after specifying around 20 parameters. It is interesting to note that this same behavior occurs for the "Product A with Perfect Information" curve. Most of the uncertainty in the model output is due to a fraction of the total activities present in the footprint. In this case study approximately 20 out of 99 activities, so 20% of the activities, contribute to the variance of the output. These activities might have a relative low uncertainty but contribute a lot to the total impact or they might have very large uncertainties associated with them.

In the tablet case study, it was found that the curves start plateauing after specifying around 20 parameters and this can be taken as the point of "sufficiency" in the data collection efforts. The relative cost of specifying 20 parameters is 0.25, or 25% of the full cost of a carbon footprint (Figure 3-5).The under-specification streamlining reduces the cost of a footprint while still providing valuable information. It is also interesting to note that the relative cost versus the number of parameters specified is linear. This might occur because the number of parameters is high and therefore each parameter contributes only a small fraction to the total.

For the integrated circuit, the curve starts plateauing after 10 to 15 activities have been specified in more detail and the false signal rate reduces to 10% (Figure 3-6). Thus, only a fraction, 0.125, of the total activities had to be specified to reach what we call sufficiency. Thus, the streamlining methodology can be applied successfully to different products.

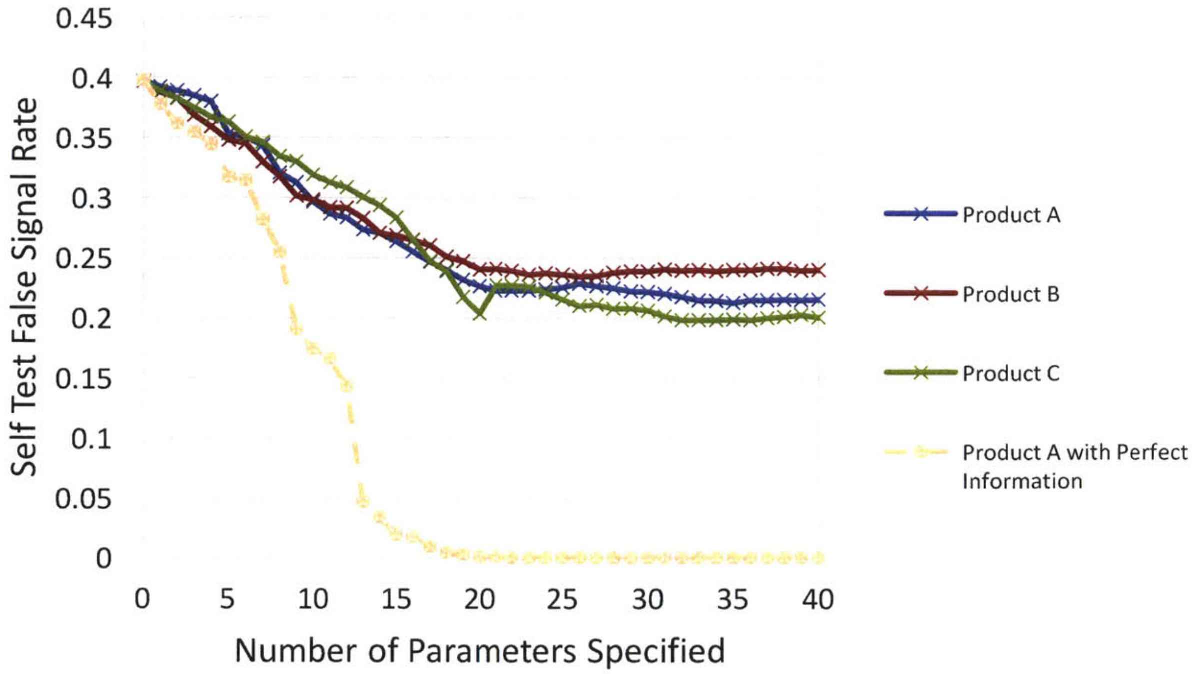


Figure 3-4: The self-test false signal rate as a function of specificity for tablets. The self-test is used as a metric for determining sufficiency. Product A, B, and C represent different tablets.

The false signal rate can also be used to compare different products. Table 3-7 shows the false signal rate between the three kinds of tablets at the high level assessment and after all the parameters have been specified. As can be seen, even after all the parameters have been specified, the false signal rate between product A and product C is still positive, while the others ones are zero or close to zero. This occurs because the two products have similar characteristics, and therefore more information is needed to be able to distinguish them.

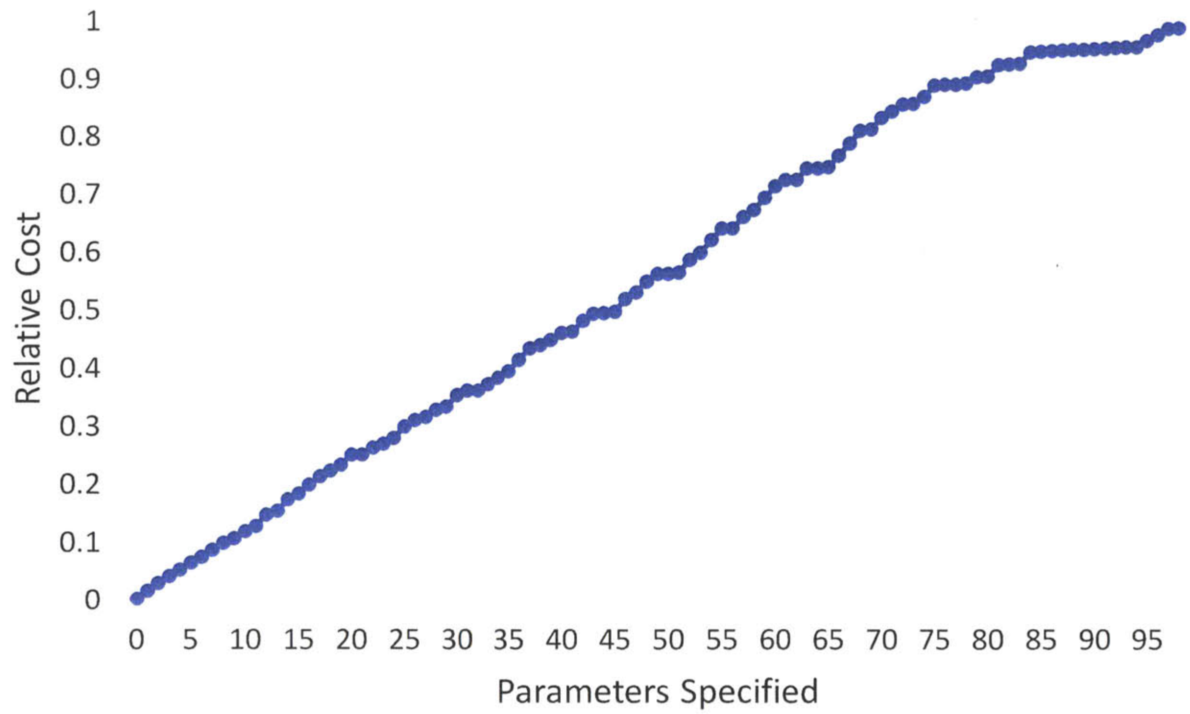


Figure 3-5: Relative cost of the footprint as a number of parameters specified.

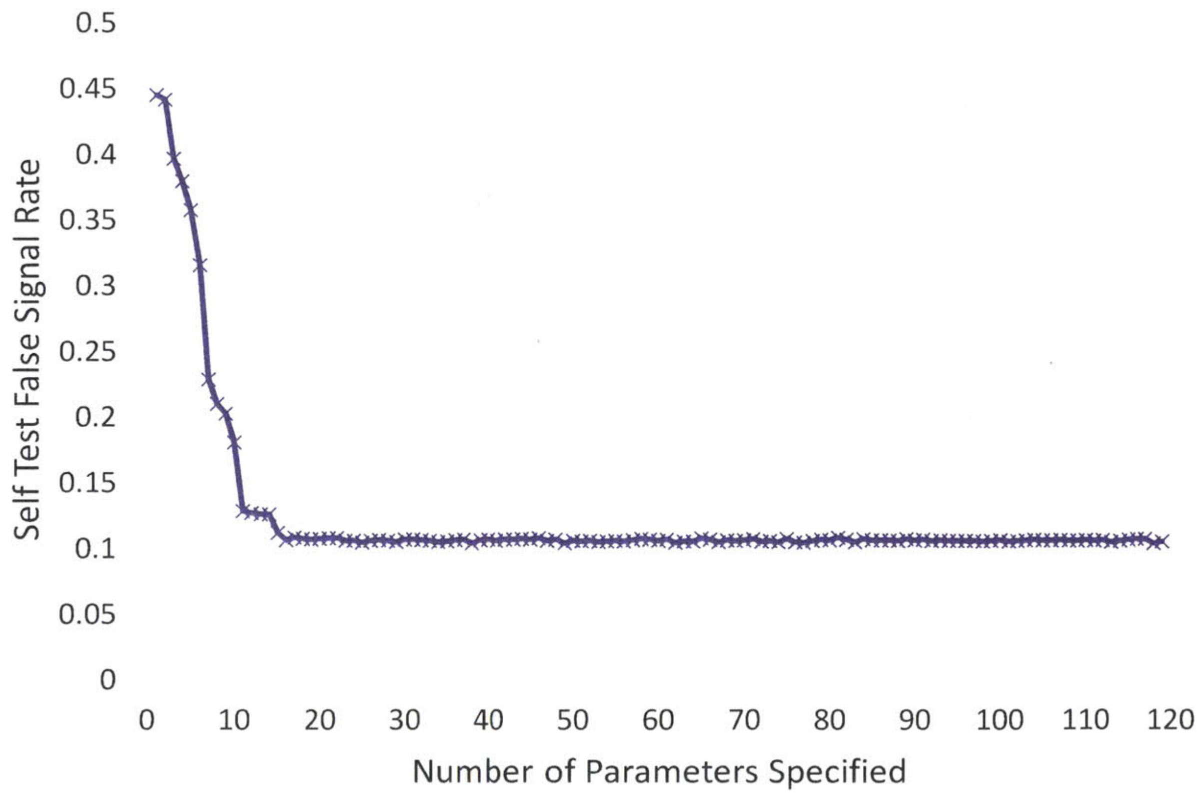


Figure 3-6: The self-test false signal rate as a function of specificity for integrated circuits. The self-test is used as a metric for determining sufficiency.

Table 3-7: False signal rate comparison for the three kinds of tablets.

Product Comparison	FS with no specification	FS fully specified
A and B	0.5	3.33E-05
A and C	0.5	0.062
B and C	0.5	0

3.3.2. Self-test and cost of additional information as a measure of sufficiency

This data can also be seen as a function of cost and degree of separation (The degree of separation is evaluated as in equation (2-9)). The relative cost is the cost normalized by the total cost of a carbon footprint. As can be seen from Figure 3-7, the cost starts increasing rapidly at a degree of separation of 0.77. The cost keeps increasing as additional information is added, however, the degree of separation gained is minimal. This can be used as a metric to determine sufficiency – the point at which the cost increases rapidly with minimal increase in the degree of separation. This figure can also be used by practitioners to decide when to stop gathering additional information if they know the budget allocated towards completing the analysis. For example, if they know they only have 20% of the cost of a full carbon footprint to use, they can stop their analysis once they have reached a false signal rate of 0.25, or a degree of separation of 0.75.

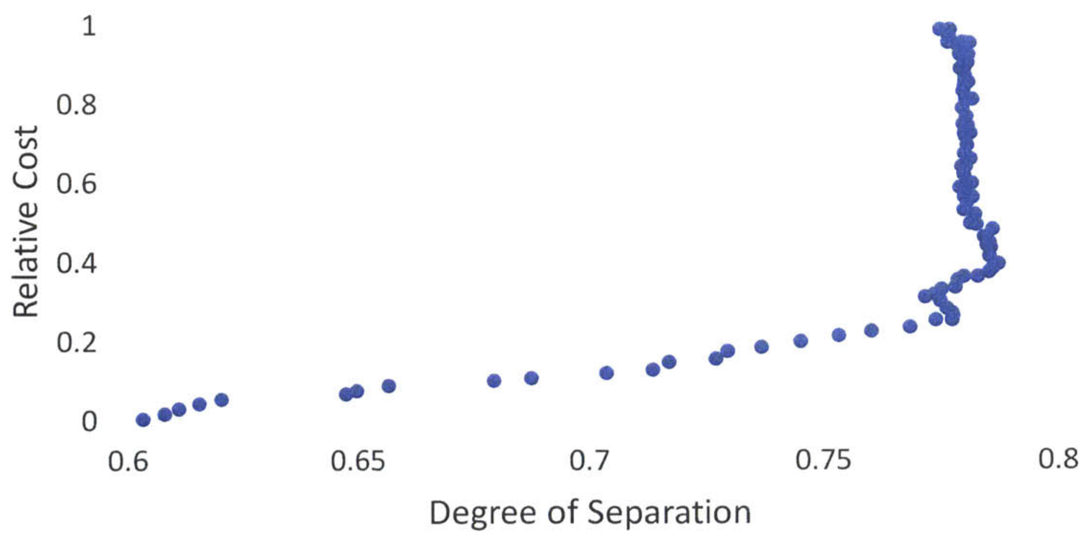


Figure 3-7: Relative cost of footprint as a function of degree of separation.

3.3.3. Robustness of the Cost on Additional Information

The data for the cost of additional information was obtained by surveying company collaborators. The survey respondents belong to the environmental affairs or sustainability groups at their company, and are involved on a day to day basis with gathering information for the life cycle assessment of their company's products. We obtained 7 responses to our survey request, but one of them did not include numerical rakings, so it was left outside the scope of the study. Even though the number of responses was small, it proved to be sufficient to demonstrate our methodology. The robustness and variation of the data was analyzed as follows.

The survey respondents ranked the relative cost of 27 groupings of activities (Table 3-8). Figure 3-8 shows the variation in the response for each grouping. A,B,C,D,E, and F represent each survey response. There is significant variation in the rankings. The activity for which there was the most agreement was specifying the type of battery in the product and this data acquisition task was ranked as easy to obtain. There was also agreement that it was costly to gather additional information on the electronic components impact factor and that determining the IC manufacturing location was low to medium cost. Of those, only the IC manufacturing location is present in the top 20 parameters to specify further. The activity that had the largest variation in responses was determining the use phase location. This is understandable as determining where the product will be used is difficult and can be modeled differently by LCA practitioners.

The responses "E" and "F" correspond to respondents from the same company. A figure showing the responses for only "E" and "F" can be seen in Appendix E. These responses are closer to each other suggesting that the variation in the rankings of the cost of the activities might be caused by factors such as where the respondents' company is located in the supply chain, the size of the company, and even the relationship the company has with its suppliers. Further work can be directed at understanding the differences in data collection efforts as a function of the industry, position within the supply chain and characteristics of the company.

Table 3-8: Group activities used for the cost of additional information survey ordered by relative cost

Num	Group Activity
1	Quantity of materials (ex. ferrous metal, glass) from an industry average to the specific value
2	GHG footprint of the materials (battery, materials, backend chemicals) from an average of the type of material GHG footprint to the specific GHG emissions
3	Use location from a country to a specific region
4	Composition of battery from an industry average to the actual composition
5	Use location from a world average to the specific country
6	Scope 3 GHG footprint for IC assembly and test from a regional industry perspective to the specific fab emissions
7	Product lifetime from an industry average to the specific value
8	Scope 1 and Scope 2 for IC assembly and test from a regional industry perspective to the specific fab emissions
9	Scope 3 GHG footprint for IC manufacturing from a regional industry perspective to the specific fab emissions
10	Scope 3 GHG footprint for LCD manufacturing from a regional industry perspective to the specific fab emissions
11	Scope 1 and Scope 2 for IC manufacturing from a regional industry perspective to the specific fab emissions
12	Electronics amounts (ex. IC die size, # of chips, PWB area, capacitor weights) from an industry average to the specific value
13	IC assembly and test location from country to specific region within the country
14	Product assembly scope 2 emissions from a regional industry perspective to the specific fab emissions
15	Yearly TEC of product from an industry average to the specific product value
16	Quantity of materials (ex. ferrous metal, glass) from an industry average to the specific value
17	IC assembly and test location from continent to specific country
18	Transportation mode from unknown (mixture of ship, rail, truck, air) to the actual transportation mode
19	Scope 1 and Scope 2 for LCD manufacturing from a regional industry perspective to the specific fab emissions
20	IC Manufacturing location from country to specific region within country
21	Product assembly location from country to specific region within the country
22	IC Manufacturing location from continent to specific country
23	LCD Manufacturing Location from country to specific region within the country
24	Number of layers in the PWB from an average to a specific number
25	Product assembly location from continent to specific country
26	LCD Manufacturing location from continent to specific country
27	Type of battery (ex. Li-ion) from unknown to the known type

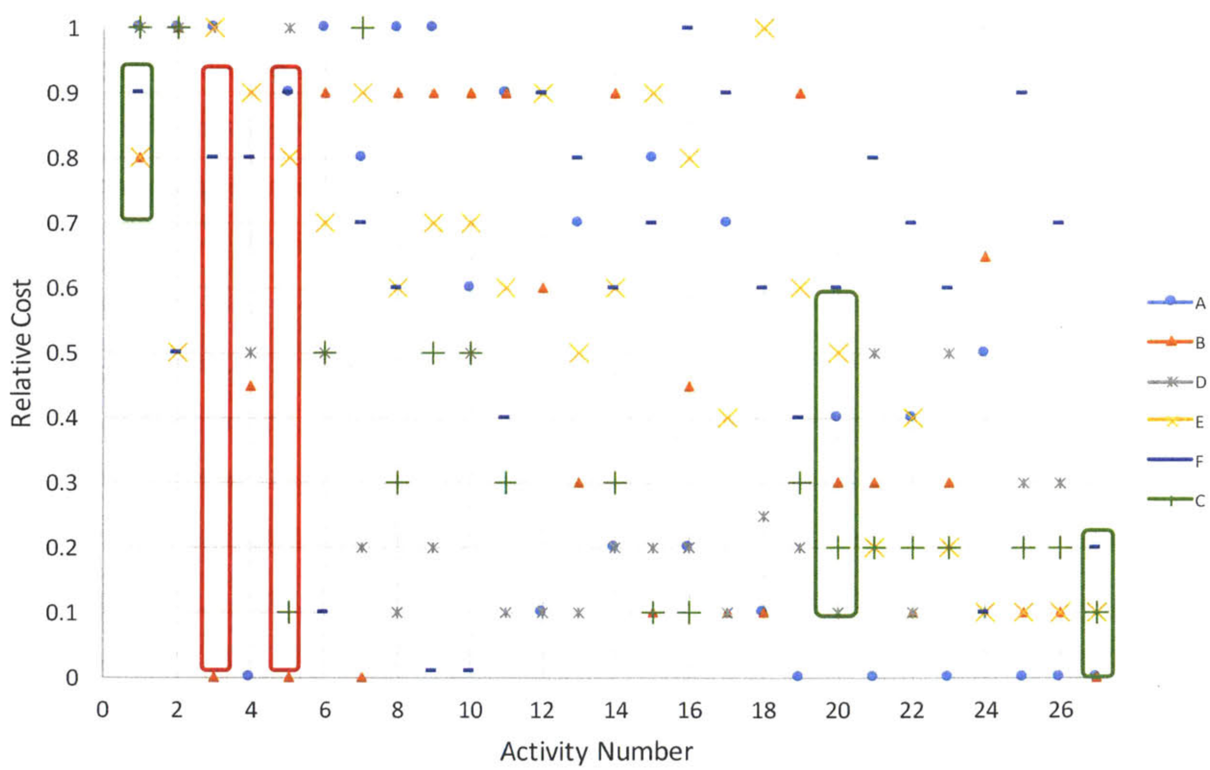


Figure 3-8: Ranking of cost for each activity by 6 survey respondents. The answers surrounded by a green box represent the ones that had the closest agreement (measured by the lowest variance), while the ones surrounded by the red box are the ones that they agreed the least (and had the highest variance). The activities are ordered by relative cost (high to low).

Despite the variation in the survey responses, a graph of the relative cost versus the number of parameters specified for each individual response also follows a linear trend, similar to the aggregated version (Appendix E). This implies that the aggregated analysis does provide accurate information.

3.4. Scenario Exploration

In order to account for scenario uncertainty, we explored the scenario space for the tablets. In the most specified level of the matrix, three different clusters of possible values were created. The parameters in each cluster were combined in all the possible combinatorial ways based on the results of the probabilistic screening from the first part. In this case, only the first 8 parameters determined in the sensitivity analysis were specified further for the scenario creation. Ideally, the top 20 parameters, which defined sufficiency in this case, would have been specified further but the analysis was limited by computational power. Each combination of parameters represents a specific scenario.

In Figure 3-9, each point in the graph represents the comparison of two products based on their false signal rate and the difference between the mean values of their global warming potential impact. The graph is composed of different combinations for each parameter using the three clusters. Only the top 8 parameters that contributed to the overall impact in the data prioritization procedure were specified further, while the rest of the parameters remained at the high level assessment. The red line in the figure represents the 95th percentile of the false signal rate at each normalized difference of means. From this, it can be observed that at a 95% confidence level, in order to be able to distinguish correctly two products at least 90% of the time, the difference in the means between their GWP has to be at least 0.42 (the cross in Figure 3-9). This analysis assumes correlation between scenarios for the product lifetime and the use phase grid mix parameters. This graph can aid decision makers and LCA practitioners to determine at what confidence level the difference in the impacts of two product designs are.

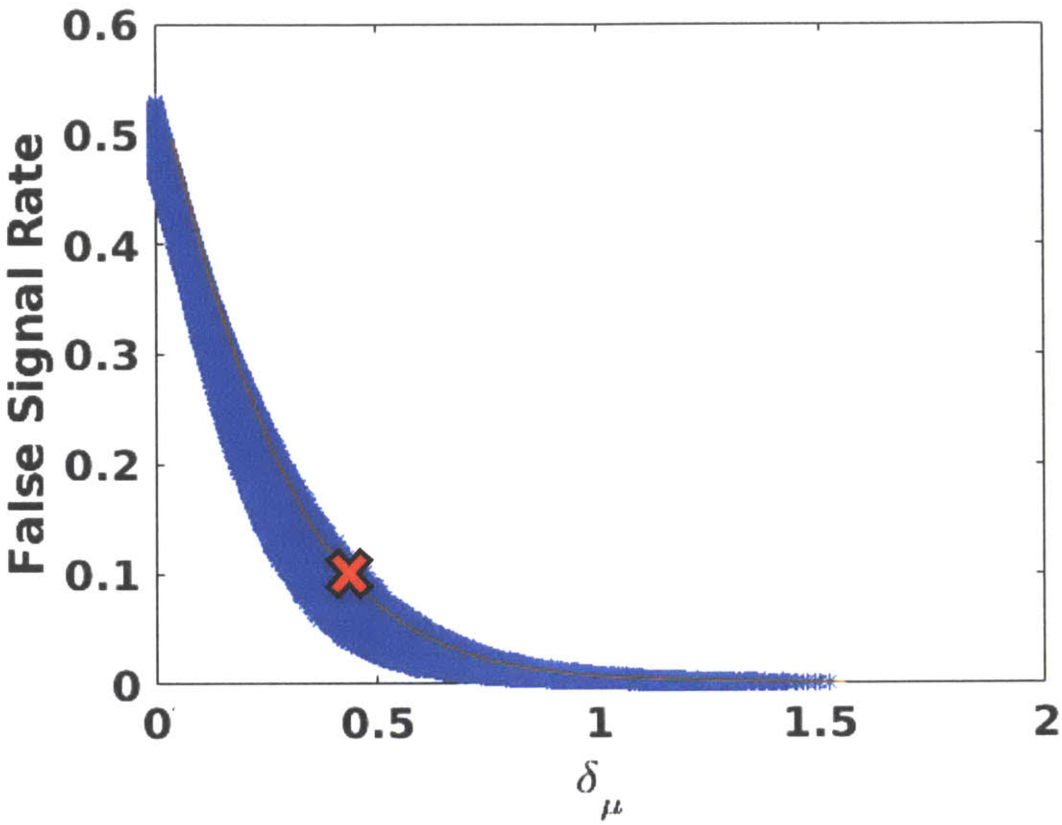


Figure 3-9: Exploration of the scenario space of impacts from tablets. Each point represents a comparison of two products. The red line represents the 95th percentile of the false signal rate at each mean difference. The cross represents an example of how this can be used: in order to distinguish correctly two products at least 90% of the time, with a 95% confidence level, the difference in the means between their average GWP has to be at least 0.42

Chapter 4: Discussion

This thesis expanded the probabilistic, streamlining methodology for life cycle assessments by developing a clear procedure for determining high contributors to uncertainty and by incorporating cost. The case study on tablets demonstrated that it is possible to streamline the assessment, resulting in a cost effective evaluation of the product or service in question. Furthermore, this thesis developed metrics to determine when sufficient information has been gathered and an analysis of the scenario space of the carbon dioxide impact of tablets. This section will discuss the merits as well as the limitations and challenges of the work presented, and areas of future work.

4.1. Tablet Case Study results

The case study on tablets and integrated circuits showed that the streamlining methodology can be used effectively to reduce the resources required to perform a life cycle assessment. By specifying only about 20 activities out of the 90 activities present in the tablet footprint, the uncertainty reduces to a false signal rate of 25%, while after specifying 40 activities, the uncertainty lowers only to 24%. Similarly, for the integrated circuit, by specifying only 15 activities, the uncertainty reduces to 0.1, and remains around the same as more activities are specified further. This shows how the uncertainty is mostly due to a partial number of parameters in the footprint and by targeting these parameters and leaving the rest at a high level assessment, the effort required to perform a life cycle assessment can be diminished significantly.

The activities identified as having the most leverage to reduce uncertainty included both activities that require contextual information and product attributes. Zgola (2011) had similar results. Thus, even though product attributes, which are easily known, can be used to lower the uncertainty of the assessment, some contextual information is still required to lower the uncertainty sufficiently.

The exploration of the major contributors to the total showed that the materials and manufacturing phase contributes significantly to the total impact of tablets. Thus, further impact reduction efforts should be directed towards lowering emissions from this phase, particularly from the semiconductor manufacturing phase. The use phase also contributes significantly to the total, but improvements in the addition of use phase modes, such as sleep and standby modes, have helped reduce the electricity consumption of electronics.

4.2. Subjectivity in Data Acquisition and the Presence of Data Gaps

The procedure presented here aims to eliminate any possible subjectivity and uncertainty in the assessment by methodologically identifying and incorporating all the life cycle stages and all the information available from publicly available studies and industry expert input. Subjectivity in the assessment is added when the analyst narrows the scope of the assessment by eliminating some of the life cycle stages or chooses which information to include in the assessment.

The analyst might narrow the scope of the assessment because it is outside the scope of interest for the purpose of the assessment or because of lack of data for some of the life cycle stages. This omission in life cycle stages introduces subjectivity in the assessment and thus comparisons between LCAs of different products or services might be difficult to carry out. When the scope is limited, any possible correlations between parameters in the different life cycle stages are lost, resulting in uncertainty. Furthermore, since the assessment uses previously published data as well as industry expert input, the information obtained is only as good as the information previously published and as good as knowledge available from industry experts. Data gaps might be present which are unknown, and therefore impossible to quantify.

The streamlining procedure presented in this thesis diminishes the amount of time and resources required to perform the LCA, thus encouraging analysts to include all the life cycle stages of the product. Specific information is required only for those activities that contribute the most to uncertainty, thus, all life cycle stages can be included even if they are specified using a wide range of values. However, it is expected that scope limiting will occur in life cycle assessments (LCA), and for assessments to be valuable, analysts should clearly communicate any scope limiting done that they are aware of as well as any assumptions and data omissions made.

4.3. Differences in Responses on the Cost of Additional Information

The work presented here demonstrated a methodology to determine the cost of gathering additional information for a life cycle assessment without having to know the specific monetary cost of each activity. The relative cost of each activity was used to develop metrics for determining sufficiency in data collection efforts and to quantify the cost saved by performing the streamlined life cycle assessment. The relative cost of each activity was determined via industry input through a survey. Different difficulties arise when aggregating survey responses.

The survey in this study was sent to different industry collaborators across the electronics supply chain. As can be seen, their responses varied (Figure 3-8). By averaging their responses, there is a risk that the responses might cancel each other out. For example, if one of the survey respondents gives a high value for the cost of an activity and another one gives a low value, their answers will end up canceling each other out and will produce a middle ranged value. In order to account for this, responses were also analyzed individually to determine whether the results obtained were the same as when aggregated. Further work can be directed towards determining whether other methods, such as rank based methods, are more appropriate for aggregating survey responses.

In the survey presented here, the cost of gathering information for similar activities was asked for as a single activity. For example, instead of asking for the cost of additional information on the impact of ferrous metal and the impact of plastic, both activities were grouped together under "materials" and the cost of gathering additional information on materials was asked for. The activities were aggregated this way in order to simplify the process of filling out the questionnaire and to obtain the largest number of responses as possible. For the survey, activities that were known to have similar cost of gathering information and that were similar were aggregated. However, this procedure might add subjectivity into the survey responses. Future work can look into whether any information is lost when activities are aggregated.

The responses to the survey from individuals from the same company were similar to each other, suggesting that the variation in the rankings of the cost of the activities might be caused by factors such as where the respondents' company is located in the supply chain, the size of the company, and even the relationship the company has with its suppliers. Further work can be directed at understanding the differences in data collection efforts as a function of the industry, position within the supply chain and characteristics of the company.

4.4. Probabilistic Nature in the Determination of High Impact Activities

The process to identify the parameters that, by fixing them, could lead to the greatest reduction in the output uncertainty is probabilistic in nature, as there is no prior knowledge on how much the variance would reduce for that parameter when more information is gathered. However, the sensitivity analysis helps identify the parameters that contribute the most to the uncertainty of the output and could, potentially, reduce the output variance if fixed to their true value. In our analysis, the Sobol indices served as a measure of the sensitivity of the output to the input parameters. For the top contributors to uncertainty activities, the Sobol indices were clearly higher, and therefore contributed more to the output variance than the other parameters. However, as parameters are specified further, the Sobol indices for the parameters become close to each other and the differences become small. Due to the combination of the probabilistic nature of the procedure and the small differences of the lower contributing parameters, it becomes more difficult to correctly identify the parameters that can reduce the output uncertainty as more parameters are specified. However, the most important parameters are identified early on in the assessment.

4.5. Use of Additional Information for Determining High Impact Activities

The cost of additional information in the study presented here was used to develop metrics for sufficiency and to quantify the savings from performing a streamlined LCA. However, future work can use this information to help prioritize activities. For example, if an activity shows up as a high contributor to the output variance but it is very costly to gather additional information about it, then it might be better to specify another activity with a lower cost. If the available funding to carry out the assessment is known, the activities to specify in detail can be identified while taking cost into account and identifying the group of activities that will reduce the output variance the most at a pre-determined cost.

A similar procedure for integrating cost in the prioritization of research activities is the procedure used by Bates et al. (2015). In their research, they explored different portfolios of research activities to identify the combination of activities that would result in the largest uncertainty reduction of the output variance. Future work should consider using this methodology to identify the most efficient research portfolio.

4.6. Scenario Exploration Challenges

The scenario exploration provided valuable information on the possible scenario space for the impact of tablets. As more information is specified for this part of the analysis, the number of possible scenarios increases. The number of scenarios increases rapidly, and the computation of the false signal rate for the comparison of the different scenarios slows down. This part of the analysis is very computationally intensive. Further work should be carried out to determine how an exploration of the scenario space can be done in a more efficient manner.

Chapter 5: Conclusion

The increase in demand for knowledge about the environmental impact of a product or service has prompted companies to carry out life cycle assessments (LCAs). LCAs provide valuable information; however, they are resource intensive, time consuming, and by the time the assessment is complete, the product profile might have changed. In this thesis, we addressed this problem by expanding a probabilistic, streamlining methodology that uses a high level assessment of the product in question and specifies further only those parameters that can reduce the output variance significantly.

This thesis applied the method of Sobol (Sobol', 1990) as described by Saltelli (A. Saltelli et al., 2008) to identify the activities that have the most leverage to reduce uncertainty. The case study demonstrated that the streamlining methodology has the potential to reduce the amount of resources needed to perform the LCA. Only 20 activities out of 90 activities present in the footprint had to be specified further. Furthermore, metrics described in this work, such as the false signal rate and the degree of separation, were used successfully to determine when sufficient information on the footprint has been gathered. This is particularly useful when prior information about the acceptable amount of uncertainty in the final footprint is not known. This "sufficiency" level identified by the metrics was observed even when the parameters were specified to a distribution rather than a single point value.

The cost of acquiring additional information for the footprint was quantified via a survey sent to industry collaborators. This information was used to determine how many activities to specify in the footprint as well as to determine the cost saved by performing the streamlining assessment. In our case study, approximately 75% of the cost of the footprint was saved by carrying out the probabilistic, streamlining methodology. The survey responses on the cost of activities varied from each other. Future work should address these differences with the goal of understanding the factors of the companies that create these differences. Possible differences might arise because of the location of the company within the supply chain, the size of the company or the company's relationship with its suppliers and buyers.

Future work should consider using the cost of acquiring additional information to identify the activities to specify further. Finally, an exploration of the scenario space of the impact of tablets was analyzed. In the case study of tablets, it was found that such analysis can help a decision maker determine whether the observed difference is significant by just knowing the difference in the means of the impacts.

In conclusion, the extended probabilistic streamlining methodology can help reduce significantly the efforts required to carry out a life cycle assessment. This can encourage more companies to evaluate the environmental impact of their products and to take environmental impact into their design decisions.

References

Ahlgren, S., & Röös, E. (2013). USING LCA AS A TOOL TO REGULATE BIOFUELS – A CONSIDERATION OF UNCERTAINTIES IN CULTIVATION. In *PROCEEDINGS OF LCM 2013 - FULL PUBLICATION. International Conference on Life Cycle Management* (pp. 172–175). Gothenburg. Retrieved from http://conferences.chalmers.se/index.php/LCM/LCM2013/paper/view/742/346

Andrae, A. S. G., & Andersen, O. (2010). Report Information from ProQuest. *The International Journal of Life Cycle Assessment*, *15*(8), 827–836.

Apple. (2014). *iPad Air 2 Environmental Report*.

Apple. (2015). *12.9-inch iPad Pro Environmental Report*.

Bates, M. E., Keisler, J. M., Zussblatt, N. P., Plourde, K. J., Wender, B. A., & Linkov, I. (2015). Balancing Research and Funding Using Value of Information and Portfolio Tools for Nanomaterial Risk Classification. *Nature Nanotechnology*, *11*(November), 1–7. http://doi.org/10.1038/nnano.2015.249

Bates, M. E., Sparrevik, M., de Lichy, N., & Linkov, I. (2014). The Value of Information for Managing Contaminated Sediments. *Environmental Science & Technology*, *48*(16), 9478–9485. http://doi.org/10.1021/es500717t

Bierer, A., Götze, U., Meynerts, L., & Sygulla, R. (2014). Integrating life cycle costing and life cycle assessment using extended material flow cost accounting. *Journal of Cleaner Production*, *108*, 1–13. http://doi.org/10.1016/j.jclepro.2014.08.036

BSI PAS 2050:2011 Specification for the assessment of the life cycle greenhouse gas emissions of goods and services. (2011). London, UK. Retrieved from http://www.evidenceondemand.info/pas-2050-2011-specification-for-the-assessment-of-the-life-cycle-greenhouse-gas-emissions-of-goods-and-services

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environmental Modelling and Software*, *22*(10), 1509–1518. http://doi.org/10.1016/j.envsoft.2006.10.004

Campolongo, F., & Saltelli, A. (1997). Sensitivity analysis of an environmental model: an application of different analysis methods. *Reliability Engineering & System Safety*, *57*(1), 49–69. http://doi.org/10.1016/S0951-8320(97)00021-5

Cariboni, J., Gatelli, D., Liska, R., & Saltelli, A. (2007). The role of sensitivity analysis in ecological modelling. *Ecological Modelling*, *203*(1-2), 167–182. http://doi.org/10.1016/j.ecolmodel.2005.10.045

Chen, J. L., & Chow, W.-K. C. W.-K. (2003). Matrix-type and pattern-based simple LCA for eco-innovative design of products. *Environmentally Conscious Design and Inverse Manufacturing, 2003. EcoDesign '03. 2003 3rd International Symposium on*, *4*, 0–5. http://doi.org/10.1109/VETECF.2003.239967

China Electric Power Industry Statistics Analysis. (n.d.). *2010*. China Electricity Council. Retrieved from http://www.purpleculture.net/china-electric-power-industry-statistics-analysis-2011-p-11777/

Clavreul, J., Guyonnet, D., Tonini, D., & Christensen, T. H. (2013). Stochastic and epistemic uncertainty propagation in LCA. *International Journal of Life Cycle Assessment*, *18*(7), 1393–1403. http://doi.org/10.1007/s11367-013-0572-6

Cooper, J. S., & Fava, J. a. (2006). Life-Cycle Assessment Practitioner Survey. *Journal of Industrial Ecology*, *10*(4), 12–14. http://doi.org/10.1162/jiec.2006.10.4.12

Crane, K., Ecola, L., Hassell, S., & Nataraj, S. (2012). *An Alternative Approach for Identifying Opportunities to Reduce Emissions of Greenhouse Gases*. Rand Corporation.

De Koning, A., Schowanek, D., Dewaele, J., Weisbrod, A., & Guinée, J. (2010). Uncertainties in a carbon footprint model for detergents; Quantifying the confidence in a comparative result. *International Journal of Life Cycle Assessment*, *15*(1), 79–89. http://doi.org/10.1007/s11367-009-0123-3

Deng, L., Babbitt, C. W., & Williams, E. D. (2011). Economic-balance hybrid LCA extended with uncertainty analysis: Case study of a laptop computer. *Journal of Cleaner Production*, *19*(11), 1198–1206. http://doi.org/10.1016/j.jclepro.2011.03.004

EPA. (n.d.). ENERGY STAR Certified Computers. Retrieved May 27, 2015, from https://www.energystar.gov/productfinder/product/certified-computers/results

EPA. (2009). *Guidance on the Development, Evaluation, and Application of Environmental Models*. Retrieved from http://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P1003E4R.PDF

Global tablet shipments projection 2010-2019. (2016). Retrieved from http://www.statista.com/statistics/269912/worldwide-tablet-shipments-forecast/

Gluch, P., & Baumann, H. (2004). The life cycle costing (LCC) approach: A conceptual discussion of its usefulness for environmental decision-making. *Building and Environment*, *39*(5), 571–580. http://doi.org/10.1016/j.buildenv.2003.10.008

Graedel, T. E., Allenby, B. R., & Comrie, P. R. (1995). Matrix approaches to abridged life cycle assessment. *Environmental Science & Technology*, *29*(3), 1–6. http://doi.org/10.1021/es00003a751

Groen, E. A., Heijungs, R., Bokkers, E. A. M., & de Boer, I. J. M. (2014). Methods for uncertainty propagation in life cycle assessment. *Environmental Modelling & Software*, *62*, 316–325. http://doi.org/10.1016/j.envsoft.2014.10.006

Heijungs, R., & Huijbregts, M. a J. (2004). A review of approaches to treat uncertainty in LCA. *iEMSs 2004 International Congress*, 8. http://doi.org/http://www.iemss.org/iemss2004/pdf/lca/heijarev.pdf

Henriksson, P. J. G., Heijungs, R., Dao, H. M., Phan, L. T., de Snoo, G. R., & Guinée, J. B. (2015). Product Carbon Footprints and Their Uncertainties in Comparative Decision Contexts. *Plos One*, *10*(3), e0121221. http://doi.org/10.1371/journal.pone.0121221

Herrmann, I. T., Hauschild, M. Z., Sohn, M. D., & McKone, T. E. (2014). Confronting Uncertainty in Life Cycle Assessment Used for Decision Support. *Journal of Industrial Ecology*, *18*(3), n/a–n/a. http://doi.org/10.1111/jiec.12085

Huang, C. Y., Hu, A. H., Yin, J., & Wang, H. C. (2016). Developing a parametric carbon footprinting tool for the semiconductor industry. *International Journal of Environmental Science and Technology*, *13*(1), 275–284. http://doi.org/10.1007/s13762-015-0869-z

Huijbregts, M. (1998). Application of uncertainty and variability in LCA. *The International Journal of Life Cycle Assessment*, *3*(5), 273–280. http://doi.org/10.1007/BF02979835

Huijbregts, M. A. J., Gilijamse, W., Ragas, A. M. J., & Reijnders, L. (2003). Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling. *Environmental Science & Technology*, *37*(11), 2600–2608. http://doi.org/10.1021/es020971+

Huijbregts, M. A. J., Norris, G., Bretz, R., Ciroth, A., Maurice, B., von Bahr, B., ... de Beaufort, A. S. H. (2001). Framework for modelling data uncertainty in life cycle inventories. *The International Journal of Life Cycle Assessment*, *6*(3), 127–132. http://doi.org/10.1007/BF02978728

ISO 14040. (2006). Retrieved from https://www.iso.org/obp/ui/#iso:std:iso:14040:ed-2:v1:en

ISO 14044. (n.d.). Retrieved from http://www.iso.org/iso/home/store/catalogue_tc/catalogue_detail.htm?csnumber=38498

ISO 14047. (2012). Retrieved from http://www.iso.org/iso/home/store/catalogue_tc/catalogue_detail.htm?csnumber=57109

ISO 14049. (2012). Retrieved from http://www.iso.org/iso/home/store/catalogue_tc/catalogue_detail.htm?csnumber=57110

Koomey, J. G., Matthews, H. S., & Williams, E. (2013). Smart Everything : Will Intelligent Systems Reduce Resource Use ? *Annual Review of Environment and Resources*, *38*, 311–343. http://doi.org/10.1146/annurev-environ-021512-110549

Krishnan, N., Boyd, S., Somani, A., Raoux, S., Clark, D., & Dornfeld, D. (n.d.). Supporting Information for " A Hybrid Life Cycle Inventory for Nano-scale Semiconductor Manufacturing ." *New York*, 1–37.

Kucherenko, S., Rodriguez-Fernandez, M., Pantelides, C., & Shah, N. (2009). Monte Carlo evaluation of derivative-based global sensitivity measures. *Reliability Engineering and System Safety*, *94*(7), 1135–1148. http://doi.org/10.1016/j.ress.2008.05.006

Lee, Y. J., Yang, X., & Blanco, E. (2012). Streamlined Life Cycle Assessment of Carbon Footprint of a Tourist Food Menu Using Probabilistic Underspecification Methodology. In *Sustainable Systems and Technology (ISSST)* (pp. 1–6). Boston, MA: IEEE International Symposium. http://doi.org/10.1109/ISSST.2012.6227980

Linkov, I., Bates, M. E., Canis, L. J., Seager, T. P., & Keisler, J. M. (2011). A decision-directed approach for prioritizing research into the impact of nanomaterials on the environment and human health. *Nature Nanotechnology*, *6*(12), 784–787. http://doi.org/10.1038/nnano.2011.163

Lloyd, S. M., & Ries, R. (2007). Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assesment: A survey of Quantitative Approaches. *Journal of Industrial Ecology*, *11*(1), 161–181. http://doi.org/10.1162/jiec.2007.1136

Masanet, E., & Chang, Y. (2014). Who Cares About Life Cycle Assessment?: A Survey of 900 Prospective Life Cycle Assessment Practitioners. *Journal of Industrial Ecology*, *18*(6), 787–791. Retrieved from https://eds-b-ebscohost-com.libproxy.mit.edu:9443/eds/pdfviewer/pdfviewer?vid=2&sid=1777a494-11b4-4670-a5e7-d35ac8fb83c5%40sessionmgr115&hid=127

Materials Systems Laboratory. (n.d.). Product Attribute to Impact Algorithm - PAIA. Retrieved from http://msl.mit.edu/projects/paia/research-approach.html

Moberg, Å., Johansson, M., Finnveden, G., & Jonsson, A. (2007). Screening environmental life cycle assessment of printed,web based and tablet e-paper newspaper. *Reports from the KTH Centre for Sustainable Communications*. Retrieved from http://www.infra.kth.se/fms/pdf/Report_epaper_final.pdf

Moberg, Å., Johansson, M., Finnveden, G., & Jonsson, A. (2010). Printed and tablet e-paper newspaper from an environmental perspective - A screening life cycle assessment.

Environmental Impact Assessment Review, *30*(3), 177–191. http://doi.org/10.1016/j.eiar.2009.07.001

Morgan, M. G., & Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge: Cambridge University. Retrieved from http://www.amazon.com/Uncertainty-Dealing-Quantitative-Policy-Analysis/dp/0521427444

Mueller, J., Griese, H., Schischke, K., Stobbe, I., Norris, G. A., & Udo de Haes, A. (2004). Life cycle thinking for green electronics: basics in ecodesign and the UNEP/SETAC life cycle initiative. In *Proceedings of 2004 International IEEE Conference on the Asian Green Electronics (AGEC)* (pp. 193–199). IEEE. http://doi.org/10.1109/AGEC.2004.1290903

Murphy, C. F., Kenig, G. A., Allen, D. T., Laurent, J.-P., & Dyer, D. E. (2003). Development of Parametric Material, Energy, and Emission Inventories for Wafer Fabrication in the Semiconductor Industry. *Environmental Science and Technology*, *37*(23), 5373–5382.

Norris, G. a. (2001). Integrating life cycle cost analysis and LCA. *International Journal of Life Cycle Assessment*, *6*(2), 118–120. http://doi.org/10.1007/BF02977849

Notter, D. A., Gauch, M., Widmer, R., W??ger, P., Stamp, A., Zah, R., & Althaus, H. J. (2010). Contribution of Li-ion batteries to the environmental impact of electric vehicles. *Environmental Science and Technology*, *44*(17), 6550–6556. http://doi.org/10.1021/es903729a

Olivetti, E., Patanavanich, S., & Kirchain, R. (2013). Exploring the Viability of Probabilistic Under-Speci fi cation To Streamline Life Cycle Assessment.

Reed, D. L. (2012). *Life-Cycle Assessment in Government Policy in the United States*. University of Tennessee. Retrieved from http://trace.tennessee.edu/utk_graddiss/1394/

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., … Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. John Wiley & Sons. Retrieved from https://books.google.com/books?id=wAssmt2vumgC&pgis=1

Saltelli, A., & Tarantola, S. (2002). On the Relative Importance of Input Factors in Mathematical Models. *Journal of the American Statistical Association*, *97*(459), 702–709. http://doi.org/10.1198/016214502388618447

Sobol', I. M. (1990). On sensitivity estimation for nonlinear mathematical models. *Matematicheskoe Modelirovanie*, *2.1*, 112–118.

Stutz, M. (2011). *Carbon Footprint of the Dell Streak Tablet*.

Sundaravaradan, N., Marwah, M., Shah, A., & Ramakrishnan, N. (2011). Data mining approaches for life cycle assessment. *Proceedings of the 2011 IEEE International Symposium on Sustainable Systems and Technology*, 1–6. http://doi.org/10.1109/ISSST.2011.5936863

Teardown - Tablets, eReaders & Notebooks Intelligence Service. (n.d.). Retrieved from https://technology.ihs.com/Services/420408/teardown-tablets-ereaders-notebooks-intelligence-service

Teehan, P., & Kandlikar, M. (2012). Sources of Variation in Life Cycle Assessments of Desktop Computers. *Journal of Industrial Ecology*, *16*, S182–S194. http://doi.org/10.1111/j.1530-9290.2011.00431.x

Teehan, P., & Kandlikar, M. (2013). Comparing embodied greenhouse gas emissions of modern computing and electronics products. *Environmental Science & Technology*, *47*(9), 3997–4003. http://doi.org/10.1021/es303012r

Todd, J. A., Curran, M. A., Weitz, K., Sharma, A., Vigeon, B., Price, E., ... Education, E. (1999). Streamlined life-cycle assessment: a final report from the SETAC North America streamlined LCA workgroup. ... *(SETAC) and SETAC ...*, (July). Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Streamlined+Life-Cycle+Assessment:+A+Final+Report+from+the+SETAC+North+America+Streamlined+LCA+Workgroup#0

USEPA. (1992). Guidelines for Exposure Assessment. *Risk Assessment Forum*, *57*(600Z-92/001), 22888–22938. http://doi.org/EPA/600/Z-92/001

Weber, C. L., Jaramillo, P., Marriott, J., & Samaras, C. (2010). Life Cycle Assessment and Grid Electricity: What Do We Know and What Can We Know? *Environmental Science & Technology*, *44*(6), 1895–1901. Retrieved from http://pubs.acs.org/doi/pdf/10.1021/es9017909

Weidema, B. P., Bauer, C., Hischier, R., Mutel, C., Nemecek, T., Reinhard, J., ... Wenet, G. (2013). *Overview and methodology. Data quality guideline for the ecoinvent database version 3. Ecoinvent Report 1(v3)* (Vol. 3). St. Gallen.

Wenzel, H. (1998). Application dependency of lca methodology: Key variables and their mode of influencing the method. *The International Journal of Life Cycle Assessment*, *3*(5), 281–288. http://doi.org/10.1007/BF02979837

Wolf, M. A., Pant, R., Chomkhamsri, K., Sala, S., & Pennington, D. (2012). *The International Reference Life Cycle Data System Handbook*. Italy. Retrieved from http://eplca.jrc.ec.europa.eu/uploads/JRC-Reference-Report-ILCD-Handbook-Towards-more-sustainable-production-and-consumption-for-a-resource-efficient-Europe.pdf

Zgola, M. L. (2011). *A Triage Approach to Streamline Environmental Footprinting : A Case Study for Liquid Crystal Displays by*. Massachusetts Institute of Technology.

Appendix A: Data and Uncertainty of Modeled Parameters in the Carbon Footprint of a Tablet

This section will show the values used at the high level, underspecified assessment of the tablet footprint.

		Activity	Source	Distribution	Mean/Min	COV/Max	Units
Materials	Ferrous Metal	Ferrous Metal amount	IHS Teardown	lognormal	0.11	0.3	Kg
		Ferrous Metal Impact Factor	Literature (1)	lognormal	2.48	1.62	KgCO2e/Kg
	Glass	Glass amount	Literature (1)	lognormal	8.11E-05	3.81E-05	Kg
		Glass Impact Factor	Literature (1)	lognormal	2.65	3.23	KgCO2e/Kg
	Nonferrous metal	Nonferrous metal amount	IHS Teardown	lognormal	0.24	0.38	Kg
		Nonferrous metal Impact Factor	Literature (1)	lognormal	9.3	19.8	KgCO2e/Kg
	Precious Metal	Precious Metal amount	IHS Teardown	lognormal	1.07E-06	6.52E-07	Kg
		Precious Metal Impact Factor	Literature (1)	lognormal	10515.67	11929.21	KgCO2e/Kg
	Thermoplastic	Thermoplastic Amount	IHS Teardown	lognormal	0.62	1.02	Kg
		Thermoplastic Impact Factor	Literature (1)	lognormal	4.14	2.3	KgCO2e/Kg
	Cardbox cardboard	Cardbox Cardboard Amount	IHS Teardown	lognormal	0.04	0.03	Kg
		Cardbox Cardboard Impact Factor	Literature (1)	lognormal	1.2	0.34	KgCO2e/Kg
	Cardbox paper	Cardbox Paper Amount	IHS Teardown	lognormal	0.4	0.53	Kg
		Cardbox Paper Impact Factor	Literature (1)	lognormal	1.2	0.34	KgCO2e/Kg
Integrated Circuit Manufacturing	IC die size	IC die size	IHS Teardown	lognormal	12.67	7.72	cm2
	IC Scope 1	IC Scope 1 emissions	Industry	lognormal	-	-	KgCO2e/cm2
	IC Scope 2	IC Scope 2 emissions	Industry	lognormal	-	-	Kwh/cm2
		IC Fabrication Grid Mix	International Energy Agency (IEA)	lognormal	0.88	0.28	KgCO2e/Kwh
	IC Fabrication Chemicals	IC Fabrication Chemicals Impact Factor	Industry	lognormal	-	-	KgCO2e/cm2
	IC Silicon	IC Silicon Impact Factor	Industry	uniform	-	-	KgCO2e/cm2
	IC Packaging Scope 2	Number of dies	IHS Teardown	lognormal	50	12.5	
		IC Packaging Scope 2 emissions	Industry	lognormal	-	-	KWh/cm2
		IC Packaging Scope 2 Grid Mix	International Energy Agency (IEA)	lognormal	0.88	0.28	KgCO2e/Kwh
	Platinum	Platinum Packaging Amount	Industry	uniform	-	-	Kg
		Platinum Packaging Impact Factor	Literature (1)	lognormal	10515.67	11929.21	KgCO2e/Kg
	Tin	Tin Packaging Amount	Industry	uniform	-	-	Kg
		Tin Packaging Impact Factor	Literature (1)	lognormal	2.05	1.21	KgCO2e/Kg
	Silver	Silver Packaging Amount	Industry	uniform	-	-	Kg
		Silver Packaging Impact Factor	Literature (1)	lognormal	10515.67	11929.21	KgCO2e/Kg
	Copper	Copper Packaging Amount	Industry	uniform	-	-	Kg
		Copper Packaging Impact Factor	Literature (1)	lognormal	2.05	1.4	KgCO2e/Kg
	Silicon Dioxide	Silicon Dioxide Packaging Amount	Industry	uniform	-	-	Kg
		Silicon Dioxide Packaging Impact Facto	Literature (1)	lognormal	2.10E-02	4.23E-03	KgCO2e/Kg
	Aluminum	Aluminum Packaging Amount	Industry	uniform	-	-	Kg
		Aluminum Packaging Impact Factor	Literature (1)	lognormal	6.59	5.19	KgCO2e/Kg
	Zinc Oxide	Zinc Oxide Packaging Amount	Industry	uniform	-	-	Kg
		Zinc Oxide Packaging Impact Factor	Literature (1)	lognormal	4.23	1.43	KgCO2e/Kg
	General Chemicals	General Chemicals Packaging Amount	Industry	uniform	-	-	Kg
		General Chemicals Packaging Impact Factor	Literature (1)	lognormal	2.9	3.8	KgCO2e/Kg
PWB	PWB	PWB Area	IHS Teardown	lognormal	0.03	0.01	m2
		PWB Emissions	Literature (1)	normal	377.4	177.91	KgCO2e/m2
LCD Manufacturing	LCD	LCD Area	IHS Teardown	lognormal	0.08	0.03	m2
		LCD Scope 1 Emissions	Taiwanese TFT LCD Association	lognormal	-	-	KgCO2e/m2
		LCD Scope 2 Emissions	Taiwanese TFT LCD Association	uniform	-	-	KWh/m2
		LCD Scope 2 Grid Mix	EIA + China Electricity Council	lognormal	0.88	0.28	KgCO2e/KWh

Other electronics	Aluminum Capacitor	Aluminum Capacitor Amount	IHS Teardown	lognormal	5.03E-04	2.09E-04	Kg
		Aluminum Capacitor Impact Factor	Literature (1)	lognormal	15.48	13.69	KgCO2e/Kg
	Ceramic Capacitor	Ceramic Capacitor Amount	IHS Teardown	lognormal	9.15E-04	4.30E-04	Kg
		Ceramic Capacitor Impact Factor	Literature (1)	lognormal	475.96	233.9	KgCO2e/Kg
	Diode	Diode Amount	IHS Teardown	lognormal	1.09E-04	1.06E-04	Kg
		Diode Impact Factor	Literature (1)	lognormal	141.5	123.43	KgCO2e/Kg
	Resistor	Resistor Amount	IHS Teardown	lognormal	1.81E-04	1.46E-04	Kg
		Resistor Impact Factor	Literature (1)	lognormal	372.83	609.87	KgCO2e/Kg
	Solder	Solder Amount	IHS Teardown	lognormal	1.13E-03	4.49E-04	Kg
		Solder Impact Factor	Literature (1)	lognormal	15.66	8.1	KgCO2e/Kg
	Tantalum Capacitor	Tantalum Capacitor Amount	IHS Teardown	lognormal	1.91E-04	2.60E-04	Kg
		Tantalum Capacitor Impact Factor	Literature (1)	lognormal	107	54.6	KgCO2e/Kg
	Transistor	Transistor Amount	IHS Teardown	lognormal	2.74E-03	5.06E-03	Kg
		Transistor Impact Factor	Literature (1)	lognormal	98.85	50.5	KgCO2e/Kg
	Low tech processing	Low Tech Processing Amount	Industry	deterministic	-	-	
		Low Tech Processing Emissions	Industry	lognormal	-	-	KWh/unit
		Low Tech Processing Grid Mix	EIA + China Electricity Council	lognormal	0.88	0.28	KgCO2e/KWh

Battery Manufacturing	Battery Weight	Battery weight	Industry	lognormal	-	-	Kg
	Carbon	Carbon proportion in battery	Literature (2) + Industry	uniform	-	-	
		Carbon Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Aluminum	Aluminum proportion in battery	Literature (2) + Industry	uniform	-	-	
		Aluminum Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Copper	Copper proportion in Battery	Literature (2) + Industry	uniform	-	-	
		Copper Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Transition Metal Oxide	TMO Proportion in Battery	Literature (2) + Industry	lognormal	-	-	
		TMO Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Lithium Hexafluorophosph	LH Proportion in Battery	Literature (2) + Industry	uniform	-	-	
		LH Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Nickel	Nickel Proportion in Battery	Literature (2) + Industry	uniform	-	-	
		Nickel Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Thermoset	Thermoset Proportion in Battery	Literature (2) + Industry	lognormal	-	-	
		Thermoset Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg
	Ethylene Carbonate	Ethylene Carbonate Proportion in Battery	Literature (2) + Industry	uniform	-	-	
		Ethylene Carbonate Impact Factor	Literature (2) + Industry	lognormal	-	-	KgCO2e/Kg

Use Phase	Use	Lifetime	Industry	lognormal	-	-	Years
		Use Scope 2	Energy Star	lognormal	18.94	9.24	KWh/year
		Use Grid Mix	IEA, EIA, China Electricity Council, literature (3)	lognormal	0.72	0.18	KgCO2/KWh

Transportation	Transportation	Transportation Weight	IHS Teardown	deterministic	5.51E-04		tons
		Transportation Leg 1 Distance	modeled based on location of ports	lognormal	9684.27	1936.85	km
		Transportation Leg 1 Impact Factor	modeled as a combination of ship, air and rail	lognormal	0.62	0.35	KgCO2e/tkm
		Transportation Leg 2 Distance	modeled based on location of ports	lognormal	10000	2000	km
		Transportation Leg 2 Impact Factor	modeled as a combination of ship, air and rail	lognormal	0.95	0.74	KgCO2e/tkm
		Transportation Leg 3 Distance	modeled based on location of ports	lognormal	962.19	300	km
		Transportation Leg 3 Impact Factor	modeled as a combination of ship, air and rail	lognormal	0.95	0.74	KgCO2e/tkm

Assembly	Assembly	Assembly Area	IHS Teardown	lognormal	0.03	0.01	m2
		Assembly Emissions	Industry	lognormal	-	-	KWh/m2
		Assembly Grid Mix	EIA + China Electricity Council	lognormal	0.88	0.28	KgCO2/KWh

(1) The impact factor was derived based on methodology from (Olivetti et al., 2013).

(2) The battery information used data in (Notter et al., 2010) complemented by industry input to adapt it to the electronics industry.

(3) The impact factors from (Weber et al., 2010) were combined with the other sources listed.

Appendix B: Survey for Cost of Additional Information

This section shows the survey that was sent to various industry collaborators to gather data on the cost of additional information for the carbon footprint of electronics.

Relative Cost of Data Gathering Questionnaire

Instructions:

The purpose of this spreadsheet and request is to score the relative effort, here referred to as "cost", of acquiring different types of information needed to perform a carbon footprint of a specific product.

The question to ask in each cell is, "what would be the relative cost of reducing the uncertainty of the____________."

Steps:

1. Please identify the most expensive data gathering task across all 27 parameter uncertainties (blue boxes at left).
2. Please give this uncertainty a score of 1.0, representing highest relative cost.
3. Please score the cost of reducing the uncertainties (blue boxes) of all the other parameters in terms of a fraction of the cost of the most expensive data gathering task. The remaining values should be between 0 and 1.
4. If you're unsure about the score of a parameter, please leave it blank or provide a range of scores.
5. If you consulted a colleague to answer the questionnaire, please fill in box "b) People Consulted" at the top. Then fill in the box "Person Consulted" next to the parameter for which you obtained help with the ID of the person consulted (from box b).

a) What is your position within the company?	
Business Unit	
Sustainability	
Other	

b) People Consulted	
ID	**Company Unit**
A	self
B	
C	
D	
E	

c)

Parameter	Score	Person Consulted
Quantity of materials (ex. ferrous metal, glass) from an industry average to the specific value		
GHG footprint of the materials (battery, materials, backend chemicals) from an average of the type of material GHG footprint to the specific GHG emissions		
Electronics amounts (ex. IC die size, # of chips, PWB area, capacitor weights) from an industry average to the specific value		
Electronics (aluminum capacitor, diode, solder, etc.) impact factors from an average of the type of electronic IF to the specific IF		
Number of layers in the PWB from an average to a specific number		
Type of battery (ex. Li-ion) from unknown to the known type		
Composition of battery from an industry average to the actual composition		

Parameter	Score	Person Consulted
Scope 1 and Scope 2 for IC manufacturing from a regional industry perspective to the specific fab emissions		
Scope 3 GHG footprint for IC manufacturing from a regional industry perspective to the specific fab emissions		
IC Manufacturing location from continent to specific country		
IC Manufacturing location from country to specific region within country		
Scope 1 and Scope 2 for IC assembly and test from a regional industry perspective to the specific fab emissions		
Scope 3 GHG footprint for IC assembly and test from a regional industry perspective to the specific fab emissions		
IC assembly and test location from continent to specific country		
IC assembly and test location from continent to specific region within the country		

Parameters	Score	Person Consulted
Scope 1 and Scope 2 for LCD manufacturing from a regional industry perspective to the specific fab emissions		
Scope 3 GHG footprint for LCD manufacturing from a regional industry perspective to the specific fab emissions		
LCD Manufacturing location from continent to specific country		
LCD Manufacturing Location from country to specific region within the country		
Product assembly scope 2 emissions from a regional industry perspective to the specific fab emissions		
Product assembly location from continent to specific country		
Product assembly location from country to specific region within the country		
Use location from a world average to the specific country		

Parameters	Score	Person Consulted
Use location from a country to a specific region		
Yearly TEC of product from an industry average to the specific product value		
Product lifetime from an industry average to the specific value		
Transportation mode from unknown (mixture of ship, rail, truck, air) to the actual transportation mode		

Glossary of Terms

GHG = Greenhouse Gas
IC= Integrated Circuit
IF = Impact Factor
LCD = Liquid Crystal Display
PWB = Printed Wiring Board
Scope 1 = All direct GHG emissions
Scope 2 = Indirect GHG emissions from consumption of purchased electricity, heat or steam.
Scope 3 = Other indirect emissions not covered in Scope 2 (ex. extraction and production of materials)
TEC = Typical Electrical Consumption of the product
(typical units : KWh/year)

Appendix C: Full List of Contributors to Variance using Iterative Approach

This section shows the full ordered list of contributors to variance for the three analyzed tablets. The work described in this thesis concludes that only the top 20 parameters need to be specified to reach "sufficiency".

Major Contributors to Uncertainty for Tablet A
1. Integrated Circuit Package Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor (KgCO2e-/m2)
3. IC Fabrication (KWh/cm2)
4. Use Phase Yearly Tec (KWh/year)
5. Total Integrated Circuit Die Size (cm2)
6. LCD Perflourocarbons Impact Factor (KgCO2e-/m2)
7. Integrated Circuit Perflourocarbons Impact Factor (KgCO2e-/cm2)
8. LCD Area (m2)
9. Integrated Circuit Fabrication Grid Mix (KgCO2e-/KWh)
10. Printed Wiring Board Area (m2)
11. IC Fabrication Grid mix (KgCO2e-/KWh)
12. Nonferrous metal impact factor (KgCO2e-/Kg)
13. PWB impact factor (KgCO2e-/m2)
14. Transportation Impact Factor (KgCO2e-/tkm)
15. Thermoplastic quantity (Kg)
16. Use Phase Grid Mix (KgCO2e-/KWh)
17. Product Life Time (Years)
18. Nonferrous metal quantity (Kg)
19. LCD Fabrication scope 2 (KWh/m2)
20. Use Phase Grid Mix (KgCO2e-/KWh)
21. Low tech processing scope 2 (KWh/unit)
22. Transistor quantity (Kg)
23. IC Fabrication Chemicals Emissions (KgCO2e-/Kg)
24. Transportation Emissions (KgCO2e-/tkm)
25. Cardbox/paper Impact Factor (KgCO2e-/Kg)
26. IC Package Scope 2 Grid Mix (KgCO2e-/KWh)
27. Assembly Grid Mix (KgCO2e-/KWh)
28. Number of IC packages
29. LCD Fabrication Grid Mix (KgCO2e-/KWh)
30. Resistor Impact Factor (KgCO2e-/Kg)
31. LCD Fabrication Grid Mix (KgCO2e-/KWh)
32. Low Tech processing Grid Mix (KgCO2e-/KWh)
33. IC Package Grid mix (KgCO2e-/KWh)

34. Cardbox/paper quantity (Kg)
35. Ferrous metal quantity (Kg)
36. Thermoplastic Impact Factor (KgCO2e-/Kg)
37. Transition Metal oxide Impact Factor (KgCO2e-/Kg)
38. IC Silicon Impact Factor KgCO2e-/cm2)
39. Assembly Scope 2 (KgCO2e-/KWh)
40. Ceramic Capacitor quantity (Kg)
41. Transition Metal Oxide Proportion in Battery
42. Ferrous Metal Impact Factor (KgCO2e-/Kg)
43. Assembly Intensity (KWh/m2)
44. Lithium Hexafluorophosphate proportion in Battery
45. Aluminum proportion in Battery
46. Ceramic Capacitor Impact Factor (KgCO2e-/Kg)
47. Cardbox.cardboard quantity (Kg)
48. Nickel Impact Factor (KgCO2e-/Kg)
49. Tantalum Capacitor Quantity (Kg)
50. IC Packaging Silver Impact Factor (KgCO2e-/Kg)
51. Nickel Proportion in Battery
52. Transistor Impact Factor (KgCO2e-/Kg)
53. Resistor quantity (Kg)
54. Solder Impact Factor (KgCO2e-/Kg)
55. Aluminum in Battery Impact Factor (KgCO2e-/Kg)
56. Transportation Leg 1 distance (Km)
57. Copper Impact Factor (KgCO2e-/Kg)
58. Diode quantity (Kg)
59. Aluminum Capacitor Impact Factor (KgCO2e-/Kg)
60. Precious Metal Impact Factor (KgCO2e-/Kg)
61. Precious Metal Quantity (Kg)
62. Transportation Leg 2 distance (Km)
63. Cardbox/cardboard Impact Factor (KgCO2e-/Kg)
64. Transportation Leg 3 Distance (Km)
65. Copper proportion in Battery
66. Lithium Hexafluorophosphate proportion in Battery

67. Tantalum Capacitor Impact Factor (KgCO2e-/Kg)
68. Diode Impact Factor (KgCO2e-/Kg)
69. Ethylene Carbonate proportion in Battery
70. Thermoset Impact Factor (KgCO2e-/Kg)
71. Battery weight (Kg)
72. Solder quantity (Kg)
73. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
74. Aluminum Capacitor Quantity (Kg)
75. Carbon Impact Factor (KgCO2e-/Kg)
76. IC Packaging General Chemicals Impact Factor (KgCO2e-/Kg)
77. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
78. Thermoset Proportion in Battery
79. Glass Quantity (Kg)
80. IC Packaging Tin Quantity (Kg)
81. Glass Impact Factor (KgCO2e-/Kg)
82. IC Packaging General Chemicals Quantity (Kg)
83. Carbon proportion in Battery
84. Ethylene Carbonate Impact Factor (KgCO2e-/Kg)
85. IC Packaging Aluminum Quantity (Kg)
86. IC Packaging Zinc Oxide quantity (Kg)
87. IC Packaging Silver quantity (Kg)
88. IC Packaging Silicon Dioxide quantity (Kg)
89. IC Packaging Tin quantity (Kg)
90. IC Packaging Zinc Oxide Impact Factor (KgCO2e-/Kg)
91. IC Packaging Copper Impact Factor (KgCO2e-/Kg)
92. IC Packaging Copper Quantity (Kg)
93. IC Packaging Silicon Dioxide Impact Factor (KgCO2e-/Kg)
94. Low tech processing quantity
95. Transportation leg 3 weight (Kg)
96. Transportation Leg 1 weight (Kg)
97. Transportation Leg 2 weight (Kg)
98. IC Packaging Aluminum Impact Factor (KgCO2e-/Kg)

Major Contributors to Uncertainty for Tablet B
1. Integrated Circuit Package Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor (KgCO2e-/m2)
3. Total Integrated Circuit Die Size (cm2)
4. IC Fabrication (KWh/cm2)
5. Use Phase Yearly Tec (KWh/year)
6. LCD Perflourocarbons Impact Factor (KgCO2e-/m2)
7. LCD Area (m2)
8. LCD Fabrication (KWh/m2)
9. Integrated Circuit Perflourocarbons Impact Factor (KgCO2e-/cm2)
10. LCD Fabrication grid mix (KgCO2e-/m2)
11. Integrated Circuit Fabrication Grid Mix (KgCO2e-/KWh)
12. Use Phase Grid Mix (KgCO2e-/KWh)
13. Printed Wiring Board Area (m2)
14. IC Package Scope 2 Grid Mix (KgCO2e-/KWh)
15. Nonferrous metal impact factor (KgCO2e-/Kg)
16. Transportation Impact Factor (KgCO2e-/tkm)
17. Thermoplastic quantity (Kg)
18. Product Life Time (Years)
19. Use Phase Grid Mix (KgCO2e-/KWh)
20. PWB impact factor (KgCO2e-/m2)
21.. Assembly Grid Mix (KgCO2e-/KWh)
22. Cardbox/paper Impact Factor (KgCO2e-/Kg)
23. Number of IC packages
24. Transportation Emissions (KgCO2e-/tkm)
25. Low tech processing scope 2 (KWh/unit)
26. IC Fabrication Chemicals Emissions (KgCO2e-/Kg)
27. Low Tech processing Grid Mix (KgCO2e-/KWh)
28. Transportation Leg 3 Distance (Km)
29. Cardbox/paper quantity (Kg)
30. Integrated Circuit Fabrication Grid Mix (KgCO2e-/KWh)
31. Transistor quantity (Kg)
32. LCD Fabrication Grid Mix (KgCO2e-/KWh)
33. Ferrous metal quantity (Kg)

34. Transition Metal oxide Impact Factor (KgCO2e-/Kg)
35. IC Package Grid mix (KgCO2e-/KWh)
36. Nonferrous metal quantity (Kg)
37. Assembly Intensity (KWh/m2)
38. Lithium Hexafluorophosphate proportion in Battery
39. Transportation Leg 1 distance (Km)
40. Thermoplastic Impact Factor (KgCO2e-/Kg)
41. Resistor quantity (Kg)
42. IC Silicon Impact Factor KgCO2e-/cm2)
43. Ceramic Capacitor Impact Factor (KgCO2e-/Kg)
44. Nickel Impact Factor (KgCO2e-/Kg)
45. Ceramic Capacitor quantity (Kg)
46. Resistor Impact Factor (KgCO2e-/Kg)
47. Battery weight (Kg)
48. Transportation Leg 2 distance (Km)
49. Diode quantity (Kg)
50. Transition Metal Oxide Proportion in Battery
51. Nickel Proportion in Battery
52. Transistor Impact Factor (KgCO2e-/Kg)
53. Tantalum Capacitor Quantity (Kg)
54. Aluminum in Battery Impact Factor (KgCO2e-/Kg)
55. Cardbox.cardboard quantity (Kg)
56. Lithium Hexafluorophosphate proportion in Battery
57. Aluminum proportion in Battery
58. Precious Metal Quantity (Kg)
59. Solder quantity (Kg)
60. IC Packaging Silver Impact Factor (KgCO2e-/Kg)
61. Ferrous Metal Impact Factor (KgCO2e-/Kg)
62. Copper proportion in Battery
63. Ethylene Carbonate proportion in Battery
64. Thermoset Impact Factor (KgCO2e-/Kg)
65. Precious Metal Impact Factor (KgCO2e-/Kg)
66. Cardbox/cardboard Impact Factor (KgCO2e-/Kg)

67. Solder Impact Factor (KgCO2e-/Kg)
68. Copper Impact Factor (KgCO2e-/Kg)
69. Carbon proportion in Battery
70. Carbon Impact Factor (KgCO2e-/Kg)
71. Ethylene Carbonate Impact Factor (KgCO2e-/Kg)
72. Diode Impact Factor (KgCO2e-/Kg)
73. Aluminum Capacitor Quantity (Kg)
74. Thermoset Proportion in Battery
'5. IC Packaging General Chemicals Impact Factor (KgCO2e-/Kg)
76. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
77. Tantalum Capacitor Impact Factor (KgCO2e-/Kg)
78. IC Packaging Silver quantity (Kg)
79. Assembly Grid Mix (KgCO2e-/KWh)
80. Glass Impact Factor (KgCO2e-/Kg)
81. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
82. IC Packaging General Chemicals Quantity (Kg)
83. IC Packaging Aluminum Quantity (Kg)
84. IC Packaging Tin Quantity (Kg)
85. IC Packaging Tin quantity (Kg)
86. IC Packaging Zinc Oxide quantity (Kg)
87. Glass Quantity (Kg)
88. IC Packaging Copper Quantity (Kg)
89. IC Packaging Copper Impact Factor (KgCO2e-/Kg)
90. IC Packaging Silicon Dioxide quantity (Kg)
91. Low tech processing quantity
92. IC Packaging Silicon Dioxide Impact Factor (KgCO2e-/Kg)
93. Transportation leg 3 weight (Kg)
94. Transportation Leg 1 weight (Kg)
95. Transportation Leg 2 weight (Kg)
96. IC Packaging Aluminum Impact Factor (KgCO2e-/Kg)
97. IC Packaging Zinc Oxide Impact Factor (KgCO2e-/Kg)
98. Aluminum Capacitor Impact Factor (KgCO2e-/Kg)

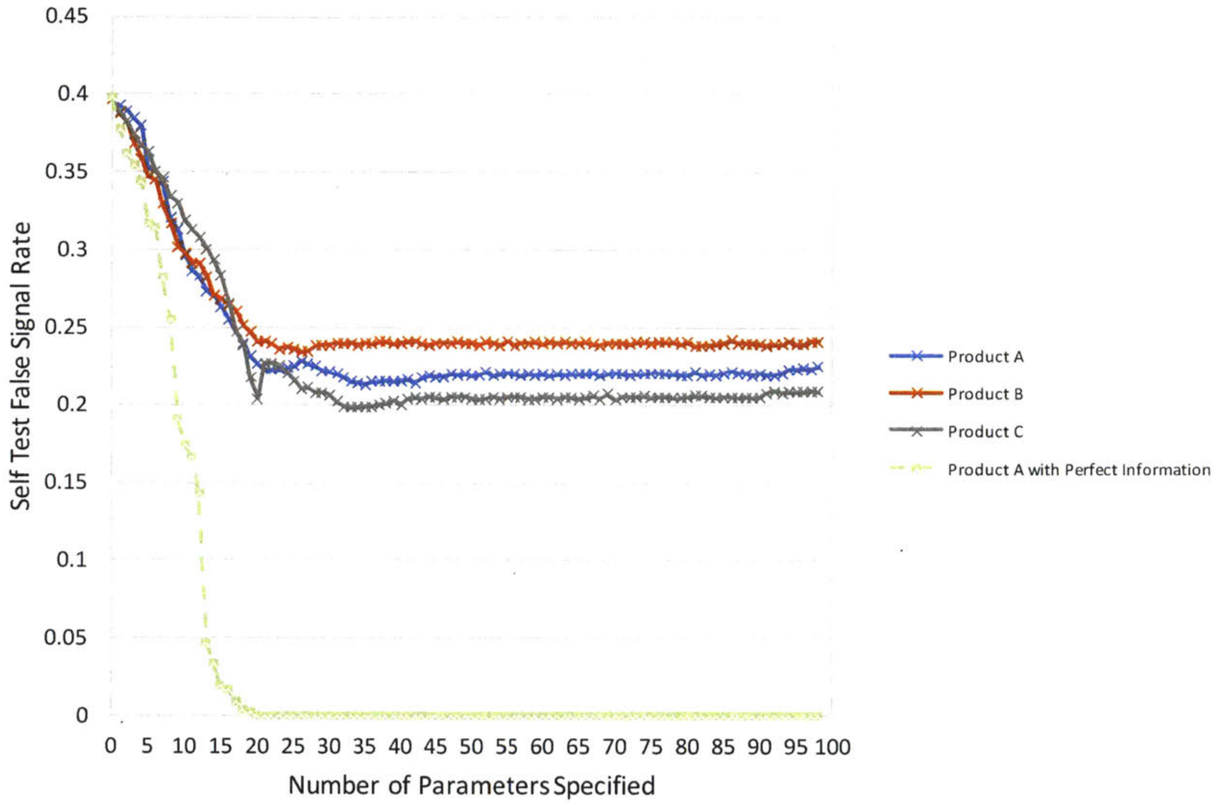
Major Contributors to Uncertainty for Tablet C
1. Integrated Circuit Assembly and Test Scope 2 (KWh/package)
2. LCD Fabrication Chemicals Impact Factor (KgCO2e-/m2)
3. Total Integrated Circuit Die Size (cm2)
4. Use Phase Yearly Tec (KWh/year)
5. LCD Perflourocarbons Impact Factor (KgCO2e-/m2)
6. LCD Area (m2)
7. PWB Area (m2)
8. Integrated Circuit Assembly and Test grid mix (KgCO2e-/m2)
9. Nonferrous metal Impact Factor (KgCO2e-/Kg)
10. IC Fabrication (KWh/cm2)
11. Transportation Impact Factor (KgCO2e-/tkm)
12. Thermoplastic quantity (Kg)
13. Use Phase Grid Mix (KgCO2e-/KWh)
14. LCD Fabrication (KWh/m2)
15. Number of IC packages
16. Product Life Time (Years)
17. Use Phase Grid Mix (KgCO2e-/KWh)
18. Integrated Circuit Perflourocarbons Impact Factor (KgCO2e-/cm2)
19. Nonferrous metal quantity (Kg)
20. Low tech processing scope 2 (KWh/unit)
21. Transportation Emissions (KgCO2e-/tkm)
22. Resistor Impact Factor (KgCO2e-/Kg)
23. Ferrous Metal Impact Factor (KgCO2e-/Kg)
24. PWB impact factor (KgCO2e-/m2)
25. LCD Fabrication grid mix (KgCO2e-/m2)
26. Integrated Circuit Fabrication Grid Mix (KgCO2e-/KWh)
27. Transportation Leg 3 Distance (Km)
28. Integrated Circuit Fabrication Grid Mix (KgCO2e-/KWh)
29 Lithium Hexafluorophosphate proportion in Battery
30. Ferrous metal quantity (Kg)
31. LCD Fabrication Grid Mix (KgCO2e-/KWh)
32. Low Tech processing Grid Mix (KgCO2e-/KWh)
33. Cardbox/paper quantity (Kg)

34. Transistor quantity (Kg)
35. Nickel Proportion in Battery
36. Transportation Leg 1 distance (Km)
37. Assembly Intensity (KWh/m2)
38. IC Fabrication Chemicals Emissions (KgCO2e-/Kg)
39. Ceramic Capacitor quantity (Kg)
40. Transportation Leg 2 distance (Km)
41. IC Package Scope 2 Grid Mix (KgCO2e-/KWh)
42. Thermoplastic Impact Factor (KgCO2e-/Kg)
43. Aluminum in Battery Impact Factor (KgCO2e-/Kg)
44. IC Silicon Impact Factor KgCO2e-/cm2)
45. Tantalum Capacitor Quantity (Kg)
46 Precious Metal Impact Factor (KgCO2e-/Kg)
47. Transition Metal oxide Impact Factor (KgCO2e-/Kg)47
48. Cardbox/cardboard Impact Factor (KgCO2e-/Kg)
49. Ceramic Capacitor Impact Factor (KgCO2e-/Kg)
50. Battery weight (Kg)
51. Cardbox.cardboard quantity (Kg)
52. Aluminum Capacitor Quantity (Kg)
53. Resistor quantity (Kg)
54. Precious Metal Quantity (Kg)
55. Transition Metal Oxide Proportion in Battery
56. Nickel Impact Factor (KgCO2e-/Kg)
57. Aluminum proportion in Battery
58. Diode quantity (Kg)
59. Ethylene Carbonate proportion in Battery
60. IC Packaging Silver Impact Factor (KgCO2e-/Kg)
61. Copper Impact Factor (KgCO2e-/Kg)
62. Copper proportion in Battery
63. Lithium Hexafluorophosphate proportion in Battery
64. Solder quantity (Kg)
65. Diode Impact Factor (KgCO2e-/Kg)
66. Thermoset Impact Factor (KgCO2e-/Kg)

67. Tantalum Capacitor Impact Factor (KgCO2e-/Kg)
68. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
69. Thermoset Proportion in Battery
70. Solder Impact Factor (KgCO2e-/Kg)
71. Carbon proportion in Battery
72.. Ethylene Carbonate Impact Factor (KgCO2e-/Kg)
73. Assembly Grid Mix (KgCO2e-/KWh)
74. Assembly Grid Mix (KgCO2e-/KWh)
75. IC Packaging General Chemicals Impact Factor (KgCO2e-/Kg)
76. IC Packaging General Chemicals Quantity (Kg)
77. Transistor Impact Factor (KgCO2e-/Kg)
78. IC Packaging Platinum Impact Factor (KgCO2e-/Kg)
79. IC Packaging Zinc Oxide quantity (Kg)
80. Cardbox/paper Impact Factor (KgCO2e-/Kg)
81. IC Packaging Tin quantity (Kg)
82. Glass Quantity (Kg)
83. Carbon Impact Factor (KgCO2e-/Kg)
84. IC Packaging Silver quantity (Kg)
85. Glass Impact Factor (KgCO2e-/Kg)
86. IC Packaging Aluminum Impact Factor (KgCO2e-/Kg)
87. IC Packaging Tin Quantity (Kg)
88. IC Packaging Silicon Dioxide quantity (Kg)
89. IC Packaging Aluminum Quantity (Kg)
90. IC Packaging Silicon Dioxide Impact Factor (KgCO2e-/Kg)
91. Low tech processing quantity
92. IC Packaging Copper Quantity (Kg)
93. Transportation leg 3 weight (Kg)
94. IC Packaging Copper Impact Factor (KgCO2e-/Kg)
95. Transportation Leg 1 weight (Kg)
96. Transportation Leg 2 weight (Kg)
97. IC Packaging Zinc Oxide Impact Factor (KgCO2e-/Kg)
98. Aluminum Capacitor Impact Factor (KgCO2e-/Kg)

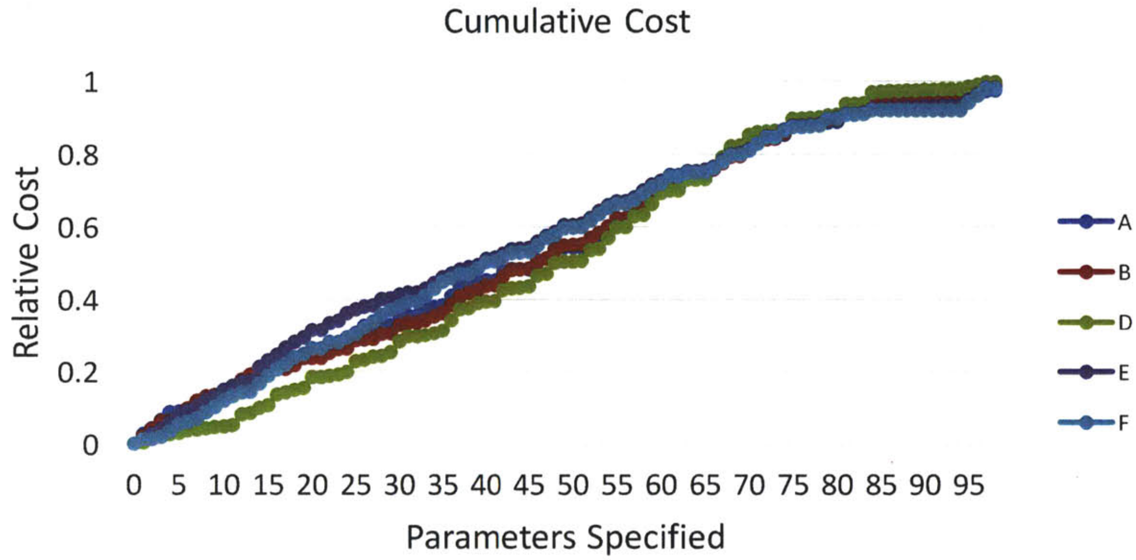
Appendix D: Self-test False Signal Rate

This figure shows the complete self-test false signal rate as a function of the number of parameters specified. Once the number of parameters specified reaches 20, the decrease in false signal rate, and therefore uncertainty, is minimal.



Appendix E: Cost of Additional Information

The figure shows the relative cost of the footprint versus the number of parameters specified for all the survey responses. The responses vary a bit, however, they all follow a rough linear trend.



The figure below shows the survey responses "E" and "F". Both respondents belong to the same company, and their answers are closer to each other than the rest of the responses.