A Triage Approach to Streamline Environmental Footprinting:
A Case Study for Liquid Crystal Displays

by

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Submitted to the Engineering Systems Division in Partial Fulfillment
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ABSTRACT

Quantitative environmental performance evaluation methods are desired given the growing certification and labeling landscape for consumer goods. Challenges associated with existing methods, such as life cycle assessment (LCA), may be prohibitive for complex goods such as information technology (IT). Conventional LCA is resource-intensive and lacks harmonized guidance for incorporating uncertainty. Current methods to streamline LCA may amplify uncertainty, undermining robustness. Despite high uncertainty, effective and efficient streamlining approaches may be possible.

A methodology is proposed to identify high-impact activities for a streamlined assessment with a high degree of inherent uncertainty. First, a screening assessment is performed using Monte Carlo simulations, applying existing activity (materials and processes), impact, and uncertainty data, to identify elements with the most leverage to reduce overall environmental impact uncertainty. This data triage is informed by sensitivity analysis parameters produced by the simulations. Targeted data collection is carried out for key activities until overall uncertainty is reduced to the point where a product's impact probability distribution is distinct from others within a specified error rate.

In this thesis, we find that triage and prioritization are possible despite high uncertainty. The methodology was applied to the case study of liquid crystal display (LCD) classes, producing a clear hierarchy of data importance to reduce uncertainty of the overall impact result. Specific data collection was only required for a subset of processes and activities (22 out of about 50) to enable discrimination of LCDs with a low error rate (9%). Most of these priority activities relate to manufacturing and use phases. The number of priority activities targeted may be balanced with the level to which they are able to be specified. It was found that ostensible product attributes alone are insufficient to discriminate with low error, even at high levels of specificity.

This quantitative streamlining method is ideal for complex products for which there is great uncertainty in data collection and modeling. This application of this method may inform early product design decisions and enable harmonization of standardization efforts.

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1. INTRODUCTION: THE CHALLENGES OF ENVIRONMENTAL FOOTPRINTING FOR COMPLEX PRODUCTS

The push for environmental performance

Manufacturers are no longer solely driven by meeting market demand for cost, performance, and quality; competitive companies must now focus on environmental performance. This push is driven by many factors including volatile energy prices, climate change legislation, corporate sustainability efforts, consumer demand for "green" products, pressure from retailers on their upstream supply chains, and, perhaps most significantly, labeling initiatives. Examples of the explosion of country-specific labeling initiatives include Japan's EcoMark, China's Environmental Labeling Program, Taiwan's Electrical and Electronic Manufacturers' Association, France's Grenelle de l'Environnement, and Germany's Blue Angel (Horne 2009; Lim and Park 2009; Weber et al. 2010).

Such labeling initiatives are supported by environmental quantification methodologies developed by the British Standards Institute (BSI), the International Standards Organization (ISO), and the World Resources Institute/World Business Council on Sustainable Development (WRI/WBCSD) (ISO 2006b; WRI/WBCSD 2007; BSI 2008). These methodologies provide guidance on various aspects of impact assessment and data collection. To respond to the aforementioned pressures and comply with these methodologies, many industry sectors are engaging in detailed environmental data collection efforts within their supply chains for use in evaluation efforts. These efforts are costly and require significant resources even for evaluating a single product, and this burden is amplified by the complexity of supply chains and the vast quantity of products. Supply chains lack infrastructure to monitor and report the basic information required to evaluate product environmental performance including material and energy input quantities, origins, and processing information, as well as outputs and emissions. Due to these data collection challenges, streamlined approaches for data collection and modeling are desired. Such streamlining efforts may include use of proxy data, screening analyses to identify hotspots, and algorithms that relate product attributes to impact.

Given the expanding environmental standards and labeling landscape, there is a growing need for harmonized, consistent, quantitative, but just as critically, streamlined environmental performance evaluation tools. To create a level playing field for such evaluation efforts, companies are forming working groups to reach consensus on focused measurement and analysis protocols. An example is a project through the International Electronics Manufacturing Initiative (iNEMI), which aims to develop a consistent quantification tool to evaluate the environmental

performance of electronics (iNEMI 2009). In addition, the Sustainability Consortium[1] is developing a Sustainability Measurement and Reporting System (SMRS), an expanded Product Category Rules (PCR) document developed in accordance with ISO 14025, established "to communicate the real impacts of products to the consumer."

However, streamlining approaches will amplify the many sources of uncertainty in these studies and therefore may undermine results. Given the urgency of quantifying environmental burden generated by the explosion of initiatives in this area, and the significant cost of conducting these assessments, streamlining seems necessary. This thesis investigates whether we are able to streamline evaluations through the use of screening to examine which elements of uncertainty we must address in order to make defensible quantitative evaluations.

Life cycle assessment challenges and opportunities

Life cycle assessment (LCA), an environmental management approach, has long been the tool of choice for quantifying the impact of a product, process or service on the world. However, LCA tends to be resource-intensive in terms of data collection, analysis, and interpretation of results. Specifically, LCA is challenged by lack of guidance for data cut-off decisions, emphasis on primary data collection, inflexibility, and lack of guidance to evaluate and communicate uncertainty. These challenges are further discussed below.

- Conventional LCA guidance encourages complete data collection but permits cut-offs based on mass, volume, or environmental impact thresholds if such cut-offs may be justified. However, there is little guidance on providing sufficient defense of such decisions (ISO 2006b; ISO 2006c; BSI 2008). Justification for a cut-off decision is therefore left to the discretion of the practitioner, introducing high levels of variability and subjectivity.

- LCA guidance tends to emphasize collection of measured primary data over secondary data (BSI 2008), though estimated or calculated data may be permitted (ISO 2006c; WRI/WBCSD 2007). Close supplier interaction is encouraged so that direct measurement and reporting of input and output material and energy flows can take place. Secondary data are considered acceptable only if primary are unavailable. Guidance does not fully discuss the inadvertent variability and error associated with inconsistencies of primary data collection efforts, and the possibility that such error could drown out any meaningful differences in measurement.

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[1] The Sustainability Consortium is an organization comprised of international collaborators working to "build a scientific foundation that drives innovation to improve consumer product sustainability through all stages of a product's life cycle," (TSC 2011) .

- LCA approaches tend to be static and not easily adaptable to accommodate evolution of products. Because data collection and analysis for a single product and its life cycle impacts may take months and are highly resource intensive, this does not bode well for highly complex products with many design and process permutations.

- Uncertainty in data and modeling may render the difference between LCA results unimportant. Although ISO 14044, 14040 and 14025 acknowledge and recommend uncertainty analysis, little guidance and structure is provided for practical implementation (ISO 2006a; ISO 2006b; ISO 2006c). In ISO 14044, uncertainty analysis is defined as "systematic procedure to quantify the uncertainty introduced in the results of a life cycle inventory analysis due to the cumulative effects of model imprecision, input uncertainty and data variability." Because mainstream LCA tends to be mean-based, it is therefore limited in ability to incorporate and communicate into the results the many forms of uncertainty associated with the LCA process.

The challenges of quantifying environmental impact are especially pronounced for information technology (IT) and other complex, quickly evolving products. Data collection is challenged by convoluted supply chains, making it nearly impossible to obtain primary data specific to fabrication facilities, lines of production, generation technology, and at the stock-keeping units (SKUs) level. In addition, many original equipment manufacturers (OEMs) purchase parts from a shared pool of suppliers, making it difficult to discriminate environmental performance by brand. This rapidly-evolving industry with high product and technology turnover quickly renders conventional, static LCA results obsolete. High product and process variability, as well as spatial and geographic uncertainty, must be incorporated and interpreted in analysis and results. This thesis explores the use of streamlined approaches to LCA for IT products in particular.

Vision for more effective and efficient method

Manufacturers looking to design electronics for environmental performance, consumers relying on labels to inform "green" purchases, and standards organizations aiming to harmonize evaluation efforts could benefit from effective and efficient evaluation methods. By effective, we mean uncertainty must be identified, analyzed and interpreted, not indefensibly omitted, to produce results of sufficient accuracy and enable a consistent method to understand the viability of labeling schemes. By efficient, we mean processes and activities may be prioritized in terms of contribution to uncertainty to streamline the evaluation process. Secondary data can stand in for primary data if a process or activity is not high priority, thus reducing data collection and analysis burdens. And once process or activity data are compiled, these data may be reused or modified to accommodate analyses of similar products.

With this vision we propose a method for robust streamlined environmental assessment. The method begins with a probabilistic triage, incorporating existing data and temporal, spatial and parametric uncertainty, to identify priority activities for targeted data collection. We then evaluate how many of those activities must be targeted for specific data collection. This targeted data collection and quantification of uncertainty enables us to explore the ability to resolve environmentally preferable decisions. While not the focus of this thesis, the proposed method then develops regressions between those priority activities, product attributes, and environmental impacts, to enable efficient approximation of the consequences of key design decisions.

We use quantification of the environmental impact of liquid crystal display (LCD) laptop modules as a case study to evaluate the methodology. The perfluoro-chemicals (PFCs) used as process materials in LCD manufacturing are significant global warming gases and have been targeted for environmental performance improvements. The worldwide production of module components involves electricity-intense processes with highly variable fuel mixes. Aging data need to be updated to reflect quickly-evolving manufacturing processes and materials (c.f., the primary LCD study used in the dominant LCA database is from 2001). These analysis challenges make LCDs an interesting product example.

1.1 Thesis outline

In this thesis we propose and evaluate a methodology for effective and efficient evaluation of environmental performance of IT products which accounts for high levels of uncertainty and defensible prioritization of data collection.

Chapter 1 provides an overview of the motivation for, and challenges of, quantitative environmental assessment of IT products. This chapter also reviews previous LCA streamlining efforts and how uncertainty has been addressed.

Chapter 2 presents the methodology, beginning with a data screening assessment, followed by targeted data collection around important activities.

Chapter 3 provides background on LCD technology, processes, materials, and impacts. In this chapter, the methodology is applied to the analysis of LCDs to evaluate which elements of the screening LCD model need to be addressed (i.e., the level of resolution required around a subset of activities) to make quantitative evaluations.

Chapter 4 presents discussion of results.

Chapter 5 provides a summary of the main ideas developed in the thesis and broader implications of this work on the development of standards, product declarations, and labeling efforts.

Chapter 6 provides a list of literature referenced in the thesis.

Chapter 7 contains appendices including A. acronyms, B. case study analysis data tables, C. a literature review of LCD life cycle environmental impacts, and D. analysis and discussion of LCD life cycle environmental impacts.

1.2 Literature review

This chapter outlines published and publicly-available literature pertaining to streamlining efforts, how uncertainty has been addressed in these efforts and environmental assessment in general, and what forms of uncertainty may be most relevant to IT products.

1.2.1 Streamlining efforts in environmental assessment

Given the resource-intensive nature of establishing the bill of materials (BOM) and processes for LCA, streamlining of data collection and modeling has been of interest in the field. Systematic methodologies to identify key-issue hotspots have long been pursued. Streamlining measures, however, increase uncertainty in the result. Several approaches, including simplifying measures, use of secondary data, screening, and correlative algorithms, are outlined briefly below.

Simplification measures
One class of simplifications is the use of qualitative information to rank the impacts of each life cycle activity (generally against some benchmark) as demonstrated by the Environmentally Responsible Product Assessment (Graedel and Allenby 1995) which employed a matrix approach to streamlining. Such simplification measures are useful when quantitative data are unavailable but information about uncertainty, reliability, completeness, age, and geographical and technological representativeness are known (Weidema and Wesnæs 1996). Socolof used decision rule priorities, including mass, environmental/toxic concern, energy concern, functional importance, and physical uniqueness, to leverage known information and prioritize efforts (Socolof et al. 2001b). Such techniques are highly flexible and subjective and may compound uncertainty in the analysis.

Secondary data
The use of secondary data as proxies for primary data can be used to simplify and streamline the evaluation process. Such data include that from publicly-available sources, pay-for-use databases, or expert opinion (Hochschorner and Finnveden 2003; Hur et al. 2005). For example, commercial databases, such as ecoinvent, provide proxy process data (ecoinvent 2010). Such proxy data may vary in relevance depending on spatial, temporal and parametric match.

Screening
The SETAC-Europe working group has long pursued tackling the problem of how iterative an LCA must be, and how thorough a screening should be before turning to a refined analysis (Heijungs 1996). Research by Lasvaux et al. sought to identify the flows that contribute the most to assessment indicators. The study acknowledged the need to compromise between precision of simplified characterization model (SCM) and number of life cycle inventory (LCI) flows (Lasvaux et al. 2010).

Stochastic analyses have been developed which incorporate an uncertainty distribution around a mean-based estimate to apply to Monte Carlo simulations. These efforts may require heavy data collection and an understanding of the independence of and correlation among parameters (Olivetti 2010). Many studies have applied Monte Carlo simulations to determine probabilistic mean values based on uncertainty approximations. The ecoinvent reports discussed the use of Monte Carlo (Hedemann and König 2003). Monte Carlo simulations were used to assess relative contributions to variance of groups of parameters related to plant-protection products, including elementary flows, energy supply, transport and packaging, and waste treatment flows (Geisler et al. 2005). Huijbregts provided an informal scheme for the analysis of parameter uncertainty, to aid in deciding which flows require more attention when assigning uncertainty distributions (see Figure 1) (Huijbregts et al. 2003).
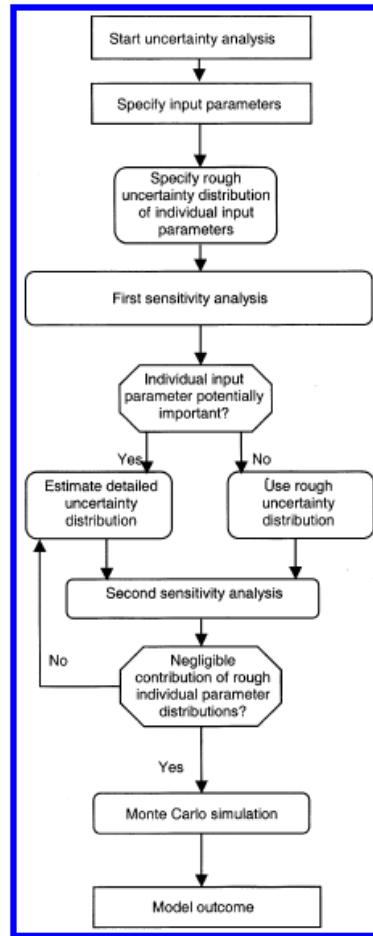
Figure 1. A rough guideline for screening assessment prior to Monte Carlo simulation (Reproduced from Huijbregts, Gilijamse et al. 2003)

Maurice et al. suggested a combination of qualitative and quantitative approaches to efficiently assess uncertainty using Monte Carlo simulations (Maurice et al. 2000). The suggestions focused

on parameters with significant leverage in affecting/contributing to cumulative results. Rank order coefficient was proposed as an activity prioritization metric (Evans and Olson).

Learning algorithms
Others have recognized the need for rapid, preliminary LCA tools to inform early design decisions based on impact tradeoffs. Sousa et al. sought to develop learning algorithms and neural networks to produce surrogate LCA models based on generic product classifications. This work produced product concept descriptors, applying an abbreviated LCI list, greatly reducing data collection requirements for environmental assessment. More work is needed to improve classification requirements and accuracy of estimates, and data availability is critical in development of such surrogate models (Sousa et al. 2001; Sousa and Wallace 2006). Such efforts may not enable the discrimination of product classes, a level much more granular than generic product classifications.

The next section contains discussion of categories of uncertainty, highlighting those particularly relevant to IT products. Such forms of uncertainty are important to consider in streamlining approaches in order to achieve robust results.

1.2.2 Accounting for uncertainty for accurate environmental assessment

In the previous section, we discussed the need to increase robustness of environmental evaluation streamlining efforts in light of amplification of uncertainty in data and modeling. In this section, we outline and discuss categories of uncertainty and the importance of accounting for it, particularly in streamlined approaches.

Importance of accounting for uncertainty for accurate evaluation
Many studies have discussed the importance of incorporating uncertainty in environmental evaluation and LCA (Heijungs 1996; Huijbregts 2002; Huijbregts et al. 2003; Heijungs and Huijbregts 2004). The apparent difference between products or systems may in fact be statistically insignificant once uncertainties are incorporated into the analysis (Huijbregts et al. 2003). Indeed, sources of error and uncertainty must be identified and quantified because they may mask the difference between comparative LCAs and make product differences insignificant (Geisler et al. 2005). Uncertainty associated with LCAs must be conveyed while still providing guidance, as uncertainty without guidance may be difficult to take action upon (Olivetti 2010).

Parameters may be levers of overall uncertainty without having high uncertainty themselves, if they are ubiquitous in the model. Geisler et al. noted that factors with large absolute contributions to impact may not have high contribution to variability if their uncertainty is small. The influence of an input parameter is therefore a combination of the impact of input values on absolute magnitude and impact on dispersion of results (Geisler et al. 2005). Indeed, Heijungs

emphasized this often neglected distinction between differing 'key' drivers, although it is of 'seminal' importance (Heijungs 1996).

Some forms of uncertainty are inherent to the system and are irreducible. Also called aleatory uncertainty, it may include parameter, scenario/choices, and model uncertainty (Huijbregts 2002). Parameter uncertainty may exist from errors in input data, functional unit definition, inventory analysis, and impact assessment. Life cycle inventory development may be process-based, economic input/output (I/O)-based, or a hybrid of the two. Process-based has heavy data requirements, requiring data for every process involved. Omissions may occur where data are not available or processes are not identified, leading to cutoff error. Economic I/O is a top-down, fully aggregated approach that may lead to 'double counting' due to sector categorizations. A hybrid of the two types is also possible (Williams 2004). Due to the continuum of methods, there is no clear way to consistently minimize uncertainty. Scenario and choice uncertainty may exist in allocation choices and definition of scales of time and geography of environmental impacts, and other normative choices in designing the model. Model uncertainty may exist if spatial and temporal differentiation is not clear or if relevant aspects of reality are not reflected within the model.

Epistemic uncertainty is reducible and may include spatial, temporal, and source/object related variability (Huijbregts 1998). Emphasis has been placed on the importance of quantifying all of these uncertainties.

Frischknecht et al. qualitatively considered the following uncertainty types in ecoinvent data: variability and stochastic error of input/output figures, appropriateness of input or output flows, model uncertainty, and neglecting important flows. The study recommended using Monte Carlo simulations to focus the effort used to understand parameter uncertainty around the most sensitive parameters so that the most important sources of uncertainty would be addressed (Frischknecht et al. 2007).

Weidema 2009 emphasized the need to address uncertainty all along the causal chain, and condemns recent misinterpretations that highly uncertain points, such as endpoints, should be ignored. He argued that it is necessary to go to the endpoint if such information is needed to make a decision, as stopping at the midpoint is simply ignoring the uncertainty at the end of the causal chain (Weidema 2009).

Although currently lacking, clear guidance to quantify and incorporate uncertainty in LCA could be developed in similar ways to how ISO standards have solidified some LCA terminology and SPOLD has solidified data exchange (Heijungs and Huijbregts 2004).

Electronics-specific uncertainty

Nearly all types of uncertainty may be important in electronics LCA (Williams et al. 2009). Of particular relevance to electronics streamlining efforts are spatial (or geographic), temporal, and source/object-related variability (Heijungs 1996; Huijbregts 2002; Huijbregts et al. 2003).

Geographic variability specific to IT may include production facility energy efficiency and electricity grid fuel mix variability associated with manufacturing and use locations. Variability in delivery distances and supply chain freight movement should also be considered (Weber et al. 2010). Electricity grid fuel mix and logistics for production and use have been assumed to be the dominant types of geographic uncertainty, given that there is little information on how production efforts vary between countries. Electricity grid fuel mix variability is on the order of 200 $kgCO_2e$ per desktop, which is on the same order of impact for the product (Hedemann and König 2003). Global distribution of supply chains and rapid evolution in the IT industry make geographic as well as temporal uncertainty relevant in environmental assessment considerations.

Temporal variability is also highly relevant to IT footprinting. However, data are few and tend to be dated, as exemplified by the Socolof 2001 monitor LCA, which is comprehensive but over ten years old (Socolof et al. 2001b). The lack of temporal data may be addressed through assumed independence of individual data: where there is no newer data, older data may be assumed to represent newer production technologies, noting that uncertainty estimates are probably underestimated.

Source/object-related uncertainty may surface due to incomplete information about an input data value, and may be high because data is scarce for electronics industry. This lack of data complicates understanding the uncertainty distributions associated with unit processes and inventories. As products evolve quickly over time, trends in BOM, parts, and manufacturing burden can significantly affect the carbon footprint.

Other uncertainty issues relate to inclusion or exclusion of capital goods given the great turnover in equipment in the industry (Olivetti 2010). The choice of impact assessment method, as well as uncertainty within methods, such as evolving characterization factors for PFCs, is particularly salient to IT (Reap et al. 2008; Olivetti 2010)[2]. In addition, allocation from facility-level energy use to product outputs, and variation in chemical use in different component manufacturing environments, present large uncertainty potential (Olivetti 2010). Other opportunities for uncertainty include boundary and scope delineation, functional unit, and goal definition.

Quantification of uncertainty

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[2] For the purposes of this thesis, we evaluate only one impact category, global warming potential (GWP 100a). This method still contains sources of uncertainty but perhaps not as great as multi-impact methods.

Efforts to quantify uncertainty are nascent. In practice, there is debate over the effectiveness of various methods to obtain and calculate required parameters and metrics (Sugiyama et al. 2005). Heijungs et al. classified methods of processing uncertainty as the following (Heijungs and Huijbregts 2004):

- parameter variation/scenario analysis (a few different models or datasets are chosen, often to investigate extreme scenarios);
- sampling methods (including Monte Carlo, which is the most common, but also including Latin hypercube sampling);
- analytical methods (explicit mathematical expressions for distributions of the model results, use of which is based on first order approximation of Taylor expansion of the underlying model); and
- non-traditional methods (such as fuzzy set theory, Bayesian methods, non-parametric statistics, neural networks).

Basset-Mens categorized methods to quantify uncertainty as stochastic analysis, scenario analysis and statistical analysis (Basset-Mens et al. 2006). Stochastic analyses require making assumptions about correlations between parameters and the probabilistic distributions around parameters, which are not often available (Basset-Mens et al. 2006). Statistical analyses may require a high mathematical level.

Stochastic analysis
For stochastic analyses, ISO 14044 guidance suggests applying either ranges or probability distributions to determine uncertainty in the results (ISO 2006c). This document also suggests specific evaluation techniques, including gravity analysis (Pareto analysis), uncertainty analysis, and sensitivity analysis. Quantification of uncertainty is recommended by BSI specifications but not outlined in detail (BSI 2008).

Monte Carlo is a sampling technique whereby a sample of model results is generated, and statistical properties of the sample such as mean and standard deviation provide an indication of the location and variance of the population parameter (Heijungs and Sun 2002). Monte Carlo provides stochastic results which are not exactly reproducible. The number of trials is not greatly affected by the number of uncertain input parameters, and is only determined by the required accuracy of the output distribution. Often only a few hundred trials will suffice (Heijungs and Sun 2002). Monte Carlo and similar approaches aim to explicitly incorporate uncertainty in LCA whereas other approaches may aim to simply reduce uncertainty in the analysis (Heijungs and Huijbregts 2004). The use of Monte Carlo simulations is recommended to focus the effort used to understand parameter uncertainty around the most sensitive parameters so that the most important sources of uncertainty may be addressed (Heijungs 1996; Maurice et al. 2000; Frischknecht et al. 2007).

Hertwich applied an uncertainty framework developed by Finkel which included four types of uncertainty and four corresponding methods for evaluation: Monte Carlo was used to assess parameter uncertainty, comparison of calculations for various geographic regions was used to assess variability in landscape parameters, comparison of values under open and closed system boundaries was used to assess decision rule uncertainty, and case studies were used to assess model uncertainty (Finkel 1990; Hertwich et al. 2000).

Perturbation theory has been proposed in relation to I/O, and is the study of the effects of perturbations of coefficients of equations on solutions to the equations (Heijungs and Sun 2002).

Estimation of probabilistic distributions
There are few established rules for fitting probability distributions to unit process data, and solutions vary. The choice of correlation coefficient does not appear to have established rules, either. One study assigned 0.5 for electricity, 0.3 for steam, and 0.1 for cooling water (Sugiyama et al. 2005).

Probability distributions ranging from normal, binomial, uniform, triangular, pert and lognormal may be found to be the best fit. The decision may be informed by expert opinion, goodness of fit statistics, or precedent (Sugiyama et al. 2005). Because the form of probability distributions is often unknown for individual parameters, Geisler chose to consistently use lognormal distributions to avoid bias in distribution choices, because it yields positive values, and its long tail is likely representative of many parameters (Geisler et al. 2005). The ecoinvent Overview and Methods document cited Hofstetter 1998 for recommending the use of lognormal distributions in lieu of normal distributions as more realistic in approximating the variability in fate and effect factors used in risk assessment and impact pathway analysis (Hofstetter 1998; Frischknecht et al. 2007). However, other analysts have chosen to bias the decision based on their judgment (Sugiyama et al. 2005).

The choice of distribution may be based on the number of data available. A uniform distribution may be used when two data points are available, a normal distribution for three or more relatively unskewed data points, and a triangular distribution where three or more data points have apparent skew. The ecoinvent database was developed based on literature by applying the Pedigree Matrix approach, a method to quantify qualitative sources of uncertainty (Sugiyama et al. 2005; Frischknecht et al. 2007). Semi-quantitative uncertainty factors (also known as the Data Quality Indicator (DQI) approach) may also be useful if only one quantitative data point is available (Weidema and Wesnæs 1996; Frischknecht et al. 2007). DQIs incorporate the following criteria and may be used to inform the strategy around data collection for LCA (Weidema and Wesnæs 1996):
  • uncertainty (spread and pattern of distribution),

- reliability (depending on the methods used for measurements, calculations, assumptions and quality control of data),
- completeness (number of data collection points and periods and their representativeness of the total population),
- age (year of the original measurement),
- geographical area for which the data is representative, and the
- process technology or technological level for which the data is representative.

Since data development methods vary from database to database, approaches for quantifying uncertainty should be carefully vetted. Heijungs raised the important point that if probability distributions are to become a standard and useful part of LCA data, it will be necessary to solidify the way uncertainty data is described. For example, in representing a uniform distribution, one must choose between specifying one of the three options: mean and width, mean and half-width, or lowest and highest value (Heijungs and Huijbregts 2004; Heijungs and Frischknecht 2005). Williams et al. cited Lloyd and Ries for showing that precision may not be possible with current LCA and footprinting methods, concluding that if more than one data point are available, all should be used to communicate uncertainty of underlying data (Lloyd and Ries 2007; Williams et al. 2009).

1.3 Literature review: Improving robustness of streamlining measures

The uncertainty issues in environmental evaluation related to data and modeling are intensified in streamlined measures. However, the literature on streamlining measures lacks discussion of how robustness may be maintained given potentially significant uncertainty; specifically, the extent to which these streamlining approaches amplify uncertainty and how to identify and address aspects of the product contributing most to that uncertainty.

Despite its potential importance, uncertainty analysis is often avoided because it may require knowledge of or making assumptions around parameter correlation and probabilistic distributions of each parameter; information which may be hard to come by (Basset-Mens et al. 2006). We see it as our research contribution to address such uncertainty issues in streamlining efforts. This thesis attempts to investigate these uncertainty issues in streamlining approaches including use of both qualitative and quantitative information, and reliance on secondary data until primary data is needed as determined by a screening assessment.

Because quantitative, primary data may not be available to represent certain activities, it may be helpful to leverage qualitative or secondary information to estimate inventory or impact data. For instance, modeling transportation activities may require data on distance traveled, mode of transport, and unit allocation of those impacts. These data need not be measured directly in order to evaluate them; they may be estimated by gathering qualitative data from the supply chain, website information, prior knowledge, literature, or database proxies. If such data prove to be key contributors of impact uncertainty, they may be targeted for specificity. This research aims to account for all potential uncertainty in data to inform the prioritization of primary data collection by leveraging secondary data.

Likewise, this research places heavy emphasis on the use of screening assessments to triage activities and materials based on this secondary data. The screening model will incorporate uncertainty estimates in the form of probabilistic density functions. The results of the screening assessment will be used to establish a hierarchy of priority areas where uncertainty needs to be addressed in order to make quantitative evaluations. Uncertainty will be addressed through targeted evaluation and data collection.

This research does not attempt to leverage the learning algorithm work, and much of the methodology, especially the literature review and screening assessment, will need to be redone for even slight product variants. However, this work is intended to be modular and re-applied to related products that may share similar life cycle phases or activities. The resulting LCD model from this research is intended to be reused for rapid evaluation of LCD classes until activities require updating due to evolving technologies and generations, geographic changes, or product design modifications. Although not the focus of this thesis work, but important to the larger

research effort, regressive algorithms will be developed for certain key activity impact drivers, relating them to easily-known product attributes and approximate impact, for facilitated evaluation of design options.

Standardization and labeling efforts would benefit from consistent methods of identifying, quantifying, evaluating and reducing uncertainty to apply to streamlining efforts. In this thesis, we propose to identify the main contributors to impact uncertainty when using streamlining measures. The methodology applies existing data and simple, conservative probability models to stochastic analysis methods such as Monte Carlo simulations. These simulations prioritize product activities based on leverage in overall uncertainty.

1.4 Larger research project

This thesis work is part of a larger research project to reduce the resource intensity of environmental evaluation by mapping characteristics (or attributes) of generic or proxy products to environmental impact. These correlative algorithms determine changes in impact based on easily-known or relevant product attributes. These product-attribute-to-environmental-impact-algorithms (PAIAs) are based on an average bill-of-materials acting as proxies for specific products. The PAIAs link a set of product attributes (e.g., type of display module, size of display, type of memory, area of printed wiring board (PWB)) to a an average bill-of-activities and finally to the resulting environmental footprint (Kirchain 2010). Such algorithms streamline the evaluation of impact and may be help to inform early design decisions. The PAIA methodology has initially focused on laptops as a product of interest and on GWP as the environmental metric.

To this end, it is the focus of this thesis research to develop a consistent, streamlined approach to identify the activities and attributes around which algorithms should be developed, based on their contribution to impact uncertainty. The proposed methodology is applied to the case study of LCDs, a relevant and interesting component of laptops for which streamlining is desired.

1.5 Central research question

Given the urgency for environmental evaluation of complex products and limits on resources, streamlined measures of evaluation are desired. However, uncertainties in data and modeling undermine the robustness of streamlining measures, as uncertainty may compete with design differences. These challenges are especially pronounced for complex products such as IT with potentially high spatial, temporal, and source/object-related variability.

Our research aims to address these uncertainty issues in streamlining efforts to improve efficiency and effectiveness of environmental evaluation. Namely, given the high levels of uncertainty that exist when streamlining measures are used, how effectively can one identify high impact activities for a life-cycle of interest?

This thesis will explore methods to identify high impact activities for a streamlined assessment with a high degree of inherent uncertainty. Furthermore, considering those high impact activities, this thesis attempts to answer a key streamlining question: how much information specificity about these activities is required to generate an assessment result with sufficient resolution (i.e., to differentiate alternatives under consideration)? The first part of this question defines how much streamlining of the analysis is possible. The latter part constrains this research approach to analyses that produce results that are useful to inform the question at hand.

In answering this question, this thesis will evaluate the impact of incremental information on the resolving power of the resulting assessment. This information will also be used to systematically comment on the limitations and possibilities associated with product comparisons informed by an evaluation method of this type.

2. METHODOLOGY

In Chapter 1 we discussed challenges associated with conventional environmental analysis tools. Evaluation measures developed in response to these challenges were then described. Figure 2 provides a visual representation of such measures, given the tension between specific and comprehensive data collection efforts to achieve a sufficient LCA result (Kirchain 2010). The approach to achieve a sufficient LCA result by pursuing specific, precise data, and then scaling data to develop a comprehensive system model may be represented by the red arrow. An alternate approach (streamlining), represented by the green arrow, involves first collecting existing data to represent a comprehensive picture of the system, accounting for necessarily high uncertainty, then screening for areas which contribute most to total uncertainty, and then specifying them in more certain detail. We feel our research contribution has been to address uncertainty issues in such streamlining measures.
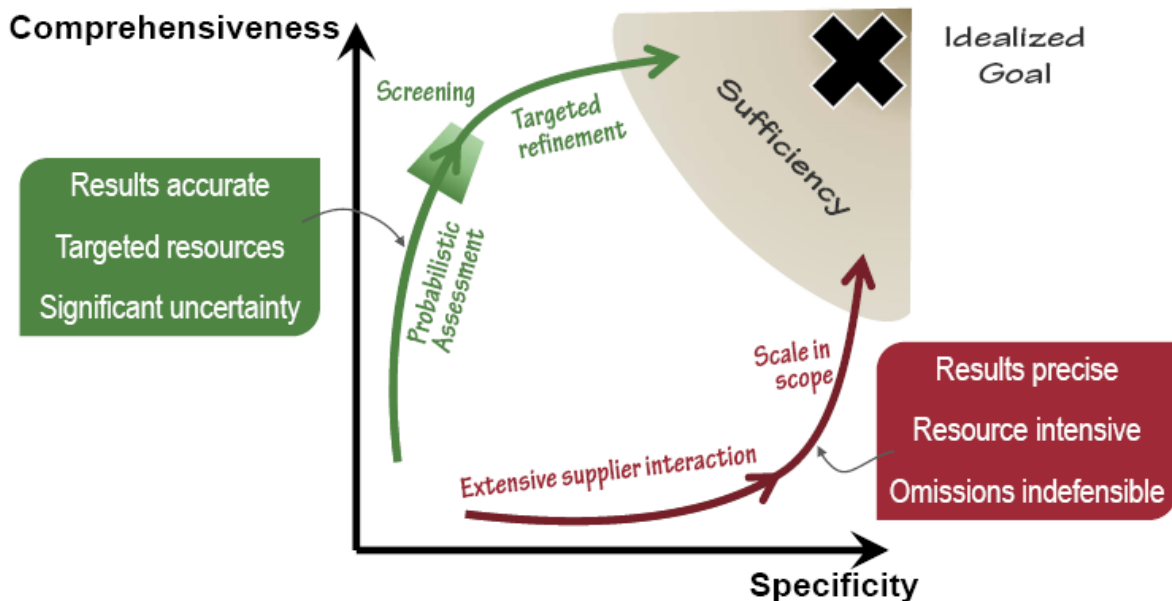
Figure 2. An approach to streamlining LCA is represented by the upper green arrow (Reproduced from Kirchain 2010)

A main goal of this research was to investigate the viability of streamlining to enable effective and efficient environmental evaluation of products, specifically those in the IT industry. Another goal was to identify key drivers of uncertainty. One way to investigate key drivers of overall uncertainty is proposed in this chapter[3]. Focusing resources on areas of uncertainty by specifying, or *resolving* them reduces overall impact uncertainty, making the impact distribution

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[3] We also evaluated potential methods of hotspot, or contribution, analysis including use of stochastic impact estimation to calculate the percent of trials for which an activity contributes a percentage of the total impact burden. This thesis document does not focus on that analysis.

more distinct. But how much uncertainty reduction, or resolution, is necessary to yield a useful result?

The extent to which activities are to be resolved depends not only on resources (time, money, analytical tools) but our tolerance for error. This error can also be described as the rate at which modeled results incorrectly identify the product with the lower environmental impact. This ***false signal rate*** is defined as the percentage of total scenarios that an environmentally-favorable product will be incorrectly labeled un-favorable based on a core assumption: the mean of the environmentally-preferred product is less than that of an alternative.

This concept can be illustrated with probability density functions for impacts associated with product classes[4] *A* and *B*, where *A* may be a 14" LCD and *B* may be a 15" LCD, and $\mu_B > \mu_A$. Based on this relationship between the means, we infer that *A* is the environmentally preferred option to *B* a majority of the time[5], though with some error rate because the two populations' impacts are not completely distinct. This false signal (FS) rate is represented by the area of overlap in Figure 3. Reducing uncertainty associated with the key drivers of environmental impact tightens the distributions and reduces the false signal rate.

Resolution analysis:
Ability to differentiate

14" screen 15" screen

Screen size attribute example

Two metrics of interest: difference in the means
and false signal rate: pair wise comparison
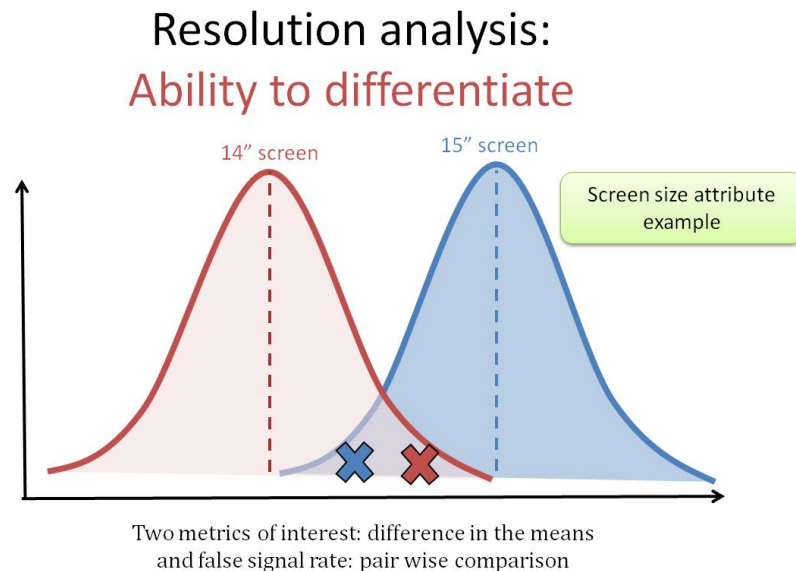
Figure 3. False signal rate represented by area of overlap of two impact probability density functions

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[4] Product *class* is the level of categorization we are interested in, as opposed to a more specific level such as SKU or less specific level such as product type (e.g., laptop).

[5] Goedkoop et al. have evaluated distribution comparisons for two products by calculating the difference distribution (*B* minus *A*). If the difference distribution is largely positive, *B* has a higher impact a majority of the time (Goedkoop et al. 2008).

A practitioner or company may tolerate a false signal rate of 10% (i.e., an accuracy rate of 90%) to produce a sufficient result and spare the resource intensity required to achieve a higher accuracy rate. It should be kept in mind that 100% accuracy is not realistic as we can neither represent each product's life cycle with complete accuracy using proxy data, nor could we count on primary data to represent a product with complete accuracy.

We apply this false signal rate metric to evaluate the number of activities to resolve. The proposed streamlining methodology is outlined below, including building a screening model with existing, low-fidelity data, performing probabilistic triage using a conservative test to develop a priority list of activities to target, then specifying those priority activities to reduce uncertainty and understand our ability to discriminate classes or scenarios. This chapter provides a generalized approach to the methodology, whereas the next chapter applies the methodology to evaluate LCD classes and discuss the nuances associated with practical application of the method.

2.1 Built an activity screening model
- Performed a literature review to create a comprehensive checklist of life cycle phases, components, and activities to represent in the screening model.
- Compiled existing data from LCAs, commercial LCA databases, published academic literature, and industry data. Three types of information were essential to create the best available estimate of environmental impact:
  - a.) life cycle processes associated with the product,
  - b.) bill of activities (BOA) with their associated quantities, and
  - c.) uncertainty associated with processes and BOA

2.2 Set goals and established priority activities using a stylized self-test
- Determined desired accuracy rate and difference threshold, given resource constraints,
- Applied a stylized "self-test" using stochastic methods (Monte Carlo simulations) to triage activities based on probabilistic contribution to overall uncertainty. This step resulted in a prioritized list of activities to target for efficient resolution of product classes.

2.3 Performed a streamlined assessment by specifying high-impact activities
- Specified priority activities until desired accuracy rate was obtained using Monte Carlo simulations. This step identified the number of streamlining elements (i.e., unresolved activities) necessary to address in order to effectively evaluate scenarios.

2.1 Built an activity screening model

2.1.1 Performed a comprehensive literature review and a created checklist of activities

The objective of this step was to develop a comprehensive model of life cycle activities by creating a checklist of things that must be accounted for in the probabilistic triage. The deliberate act of creating a checklist helped to reduce data availability- and modeler-bias. Here, low-fidelity data were acceptable as we balance resources with urgency of result. The checklist was populated with information gathered in the literature review to develop a comprehensive picture of the life cycle phases, components, subcomponents and activities that must be modeled, including transportation, materials procurement, materials processing, manufacturing, retail, use, and end-of-life (EoL). Retail and Eol were considered at the product (laptop) level in the larger research effort. Use was considered both at the LCD (component) level and the product level. Environmental hotspots highlighted in previous work were noted for thorough consideration in the model.

2.1.2 Leveraged existing bill of activity and uncertainty data

The checklist of life cycle phases, subcomponents, and hotspots identified in the previous step was populated with low-fidelity, existing data. Data included BOM, BOA, as well as cut off criteria, product characteristics to be used in the larger PAIA effort of mapping impacts to product characteristics to facilitate analysis, and life cycle inventory/unit process data. The BSI recommends including materials and activities that contribute at least one percent of total impact, up to a total which should not exceed five percent of impact (BSI 2008). At this stage, it was difficult to make this cutoff assessment/judgment, so we attempted to include all materials and activities for the screening until they could be defensibly omitted. Datasets considered include commercially available such as ecoinvent and GaBi electronics databases (PE International GmbH 2006; ecoinvent 2010), publicly available such as NREL (NREL 2008), existing OEM and academic LCAs (CMO ; Williams et al. 2002; Krishnan et al. 2008; AUO 2009; Gutowski et al. 2009), and other publicly-available data (Socolof et al. 2001b; Horowitz 2003; Kobayashi et al. 2009; IEA 2010). A range of regional electricity fuel mix proxies were used to represent electricity impacts associated with manufacturing, machining and product use. Country-level electricity grid fuel mix proxies were provided by ecoinvent and GaBi electronics databases, as well as International Energy Agency and WRI reports (PE International GmbH 2006; WRI/WBCSD 2007; IEA 2009; ecoinvent 2010; IEA 2010). Other activity estimates were developed through expert consideration by the modeler. A concerted effort was made to capture all realistic uncertainty and variability by considering extreme conditions (water, rail, truck or air transport), thoroughly mining databases, investigating manufacturing and grid market data, and using government or third-party usage studies. Any and all data points were accounted for in this initial modeling step so that uncertainty was represented as thoroughly as possible. Maurice et al.

notes that, "LCA may be used to compare different processes or products in relative terms only. The aim is to attempt to identify the best option rather than to have the best estimation of the confidence interval of the results. Therefore a rough overestimation of uncertainty should be achieved in a first step," (Maurice et al. 2000). Prior screening efforts have assigned a normal distribution to a single data point, a uniform distribution to two data points, and a triangle distribution to several points when a mean value can be inferred. Often in this research, extreme scenarios were estimated and thus uniform distributions were chosen as a model for many activities.

Before performing the probabilistic triage on the unresolved data to develop a hierarchy of activities, correlations between activities and attributes within products were considered in the model. We assigned mass and size a moderate positive correlation of 0.5 and backlight bulb number and size a weak positive correlation of 0.2. A positive correlation coefficient greater than zero and less than one may be considered for such direct relationships.

Once the screening model was populated with BOA and uncertainty information, these activities were triaged based on probabilistic contribution to overall GWP.

2.2 Set goals and established priority activities using a stylized self-test

Environmental impact may be evaluated using a number of various metrics. Hotspots may be evaluated through a contribution analysis by estimating impact with stochastic trials and calculating the proportion of trials each life cycle phase or specific activity impact meets a percentage threshold. Our approach uses stochastic methods to triage activities based on probabilistic contribution to variance. Once priority activities were identified, uncertainty for those activities was reduced until accurate scenario comparisons were possible.

2.2.1 Determined acceptable error rate and difference threshold

Jumping ahead to Section 2.3, the extent to which uncertainty was reduced in the streamlining assessment depended on the resources available to expend and the level of error tolerated. Therefore, it was critical to have chosen a specific error rate for that analysis. For the purposes of establishing the priority activity list the streamlining assessment will implement, it was important to have a sense for that desired error rate so that a sufficient number of priority attributes were included on the list, in order to meet (or exceed) the target in subsequent steps.

Another decision was the "difference threshold", or level of granularity, below which we were no longer interested in attempting to discriminate products. We assumed there is a threshold distance between the mean that falls below a level of granularity that is affordable to measure or meaningful to consumers.

Convergence on these metrics should be set in a larger conversation with project participants, consumer research representatives, and modelers, based on further information about meaningful levels of granularity of information to consumers and how such meaning can be clearly communicated on labels for consumer goods. The costs of measurement will also need to be considered in this decision.

2.2.2 Identified priority activities using stylized self-test and probabilistic triage

The purpose of this step was to identify the activities in our model with the highest leverage in overall result. These high priority activities were targeted for specification (thereby reducing the uncertainty bars around them) to reduce uncertainty of the result to the desired false signal rate.

The data and uncertainty information gathered for the unresolved population of LCDs were applied to Monte Carlo simulations (using Crystal Ball software) to produce stochastic estimates of total global warming potential impact, as well as sensitivity parameters reflecting how changes in each assumption (activity) affected overall impact. The sensitivity analysis and our judgment about the practical feasibility of collecting data for the activity informed the list of

priority activities for targeted data collection to reduce uncertainty. To most conservatively evaluate high leverage activities, false signal rate was calculated by comparing an impact distribution (for many thousands of trials) to a benchmark: the same distribution displaced by the difference threshold established earlier. This displacement distance was defined as a percentage of the magnitude of the mean, i.e., shifting the mean of A (μ_A) by 10%. This conservative test was defined as the stylized **self-test**, and this term will be used throughout the remainder of the methodology, analysis and discussion.

Magnitude and uncertainty determine which activities have high leverage in overall uncertainty (Geisler et al. 2005). The Monte Carlo simulations produced sensitivity parameters for all activities/assumptions, called contribution to variance parameters, which indicated the sensitivity of the overall impact result to changes in each activity/assumption[6]. Beginning with an unresolved product model, simulations were executed and the sensitivity analysis was produced. The activity with highest contribution to variance became the priority activity for resolution. We resolved the activity tightly, documented the activity on our priority list for later use, and then re-executed the Monte Carlo simulations to refresh the sensitivity analysis. We refreshed the analysis because results were prone to change with each resolved activity due to correlation between activities. We continued this process to make a list of priority activities that had been resolved until the false signal rate was reduced to at least the target false signal rate.

The formulation for this false signal rate (FS) is expressed in Equation (1).

$$\textit{false signal}(FS) = P(B < A) \tag{1}$$

The false signal rate can be calculated directly from Monte Carlo simulation results by comparing scenario pairs A and B where $\mu_B > \mu_A$ and calculating $P(B < A)$[7], or the false signal rate can be analytically derived (**FS*** will be used to denote the analytically derived false signal rate). For the purposes of the self-test, the analytical method will be used. There is a body of literature to calculate $P(B<A)$ analytically given that the impact distributions resemble, or can be transformed to resemble, common probability models such as normal, beta, exponential, gamma, couchy, and Weibull (Cook 2008; Cook 2009). Based on μ_A and the coefficient of variation[8] of A, (COV_A), the necessary distance between μ_A and μ_B can be derived for a target false signal rate, FS^*. Conversely, FS^* can be derived given a desired distance between μ_A and μ_B.

For example, if B is the product to which we are comparing A and we know $\mu_B > \mu_A$, the standard deviation of A is equal to that of B ($\sigma_A = \sigma_B$), and A, B, and Z are normal random variables

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[6] Spearman rank order coefficient may be used in Monte Carlo to determine overall model uncertainty sensitivity to each parameter (Evans and Olson). An alternative is the sensitivity parameter in a Taylor series expansion to determine the parameters that contribute to overall uncertainty (Quantis 2009; Hong et al. 2010).

[7] The direct, pair-wise method of calculating FS will be used to compare multiple scenarios in Section 2.3.

[8] Coefficient of variation is equal to the standard deviation divided by the mean and is a normalized metric of uncertainty.

$\left(A, B \sim N(\mu_{A,B}, \sigma_{A,B})\right)$, we can derive the distance μ_B must be from μ_A in order to discriminate the two populations with *FS**. This distance will be denoted $(k-1)\mu_A$, where

$$k = \frac{\mu_B}{\mu_A} \tag{2}$$

FS* is defined as the probability with which the standard normal random variable Z is less than zero, where Z is the difference between random variables B and A.

$$FS^* = P(Z = B - A < 0) \quad \text{(Cook 2008)} \tag{3}$$

In the subtraction of independent random variable $A \sim N(\mu_A, \sigma_A)$ from $B \sim N(k\mu_A, \sigma_A)$ the mean of A is subtracted from that of B whereas the variances are additive, resulting in the following function of Z.

$$Z \sim N\left((k-1)\mu_A, \sqrt{2}\sigma_A\right) \tag{4}$$

The normal cumulative distribution function $F(x)$ at $Z = 0$ can be formulated as the following.

$$F\left(0, (k-1)\mu_A, \sqrt{2}COV_A\mu_A\right) \tag{5}$$

Cook provides the following formulation for $P(B < A)$ which we defined as *FS** in Equation (3), where capital phi (Φ) is the cumulative distribution function of a standard normal (Cook 2008).

$$FS^* = P(B < A) = \Phi\left(\frac{\mu_A - \mu_B}{\left(\sigma_A^2 + \sigma_B^2\right)^{1/2}}\right) \quad \text{(Cook 2008)} \tag{6}$$

We can rewrite Equation (6) in terms of the error function *erf*[9], which is a scaled and translated form of Φ :

$$FS^* = F(x, \mu, \sigma) = \Phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{2}\left(1 + erf\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right) \quad \text{(Abramowitz and Stegun 1970)} \tag{7}$$

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[9] The error function can be reformatted as the following for ease of computation in Excel, $erf(X) = 2P\left(X\sqrt{2}\right) - 1$, where *P* is replaced with the *normsdist* standard normal function (whereas the function *ERF* in Excel contains a bug for some ranges of *x*) (Abramowitz and Stegun 1970; ExcelBanter 2011).

Replacing x, μ, σ with the parameters from Equation (5) results in the following formulation for *FS** based on k and *COV$_A$*.

$$FS^* = \frac{1}{2}\left(1 + erf\left(\frac{1-k}{2COV_A}\right)\right) \tag{8}$$

Using Equation (8), *FS** can be analytically derived for normally (or almost normally) distributed data if the distance between the means and *COV$_A$* are known. As mentioned earlier, the false signal rate may also be derived directly from the Monte Carlo simulation data by comparing scenario pairs *A* and *B* where $\mu_B > \mu_A$ and calculating $P(B < A)$. Although the analytical solution is less accurate than direct comparison of scenario pairs because the analytical method requires fitting the data to a probability model, it provides insights into what drives this type of result. In particular, we can see that spacing $(k-1)\mu_A$ grows linearly with COV and is directly related to *FS**.

2.3 Performed a streamlined assessment by specifying high-impact activities

2.3.1 Streamlined assessment of product classes by resolving activities until target was met

In the previous section, the stylized self-test enabled the identification of a priority list of activities. To establish how many of these key attributes were necessary to enable the discrimination of *two different product classes* or *product scenarios*, the priority activities were resolved one by one (to be sure we minimize resource expenditure), specifying each activity to nearly a point estimate, *at two different levels* (to reduce the total number of scenarios to be compared for this illustration), using the pair-wise calculation for the Monte Carlo data, until the target FS was achieved. Specificity was based on the modeler's judgment of measurement practicality. Some activities were tightly resolved; for instance, screen size was deemed possible to resolve at near point estimates, such as 14" and 15", which could be mapped to corresponding, precise, near standard areas. On the other hand, manufacturing electricity fuel mix was deemed less possible to specify, so a wider range is more realistic.

Tradeoffs may be considered between the number of activities resolved and the level at which they are resolved: if high precision is possible, fewer priority activities will need to be targeted. If precision is difficult and wider specification ranges are helpful, then more activities may need to be targeted. Results may vary depending on the levels chosen for evaluation. In the screen size example provided above, if two highly similar sizes were chosen (e.g., 14" and 15"), a conservative level of resolution would be required. If two quite different sizes are chosen (e.g., 10.1" and 17"), the level of resolution required would be less stringent given highly similar product classes. This effect is compounded by the multitude of activities resolved. For the purposes of this thesis, the conservative estimate was not stringently adhered to, but we tried to err towards it.

Before executing the Monte Carlo simulations on the unresolved data, correlations between products were considered. Some activities were not product-dependent or could not be known *a priori*. For such independently-varying attributes, we considered them to strongly correlate between products. An example was the use phase electricity fuel mix because we could not determine in advance how the use phase electricity mix would vary between products or scenarios. Therefore, this activity was modeled not to contribute uncertainty to indefensibly favor any scenario. To represent these strong correlations in the Monte Carlo simulations, we modeled each at only one level, using a mean or hypothetical value, removing uncertainty parameters, so that undue imbalance of uncertainty between products would not occur.

By specifying a couple dozen activities at two levels each, a large number of product scenario permutations were produced in the Monte Carlo simulations, resulting in a large number of

false signal rate calculations. Due to this large number of product scenarios under evaluation, the primary metric we have chosen to represent the performance of the model is the **average FS**. This is the average false signal rate of scenario comparisons for which $\mu_B > \mu_A$ and the difference threshold (between μ_B and μ_A) were met, with each permutation given equal weight in the model. Other metrics will be discussed in Chapter 4.

3. ANALYSIS: CASE STUDY FOR LIQUID CRYSTAL DISPLAYS

In this chapter we demonstrate the application of the methodology to a complex IT product for which rapid evaluation tools are highly sought: LCDs modules.

Liquid crystal displays are one type of IT product for which improved efficiency and effectiveness in environmental assessment is desired. The time required to perform an LCA for an LCD may exceed the lifespan of the product, manufacturing technology, or materials used due to high turnover and product evolution in this industry. Other electronics that are similarly challenged include desktops, servers, televisions, and cell phones.

In the first section of this case study, a BOA and associated uncertainty were compiled. Then, to identify the main contributors of overall uncertainty, a sensitivity analysis was produced using Monte Carlo simulations. The main drivers of uncertainty included not only ostensible product activities but activities associated with manufacturing processes and other "contextual" characteristics. Then, by targeting/specifying 22 of the priority activities (out of almost 50 total activities) we were able to achieve a false signal rate of 9%. This case study demonstrates that activity prioritization and streamlined assessment are possible despite high uncertainty.

Background and prior evaluation for liquid crystal displays

This LCD analysis evaluated materials and manufacturing for a specific LCD technology: twisted-nematic (TN) amorphous-silicon (a:Si) thin-film transistors (TFTs) within the active matrix (AM) LCD type. In this thesis, the generic term "LCD" will refer to this specific technology because the available literature emphasizes this most commonly manufactured and purchased type of laptop display. The TFT LCD technology makes up the majority of market share for LCDs, for which 2007 revenue was projected between $77.5 billion of $98 billion of the flat-panel display (FPD) market. The TFT LCD materials market was expected to grow at a compound annual growth rate of 13% between 2004 and 2009 (DisplaySearch 2006). The other leading light modulating technology, in-plane switching (IPS), was not explicitly excluded from the analysis though its processing steps differ from TN and has different backlight energy requirements to achieve performance similar to TN. We considered these differences to be too granular to be explicitly modeled for the purposes of this thesis; further investigation between the technologies will be evaluated in the larger research project. In addition, IPS is a design/performance attribute and is not typically a negotiable choice. Figure 4 provides a cross-sectional representation of a liquid crystal cell before subcomponents are added. Subcomponents include the backlight unit (BLU) which may use either cold cathode fluorescent lamps (CCFL) or light emitting diodes (LEDs) as light sources, as well as PWBs, ICs, casing, and wires (Lueder 2010).
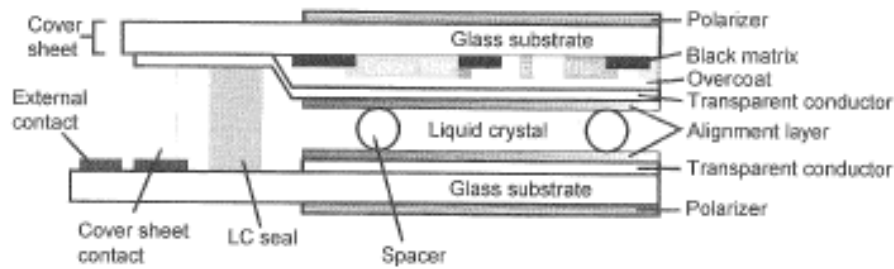
Figure 4. Cross-section of an assembled liquid crystal cell (Reproduced from Lueder 2010)

Existing LCA results from Dell and from the ecoinvent database highlight the potential significance of LCDs in the overall environmental footprint of laptops (ecoinvent 2010; O'Connell and Stutz 2010). However, the evaluation of this component presents a challenge due to the great complexity of LCDs as well as the age of existing life cycle inventory data. To illustrate the complexity of the product and challenge of comparing existing studies, some examples of bills of materials (BOMs) are listed below in Table 1 for TFT LCDs. These data are from a Chimei-Innolux (CMI) Product Category Footprint (PCF) for a 15.4" module (of 1680x1050 resolution), a European Commission energy-using products (EuP) 2007 evaluation of the industry average of best-selling 17" LCD monitors (of 1280x1024 resolution) in 2005, and Socolof and coworkers' 2001 analysis of a 15" LCD monitor (of 1024x768 resolution) (CMO ; Socolof et al. 2001b; EuP 2007). The latter reference is from which the ecoinvent LCI is derived. Here, the distinction between monitors and modules should be highlighted. Monitors are commercially-available, stand-alone products with a display screen and associated electronics encased in a single housing that is capable of displaying output information from a computer via one or more outputs. To qualify as a monitor under Energy star, the screen must be larger than 12 inches (EuP 2007). Modules, however, are integrated into a computer or laptop, and the computer and module function as a single unit which receives AC power through a single cable (EuP 2007)[10]. This report focuses on modules, as they are integrated component of laptops. However, monitors will also be discussed due to the overall similarity in the materials and manufacturing and because more data were available for monitors.

The three BOMs presented in Table 1 demonstrate the complexity of LCDs. For example, the monitors contain metals such as aluminum and stainless steel for the frame, while the module does not. The quantity and type of plastic varies widely between the three BOMs. Some BOMs may contain itemized subcomponents such as printed wiring boards (PWBs), CCFLs and LEDs while others have disaggregated those subcomponents by material. This table highlights the

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[10] The Swedish Environmental Management Council reports the following technical specifications for an LCD Product Category Rule (PCR): resolution, diagonal size, light modulating mode (e.g., TN, IPS), weight, number of colors, and back light type (SEMC 2005).

challenges of comparing existing studies and the need to develop consistent methods for the evaluation of environmental impact.

Table 1. High variability exists between LCD BOMs

Material	Unit	Comments	15.4" LCD module (CMO)	17" LCD monitor average of best-selling in 2005 (EuP 2007)	15" LCD monitor (Socolof et al. 2001b)
Inputs					
aluminum	kg			0.039	0.13
stainless steel	kg	bezel		1.854	2.53
copper	kg			0.19	
iron	kg		0.05119	1.165	
panel glass	kg	panel glass	0.22636	0.308	0.59
ITO	kg		0.000578		0.0005
fiberglass	kg		0.01476		
E-glass fiber	kg		0.12		
aramid fiber	kg		0.0065		
powder coating	kg			0.001	
plastics:	kg	TAC, polarizer			1.78
LDPE	kg	Panel protector film		0.164	
PP	kg				
PMMA	kg	light guide, diffuser	0.13311	0.153	0.45
PET	kg	polarizer, etc	0.06973		0.06
PC	kg		0.0165	0.385	0.52
rubber	kg		0.00036		
EPS	kg			0.279	
PVC	kg			0.043	
ABS	kg			0.679	
PA	kg			0.422	
styrene-butadiene copolymer	kg				0.36
PEE	kg				0.3
triphenyl phosphate	kg				0.09
big caps & coils	kg			0.041	
slots/ports	kg			0.037	
solder (SnAg4Cu0.5)	kg			0.0076	
solder (60% tin 40% Pb)	kg				0.04
polyimide alignment layer	kg				0.0005
color filter pigment	kg				0.04
thin film transistor	kg				0.01
Subcomponents brought into the LCD facility					
LCD screen m^2	kg			0.091	
PCBA & components	Kg		—		0.37
PWB 1/2 lay 3.75 kg/m^2	kg			0.03	
PWB 6 lay 4.5 kg/m^2	kg			0.02	
ICs	kg/#	logic type			

	kg			0.013	
ICs, 5% Si, Au	kg			0.013	
ICs, 1% Si	kg			0.02	
BLU	kg		—		
lamp (CCFL)	kg	only the bulb?	0.00089		0.0019
SMD & LEDs average	kg			0.011	
glass for lamps	kg			0.026	
liquid crystals	kg				0.0023
chassis	kg				
stainless steel	kg	bezel			
wire & cables	kg		0.00144		0.23

Several LCA studies for LCDs are summarized in Table 2 to demonstrate variability in scope, assumptions, and results. These studies vary with regard to life cycle phases evaluated, year the product was manufactured (not always explicitly stated), year of study, display size, and product type (module versus monitor). Not surprisingly, the results vary widely, with estimated primary energy demand and global warming potential (GWP) varying from 624 to 2,840 MJ and 38 to 593 kgCO$_2$e, respectively, for a range of life cycle phases. Such variability motivates efforts to provide structure to LCA methodology and identify the primary drivers of impact so that those drivers can be thoroughly analyzed and communicated in LCA. Furthermore, the lack of consistency across these studies diminishes the ability to compare results. For instance, although the Socolof and O'Connell studies evaluated a similar set of life cycle phases (manufacturing, assembly, logistics, use and EoL), their results are quite different. Different use phase assumptions and data may have contributed to such divergent results. O'Connell assumed a lifetime of four years whereas Socolof assumed a lifetime of at least four years for some LCDs and six and a half years for others.

Table 2. Data sources for primary energy demand and GWP impacts of LCDs

Functional unit (FU) (module/monitor)	Screen size (")	Primary energy (MJ/FU)	GWP (kg CO$_2$eq/FU)	Source	Scope
TFT-LCD **monitor**	15	2,840	593	(Socolof et al. 2001b)	all life cycle phases
TFT-LCD **monitor**	17	985	55	(EuP 2007)	production (use and EoL are also available)
TFT-LCD *module*	14.1	N/A	38	(O'Connell and Stutz 2010)	all life cycle phases
TFT-LCD *module*	15.4	624.4	29.8	(CMO)	production, assembly, and transport between

The most comprehensively documented monitor study was sponsored by the USEPA in 2001 and assessed the life cycle impacts of cathode ray tubes (CRTs) and LCDs but it is now dated

(Socolof et al. 2001b). Nevertheless, the Socolof report provides useful manufacturing and materials information which serve as the base of our research efforts. The report provides decision rules for establishing the inventory list for an LCA, and it is the data upon which we base much of our screening analysis. These reports informed the ecoinvent dataset on electronics (ecoinvent 2010).

Dell performed a product carbon footprint (PCF) for the Dell Latitude E6400 laptop using primarily data found in the GaBi electronics database (PE International GmbH 2006; O'Connell and Stutz 2010). The study identified four components that make up 95% of laptop GWP as the PWB mainboard, display, chassis, and battery. O'Connell points out that despite the display's relatively low mass, its impact is disproportionately large. The display is considered a process-intensive component because energy requirements and auxiliary materials are largely responsible for the GWP (O'Connell and Stutz 2010). Although the Dell study does not state this explicitly, it may have assumed a relatively high level of PFC abatement in LCD module production (as well as IC manufacturing, see IC section), to align more closely with current abatement goals in the industry.

Au Optronics Corporation (AUO) performed a life cycle carbon footprint for a 32-inch TFT-LCD television according to BSI PAS 2050 specifications, the first evaluation of its kind for televisions. This cradle-to-grave study revealed total emissions to be 1,255 kgCO2e, with about 40% from materials and manufacturing, 59% from use, and a small fraction from disposal, distribution and retail (Chang et al. 2010). The study applied the IPCC AR4 GWP assessment tool for GWP. Data included those available in Simapro 7.1 for materials, Taiwanese Power Company electric power data, and Taiwanese Water Corporation data. The authors highlighted the enormous resource intensity of performing this environmental footprint.

A Chimei-Optoelectronics (CMO) environmental product declaration (EPD) assessed all life cycle phases of a 15.4" CMO TN CCFL-backlight LCD module (CMO). The study reported several impact categories, including GWP, acidification, energy consumption, ozone depletion, summer smog, and eutrophication. It is likely that additional EPD studies and corporate social responsibility (CSR) reports will be produced as environmental performance becomes increasingly used as a marketing tool for manufacturers.

Other studies have focused on specific life cycle phases or components of LCDs and modules. Some have focused on end of life scenarios, such as the King County Literature Review for Flat Panel Displays, Lee's LCD Material Flow Analysis, and Lee's study of Recycling in Washington (KCSWD 2007; Lee 2008; Lee et al. 2009a). Other studies have focused on backlights, such as the technical analysis of LCD backlight options (Kobayashi et al. 2009), backlight technologies (OSRAM 2009) and lighting technologies which may be applied to LCDs (Slocum 2005).

Although CRTs are beyond the scope of this LCD-based analysis, it is worth mentioning some of the CRT assessment efforts. Kim performed an LCA of a CRT computer monitor and found that the use phase was the largest contributor to impact (Kim 2001). Site-specific data were used in the foreground system, while secondary data were used in the background system. Williams evaluated the life cycle energy intensity of CRT monitors and found that overall impact was dominated by the production phase (81%). The author recommends extending the usable lifespan of CRT monitors by reselling or upgrading to mitigate the burdens associated with manufacturing and disposal (Williams 2004).

3.1 Building the activity screening model

3.1.1 Comprehensive LCD literature review and checklist

The objective of this step was to create and populate a checklist of activities to account for in the comprehensive probabilistic triage so that modeler and data availability bias were minimized. All life cycle phases, components, and hotspot activities of interest were noted from the literature. Existing LCD LCA literature was reviewed to form a comprehensive BOA for LCDs. Results of the literature review can be found in Appendix C.

Checklist of life cycle phases
- Materials Processing
- High-tech Processing
- Transportation
- Retail (not addressed the LCD-module level but addressed at laptop product-level)
- Use (mainly addressed at laptop-product level, although for this thesis research, LCD backlight energy demand—for both LED and CCFL backlights—was modeled)
- End-of-Life (as in the case of retail, EoL was not addressed at LCD-module level but was addressed at product-level)

Checklist of components that comprise most LCDs
- LCD array: substrate plus color filter and thin film transistor
- LCD cell: LCD array plus polarizers, spacers, liquid crystals, drivers
- LCD module: LCD cell plus PWBs, IC tabs, backlight unit, power supply, cables, wires

Checklist of hotspot activities (in terms of GWP)
- PWB manufacture: high energy demand
- IC manufacture: use of PFCs, high energy demand
- LED semiconductor manufacture: use of PFCs, high energy demand
- LCD array manufacture: use of PFCs, high energy demand

3.1.2 Existing LCD bill of activity and uncertainty data

Life cycle data for LCDs are not abundant, especially for manufacturing processes. Data were collected and pieced together as best as possible to represent the life cycle. Standard screen diagonal sizes 10.1, 11.6, 12.1, 13.3, 14, 15, 16 and 17" and corresponding standard screen areas (m^2) were used. In our BOA model, many activities were assumed to correlate with screen size. Unless otherwise specified, we modeled LCD mass to correlate at 0.5 with screen size and bulb number to correlate at 0.2 with screen size. LCD mass was estimated using Chimei-Innolux data

for LCD sizes 10.1 to 17.3". Spatial, temporal and source/object-related uncertainties were estimated for each activity. Summarized below are the assumptions made for the BOA, with specific details and values provided Appendix Table 5. Unless otherwise stated, it is implicit that most activities were modeled to correlate to screen size or mass.

Materials processing

To model materials processing activities and impacts, we evaluated material proportion, material and machining emission factors, mass, and backlight bulb variability.

- Material classes were modeled to include varying proportions of minerals (specifically glass), metals and polymers. Within and between classes, we assumed a high degree of variation in materials, including steel versus aluminum, and poly-lactic acid versus petroleum-based plastic.
- Material mass (kg) was modeled to vary widely and was estimated based on BOMs from OEM surveys. It was assumed that minerals could comprise 10-30% of mass, polymers could comprise 20-50% of mass, and metals could comprise the remaining mass.
- Material production emissions factors ($kgCO_2e/kg$) from the ecoinvent database were used to represent the broad categories of materials described above, including minerals, metals and polymers (ecoinvent 2010).
- Material machining energy demand variability (kWh/kg) was estimated from a range of values including injection molding, machining, and finish machining (Gutowski et al. 2009).
- Material machining energy demand emissions factors ($kgCO_2e/kg$) were modeled based on extreme electricity fuel mixes, specifically a minimum of 0.28 $kgCO_2e/kWh$ for California and a maximum of 1.58 $kgCO_2e/kWh$ for India (PE International GmbH 2006; ecoinvent 2010).
- Backlight bulb number was estimated for edge light design rather than direct light design because the edge design is much more common for laptop applications. Bulb number was modeled to correlate with screen size at 0.2 unless otherwise specified. Between one and four CCFLs are typically used (Socolof et al. 2001b) whereas an LED backlight may have 20 diodes for a screen greater than 7" (Chien 2008) and common screen sizes typically have between 15 and 30 diodes (Myers 2011).
- Backlight bulb manufacturing energy demand (kWh/bulb) associated with manufacturing CCFLs and LED bulbs was approximated using values for compact fluorescent lamp (CFL) lighting and LED-SSL lighting (Slocum 2005). LED semiconductor chips were evaluated separately under High-tech processing (below).

High-tech processing and manufacturing

To model activities and impacts associated with high-tech processing and manufacturing, variability within LCD array, backlight semiconductor, IC and PWB primary and secondary

materials and energy were considered, including PFC type, PFC abatement levels, and PFC degradation rates.

- LCD array manufacturing GHGs were modeled to reflect variability in gas type, characterization factor, mass, abatement levels, and degradation rates.
  - NF_3 and SF_6 were modeled to represent array manufacturing PFCs as they are among the most potent greenhouse gases used for array production (IPCC 2007; Krishnan et al. 2008).
  - Characterization factors ($kgCO_2e$/kg PFC) for processes dominated by SF_6 were modeled at 22,800 and those dominated by NF_3 were modeled at 17,200.
  - PFC mass ($kgPFCs/m^2$ array) was modeled to vary based on the number of color filter and thin film transistor layers used. A minimum value was estimated using Intergovernmental Panel on Climate Change (IPCC) figures for LCD manufacturing (IPCC 2006). A maximum was estimated based on a silicon wafer process BOM for various numbers of processing steps, including deposition, lithography and etching (Krishnan et al. 2008), as well as estimates provided by the MSL supplier survey (MSL 2010b).
  - PFC emissions abatement levels vary by fabrication facility, generation line, and by time. Therefore, a range of extreme abatement levels were modeled between 1 and 100%.
  - PFC degradation rates were estimated at 1 to 2% for SF_6 and 10 to 15% for NF_3.
- LCD array manufacture energy demand was modeled to reflect variability in high-tech processing energy demand, mass of trace materials used, and electricity fuel mix.
  - High-tech process energy demand (kWh/kg trace material) was modeled based on analyses by Gutowski et al., including deposition, lithography, and etching (Gutowski et al. 2009). A minimum estimate from OEM survey responses was also used (MSL 2010b).
  - Masses of trace materials were modeled to vary with processing steps and screen size, using ancillary BOMs from the Socolof report (Socolof et al. 2001b).
  - Array and cell manufacturing electricity fuel mix emissions factors ($kgCO_2e$/kWh) were estimated based on proxy fuel mixes for Korea (manufacturing location of LG and Samsung) and Taiwan (manufacturing location of AUO and CMI), modeled in equal proportions, though a market share weighting would improve accuracy (PE International GmbH 2006; ecoinvent 2010).
- Module fuel demand was modeled based on estimated fuel energy quantity and fuel mix emissions factors.
  - Module fuel energy amount (kWh/kg LCD) was modeled using a range of values to represent variability in LCD size, module facility, and fuel type based on fuel quantity approximations (Socolof et al. 2001b).

- o Module electricity fuel mix emissions factors ($kgCO_2e/kWh$) were modeled using regional proxies representing impact extremes (California and India).
- LEDs are mounted on semiconductor chips and so LED BLUs were modeled accordingly. Variability in semiconductor area, PFC quantity, abatement, characterization factors and degradation rate were considered.
    - o Area (mm^2) was estimated using data for LED-SSL semiconductor chips, on the order of 0.5 to 2.5 mm^2 (Slocum 2005).
    - o PFC quantity used per unit area ($kgPFCs/mm^2$) was approximated using inputs of PFCs required for 32MB DRAM IC semiconductor manufacturing (Williams et al. 2002).
    - o PFC abatement level (%) was assumed to vary between 1 and 100%.
    - o PFC characterization factors ($kgCO_2e/kg$ PFC) for SF_6 and NF_3 were used, as estimated for array manufacturing (IPCC 2007).
    - o PFC degradation rate was estimated at 2 to 3% for SF_6 and 12 to 20% for NF_3.
- IC manufacturing GWP was modeled based on varying die area and PFC emissions factors. No distinction between logic and memory was made as data was unavailable to differentiate impacts.
    - o Die area (m^2) was estimated to vary in number and area based on disassembly observations of IC package size and number. A die-to-package ratio of 0.2 was used.
    - o PFC emissions factors ($kgCO_2e/m^2$ die) were modeled based on emissions as reported by IC manufacturers to a 2008 industry survey (SIA 2008).
- IC manufacturing energy demand was modeled based on varying wafer production area and electricity demand per wafer area. No distinction between logic and memory was made as data was unavailable to differentiate impacts.
    - o Die area (m^2) was estimated based on disassembly observations of variability in number and package area of ICs. A die-to-package ratio of 0.2 was used.
    - o Electricity demand (kWh/m^2) was modeled based on energy demand as reported by IC manufacturers to a 2008 industry survey (SIA 2008).
- PWB GWP and energy demand were modeled based on varying PWB area and emissions factors.
    - o Area (m^2) was estimated to vary between 20 and 100% of screen area.
    - o PWB emissions factors ($kgCO_2e/m^2$) were modeled using extremes for varieties of PWBs in ecoinvent and GaBi electronics databases (PE International GmbH 2006; ecoinvent 2010).

Transportation

To model transportation, we considered variability of mode, distance, number of legs, and emissions factors.

- Transport distances and number of legs (km)

- o Realistic minimum and maximum distances for each of the potential transport legs were calculated, to include (a) raw material extraction to manufacturing, (b) from manufacturing to assembly, (c) from assembly to retail, (d) from retail to consumer, and (e) from consumer to end of life.
- Transported mass (t)
    - o It was estimated that the mass transported along any of the potential legs may range from a minimum of the mass of the LCD itself to a maximum of four times the mass of the LCD.
- Transport mode and resulting emissions factors ($kgCO_2e$/tkm)
    - o It was estimated that modes of transport carbon emissions could range from a per-unit mass basis ocean tanker, air freight, or van. The corresponding emissions factors for these modes were derived from ecoinvent (ecoinvent 2010).

Use

Variability of LCD-component energy demand, electricity fuel mix, duty cycle and product lifetime were considered. Use was also evaluated at the LCD-product level (laptop) in the larger research project at the MIT Materials Systems Laboratory.

- Energy demand (kW) was estimated using CMI LCD LED backlight specifications as a minimum. This value was multiplied by a factor of 3.334 as described by Slocum to estimate the equivalent CFL luminance, then multiplied by two to approximate an upper extreme (Slocum 2005; CMI 2011).
- Lifetime (yr) was estimated using extreme but realistic scenarios based on literature values (Socolof et al. 2001b; O'Connell and Stutz 2010).
- Duty Cycle (hrs/yr) was estimated using extreme scenarios of few hours of use to maximum hours of use.
- Grid Emissions Factors ($kgCO_2e$/kWh) were assumed to vary based on geographic location of LCD use, so extreme regional proxies were used (PE International GmbH 2006; ecoinvent 2010).

Retail

- Retail impacts were not addressed at the component (LCD) level, but were addressed at the product (laptop) level in the larger research project at the MIT Materials Systems Laboratory.

End of Life

- As in the case of the Retail phase, EoL impacts were not addressed at the component (LCD) level, but were addressed at the product (laptop) level in the larger research project at the MIT Materials Systems Laboratory.

3.2 Setting goals and establishing priority activities for efficiency

3.2.1 Convergence upon acceptable error rate and difference threshold

A tentative target average *FS** of 10% was set by the research group. A tentative difference threshold was set at 10% of the mean impact of the product class under evaluation (μ_A).

3.2.2 Identification of priority activities using probabilistic triage

The literature review and data scavenge of existing LCD data informed the low-fidelity quantitative estimates of activities, as described in Section 3.1.2 and further summarized in Appendix Table 5. With this comprehensive list of nearly 50 activities, we performed probabilistic triage using Monte Carlo simulations based on a stylized self-test to identify activities with the greatest leverage in reducing uncertainty of overall impact.

Crystal Ball software was used to facilitate the stochastic analysis. The sensitivity analysis produced by the software, as well as our judgment about the practical feasibility of collecting data for the activity, informed the list of priority activities for targeted data collection. In order to most conservatively evaluate high-leverage activities, an analytical, stylized self-test was used to calculate the *FS** and evaluate uncertainty reduction. For this LCD case study, the impact density functions were fairly normal and therefore the analytical *FS** formula presented in the Methodology was applied. Although perfect normality was not achieved for each set of trials after resolving an activity, we believe it would have been quite resource-intensive to attempt to represent each function with a best fit probability model. We believe the assumption of normality was reasonable for the purpose of this exercise.

The initial self-test for the unresolved product class unsurprisingly yielded a high *FS**, insufficient based on the target of 10%. The contribution to variance parameters for this set revealed the *use phase duty cycle* to be the activity with highest leverage in the overall result, with a contribution to variance of nearly 22%, as shown in Figure 5 (complete sensitivity results can be found in Appendix Figure 7). The number is less important than identifying the activity with the highest contribution to variance, targeting it, and then removing it from further contention so the next priority activity can be identified and a list can be formed.

Assumptions	Contribution To Variance
Use Duty Cycle (hrs/yr)	0.219
Use Grid Emissions Factor (kgCO2e/kWh)	0.159
Use Lifetime (yrs)	0.135
Screen size (m2)	0.088
Cell Grid Emissions Factor (kgCO2e/kWh)	0.045
Array PFC mass (kg PFCs/m2 semiconductor)	0.039
Deposition/sputtering electricity (kWh/kg)	0.037
PWB area (m2)	0.033
LCD mass (kg)	0.033
...	

Figure 5. Contribution to variance parameters for an unresolved product class revealed duty cycle to have highest leverage in overall uncertainty. Duty cycle was therefore specified before the next set of simulations

Although the list of sensitivity results shows other high-leverage activities that could be added to the priority list, these results are prone to change after each resolved activity due to correlation between activities. We therefore refreshed the sensitivity analysis by re-executing the Monte Carlo simulations after specifying duty cycle at 4,380 hours per year from its initial range of 1,000 to 8,760 hours per year. As shown in the second set of sensitivity results in Figure 6, duty cycle is no longer listed and the following four activities from the first set remained high on the list, but deposition electricity overtook array PFC mass for the fifth spot (additional sensitivity results are provided in Appendix Figure 8).

Assumptions	Contribution To Variance
Use Grid Emissions Factor (kgCO2e/kWh)	0.214
Use Lifetime (yrs)	0.185
Screen size (m2)	0.095
Cell Grid Emissions Factor (kgCO2e/kWh)	0.054
Deposition/sputtering electricity (kWh/kg)	0.053
Array PFC mass (kg PFCs/m2 semiconductor)	0.050
Array PFC non-abatement (%)	0.040
LCD mass (CMI) (kg)	0.037
PWB area (m2)	0.032
...	

Figure 6. Contribution to variance parameters for the second round of simulations after duty cycle had been resolved revealed use phase electricity fuel mix as the next priority activity

Based on the sensitivity results of the second round of simulations (shown in Figure 6), the use-phase electricity grid fuel mix emissions factor was added to our list of priority activities after duty cycle. Then, to remove it from further contention, we resolved it from its initial highly uncertain range of 0.28 to 1.58 $kgCO_2e/kWh$ to a point estimate of 0.78 $kgCO_2e/kWh$. This process of resolving priority activities was carried out until the *FS** had been highly reduced, beyond the target.

We created a priority activity list of 20 activities, reducing *FS** from 44.2% to 1.3%. These activities are listed below and complete details are provided in Appendix Table 6.

1. Duty cycle (hrs/year)
2. Use grid electricity fuel mix ($kgCO_2e/kWh$)
3. Lifetime (yrs)
4. Screen size (m^2)
5. LCD cell manufacture fuel mix ($kgCO_2e/kWh$)
6. Use phase energy demand (depends on bulb type, CCFL or LED) (type)
7. LED semiconductor manufacture PFC abatement level
8. LCD array manufacture PFC mass (depends on PFC type used: NF_3 or SF_6) (kg)
9. LCD array manufacture PFC emissions abatement level (%)
10. LCD array manufacture deposition electricity (kWh/kg)
11. LCD array manufacture PFC mass (kg)
12. LCD array manufacture deposition materials mass (kg)
13. LCD mass (kg)
14. Number of bulbs (#)
15. LCD array manufacture etching materials mass (kg)
16. Area of LED semiconductor (mm^2)
17. Use phase energy demand (kW)
18. LCD module manufacture fuel mix ($kgCO_2e/kWh$)
19. PWB emissions factor ($kgCO_2e/m^2$)
20. Materials machining energy (kWh/kg)

The priority activity list above was based on choice of LED at Step 6, Bulb type. To test the sensitivity of self-test results to variability of activity choice, we reproduced the list, choosing CCFL bulbs instead at Step 6. These two choices resulted in highly similar self-test priority lists, though *FS** is reduced more efficiently for CCFLs, with only 17 levels of resolution for a *FS** of 0.0%. More details are provided in Appendix Table 7.

1. Duty cycle (hrs/year)
2. Use grid electricity fuel mix ($kgCO_2e/kWh$)
3. Lifetime (yrs)

4. Screen size (m^2)
5. LCD cell manufacture fuel mix ($kgCO_2e/kWh$)
6. Use phase energy demand (depends on bulb type, CCFL or LED) (type)
7. LCD array manufacture PFC mass (depends on PFC type used: NF_3 or SF_6) (kg)
8. LCD array manufacture PFC mass (kg)
9. LCD array manufacture deposition electricity (kWh/kg)
10. Use phase energy demand (kW)
11. LCD array manufacture deposition materials mass (kg)
12. LCD mass (kg)
13. LCD array manufacture etching materials mass (kg)
14. LCD array manufacture PFC emissions abatement level (%)
15. LCD module manufacture fuel mix ($kgCO_2e/kWh$)
16. PWB emissions factor ($kgCO_2e/m^2$)
17. Materials machining energy (kWh/kg)

The similarities between the two lists is reassuring because if we were to have produced only one list for one bulb type, the results would still be highly relevant to resolve a class with the other bulb type. The main differences are that the LED priority list requires resolution of LED PFC emissions abatement, LED semiconductor area, and number of bulbs, whereas the CCFL priority list does not. Furthermore, the order of activities is not exact, but quite close. Future work could be done to evaluate whether this low sensitivity holds true for other activities such as bulb number, screen size, or materials mass. Because this self-test exercise is meant to be a relatively rapid and efficient method of producing a priority activity list, a rough analysis using mean values as resolution levels may suffice. In this case in which we found the choice of LED to produce a more rigorous list, we chose it over the less-comprehensive CCFL list. For both scenarios, this exercise revealed the main drivers of impact to reside within the manufacturing and use phases.

In this self-test exercise we conservatively bounded the maximum number of activities needed to discriminate classes under practically any scenario. However, these priority activities were resolved with a high level of precision that may not be practical in terms of measurement and reporting. In the following section, we will resolve these activities one-by-one at feasible levels until effective scenario comparisons can be made.

In light of the larger PAIA research pursuit to develop easy-to-use algorithms to test design parameter impacts, an interesting question is whether ostensible product attributes alone could provide enough opportunity to reduce uncertainty. Or are manufacturing and use phase activities, as identified by the self-test, necessary? Manufacturing and use phase activities tend to depend on the context of location of production and use, generation of equipment, and choices made by particular fabrication facilities, making them difficult to obtain data for, since infrastructure for

measurement and reporting are nascent at best. It may therefore be challenging and expensive to rely on such attributes for an analysis. If we are to consider only ostensible product attributes, leaving out these "contextual" attributes, and attempt to reproduce this analysis to identify levers for targeted data collection, we will find that we are limited to the following attributes/activities: screen size, bulb type, bulb number, LCD mass, LED semiconductor area, and materials proportions. By reproducing this priority activity exercise using only these ostensible attributes, we were able to obtain a minimum $FS*$ of 41%, far exceeding our target of 10%. Therefore, accurate discrimination of product classes will depend on access to contextual, manufacturing and use phase activity data relating to fabrication facility policies, and perhaps equipment generation and technology, as product attributes alone do not suffice. A summary of the results is provided in Table 3 and further details are provided in Appendix Table 8.

Table 3. Ostensible product attributes alone are insufficient to attain a low false signal rate

Run No.	Activity/ attribute to resolve	Unresolved values	Resolved values	Unit
1	Unresolved	N/A	N/A	N/A
2	Screen size	0.045024 – 0.1271	0.07976	m^2
3	Bulb	CCFL or LED	LED	Type
4	Bulb no.	LEDs: 15-30	20	#
5	LCD mass	0.16-0.66	0.25	kg
6	LED semiconductor area	0.5-2.5	0.5-0.6	mm^2
7	Material proportions	Minerals: 10 to 30% of LCD mass; polymers: 20 to 50% of LCD mass; metals: 20 to 70% of LCD mass	Minerals = 20%, polymers = 30%, metals = 50%	%

3.3 Streamlining assessment through targeted specificity

In the previous section, the stylized self-test enabled the identification of a priority list of activities for LCDs. To establish how many of these key attributes were necessary to enable the discrimination of *two different classes or scenarios*, the priority activities were resolved one by one (to be sure we minimize resource expenditure), specified at nearly a point estimate *at two different levels*, until the target average false signal rate was achieved. For example, screen size was highly resolved at two levels, 14 and 15".

First, we considered which activities might correlate between products and therefore should not be included in the average FS calculation. To represent such independently varying attributes in the Monte Carlo simulations, we modeled each at a single level of resolution, typically using a mean value, to minimize its uncertainty contribution. Examples of such activities include duty cycle, for which we had originally assumed a full range of possibilities (1,000 to 8,760 hours per year, uniformly distributed) then specified at a single-level point estimate (4,380 hours per year). Use phase grid fuel mix was also presumed to strongly correlate between products and so a specific value of 0.78 kgCO$_2$e/kWh for the United States grid was chosen. Lifespan had been originally modeled uniformly between one and six years then was resolved to three years. Perfluoro-compound (PFC) type should be modeled consistently between products although it was modeled to vary 50/50 and characterization factors for those PFCs should likewise be correlated. Degradation rate could also correlate, though it was not modeled to. As was considered for the self-test, we assumed certain attributes and activities to have strong correlations within a product scenario. For example, if not otherwise specified, we modeled LCD mass to positively correlate with screen size with a correlation coefficient of 0.5. In addition, if left unspecified, bulb number correlates positively with screen size with a correlation coefficient of 0.2.

3.3.1 Resolving attributes until target is met

After resolving each of the correlated attributes (duty cycle, use grid mix, lifetime) at a very narrow level (as described earlier), we began by executing Monte Carlo simulations on the otherwise unresolved LCD model. These highly unresolved scenarios produced a high average FS, so we continued to resolve attributes. Next on the priority list was screen size, which we then resolved at 14" and 15". These two levels divided the unresolved distribution into two distributions (for μ_{14} and μ_{15}) permitting the possibility of evaluating scenarios (μ_{14}-μ_{14}), (μ_{15}-μ_{15}), (μ_{14}-μ_{15}) and (μ_{15}-μ_{14}). None of these four comparisons were valid for the average FS calculation because the difference threshold was not met. We then proceeded to resolve the cell manufacturing fuel mix at two precise levels (0.50 to 055 kgCO$_2$e/kWh for Korea (*K*) and 1.04 to 1.09 kgCO$_2$e/kWh for Taiwan (*T*)), resulting in four scenario distributions ($\mu_{14,K}$, $\mu_{14,T}$, $\mu_{15,K}$ and $\mu_{15,T}$) and sixteen scenario comparisons with an average FS of 26%. We continued to resolve

attributes and test FS until an acceptable rate was met. A large number of scenario permutations were created as a result of specifying two levels for each of 19 activities, and this is one main reason we limited our analysis to two levels apiece. As mentioned earlier, resolving to a point estimate (or near point estimate) was not considered practical for some activities but reasonable for others. Activities deemed reasonable to resolve tightly include screen size (because once the screen diagonal is specified, there is little variation in area), bulb type (a precise bulb type of LED or CCFL should be possible), bulb number (a precise bulb number between 1-4 for LEDs and 15-30 for CCFLs should be possible), and LCD mass (should be fairly precisely measurable). Other activities deemed to benefit from more flexible ranges include deposition electricity and mass, fuel mixes, energy demand of bulbs, and PFC abatement levels. Table 4 displays a summary of the attributes resolved and respective levels of specificity. These specifications permit a **low average FS of 9%**. The complete analysis details are presented in Appendix Table 9.

Table 4. Discrimination of LCDs is possible at 9% false signal rate when two different scenarios are highly specific

Run No.	Activity/ attribute to resolve	Resolution range
1	Duty cycle	One thousandth hrs/yr
2	Use grid fuel mix	One thousandth $kgCO_2e/kWh$
3	Lifetime	One thousandth yr
4	Screen size	One ten-thousandth m^2
5	Cell manufacturing grid fuel mix	Five hundredths $kgCO_2e/kWh$
6	Bulb type[11]	type
7	Bulb no.	One bulb
8	Bulb manufacturing energy	One kWh/bulb
9	LED PFC mass	Unresolved $kgPFC/mm^2$
10	LED PFC un-degraded	Ten %
11	Bulb electricity demand	One hundredth kW (ten watts)
12	LED semi-conductor area	Five tenths mm^2
13	LED PFC un-abated	Ten %
14	Array PFC un-abated	Ten %
15	Array PFC type	
16	Array PFC char. Factor	Ten CO_2 equivalents
17	Array PFC un-degraded	Ten %
18	Array PFC mass	Five hundredths $kg PFC/m^2$
19	Deposition electricity	One hundred kWh/kg
20	Deposition mass	One tenth kg/m^2
21	LCD mass	Five thousandths kg
22	Module manufacturing grid fuel mix	Five hundredths kWh/kg LCD

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[11] Bulb type was modeled to resolve variables 7-13 to the following extent:

Specification of <u>LED</u> resolves to the following: 1-4 bulbs, bulb manufacture energy 1.26-1.54 kWh/bulb, LED PFC mass 0.014-0.026 $kgPFC/mm^2$, LED PFC degradation 1-20%, bulb energy demand 0.022-0.028 kW, LED semiconductor area 0.5-2.5mm^2, LED PFC abatement 0-99%.

Specification of <u>CCFL</u> resolves to the following: 15-30 bulbs, bulb manufacture energy 10.35-12.65 kWh/bulb, bulb energy demand 0.07335-0.09335 kW, zero LED PFC mass, LED PFC degradation, LED semiconductor area, and LED PFC abatement.

These ranges should be fairly reasonable and practical to implement, such as specifying electricity fuel mixes for cell manufacturing, module manufacturing, and use within five hundredths $kgCO_2e/kWh$; bulb manufacturing energy demand within one kilowatt-hour per bulb; LED semiconductor PFC mass to go unspecified; PFC emissions abatement rates for array manufacturing and LED semiconductor manufacturing within a range of 10% (e.g., between 80 and 90%); PFC emissions degradation rates within 10%; bulb electricity demand within ten watts; PFC characterization factors within ten carbon-dioxide equivalents; array manufacturing PFC mass within five hundredths kg PFC/m^2; array manufacturing deposition materials electricity demand within one hundred kWh/kg; deposition materials mass within one tenth kg/m^2; and LCD mass within five grams.

There may be countless permutations depending on the number of activities on the priority list, the practical feasibility of collecting data for attributes, and the resolution at which data can be specified. The example above is intended to illustrate our approach. The practical feasibility of the resolution levels will be further discussed in Chapter 4, along with other observations regarding the need for contextual information in robust streamlining assessments, the balance between number of activities specified and level of specification, and the quality of our methodological assumptions. Also discussed will be areas of future work, including addressing the methodology's propagation of data gaps, consideration of various ways to define and address uncertainty, and how metrics used in this methodology could be solidified or improved.

4. DISCUSSION

This thesis presented a methodology to streamline environmental assessment by consistently identifying the high-impact activities within the lifecycle of interest. The methodology was applied to a case study of LCDs to produce an abbreviated list of priority activities which were then specified. The twenty-two priority activities included both ostensible product attributes as well as "contextual" attributes associated with manufacturing processes and use. Specifying these priority activities enabled the differentiation of LCD classes whose average impact differed by at least 10% with an average false signal rate below 10%. Interestingly, high-tech manufacturing and use activities were heavily represented among the priority subset whereas transportation- and materials processing-related activities did not require specification.

Although the nature of case-based research precludes complete generalization, these results show promise for the use of streamlined assessments to identify key contributors to environmental performance and to differentiate the performance of product classes. Specifically, the case analysis demonstrated the feasibility of generating sufficient quantitative environmental evaluation based on limited information. Furthermore, this method provides a consistent approach to justify and target data collection efforts.

Nevertheless, this method is still under development. The method specifics and case analysis presented here serve as jumping-off points for improvements. This chapter presents some observations and thoughts on strengths, as well as areas for future work. Among the observations and strengths are the merits of simplification measures given resource constraints, the need for contextual information, ability to make tradeoffs between activities and resolution levels, and fitness of assumptions. Areas for future work include the propagation of data gaps, defining and identifying uncertainty, and improvement of metrics including the average false signal calculation to reflect demographic realities.

4.1 Observations

Merits of simplification to reduce and focus effort
The LCD case study demonstrated that triage is possible (and therefore much lower data collection burden is possible) despite high uncertainty. Simplification measures may be leveraged to reduce and focus effort. Our analysis identified a clear hierarchy of important impact drivers for LCDs. Out of around 50 activities, 22 key activities that account for most variation of impact were prioritized. Resolution of these strongest drivers of variability provided significant improvement in the fidelity of an estimate of LCD impact and allowed us to discriminate with reasonable confidence—only 9 percent false signal rate. In the end, this study represents just a piece in a larger effort to reduce the cost of impact assessment and to, therefore, allow it to be used throughout the IT industry.

Although for the purposes of the screening assessment it is important to use a broad set of data that reflect the current state of industry, it may be possible beyond the screening set to limit the collection of primary data. Once priority activities have been identified, data collection efforts can be more focused and less resource intensive. For instance, in the LCD case study, the hierarchy of activities revealed all transportation activities to be low in importance. The screening estimates, which embedded minimum and maximum potential distances, extreme emissions factors resulting from extreme potential modes of transportation, and extreme mass estimates of transport, indicated that it was unnecessary to collect primary data for. (Of course, this is a probabilistic conclusion based on some specified risk tolerance of the analyst. As risk tolerance drops, the number of activities which must be considered will increase.)

Necessity of contextual information

Our preliminary assessment for the LCD case study revealed ostensible product attributes alone were insufficient to achieve a low false signal rate. Included among the these attributes were screen size, bulb type, bulb number, LCD mass, LED semiconductor area, and materials proportions. The lowest false signal rate attainable when this activity subset was specified was 41%. This result implies the need for additional "contextual" information, including high-tech manufacturing and use phase activity data. These results are summarized in Table 3 and further details are provided in Appendix Table 8.

Technology generation may be another helpful piece of contextual information. It may be possible to derive information about product attributes and activities based on technology generation of products and manufacturing equipment. At this time, generation information is not a silver bullet for environmental evaluation. Within a plant there may be multiple generation lines, and some products may be produced on multiple generation lines. If generation number is known by the OEM, each generation has a range of performance in terms of energy demand and yield. Unless specific contracts are written, an OEM rarely is able to receive a single generation type, instead receiving a varying percent breakdown of multiple generations. These complications challenge data collection efforts because impact calculations often are based on allocating facility-level measurements to yield and generation performance.

If generation information were straight-forward, it would allow us to infer electricity use, which is probably appreciable. We may also be able to infer something about PFC abatement because although abatement technologies are not generation-specific, we could derive information from the manufacturer and location of production.

For this thesis effort, contextual activities were based on industry averages, and generation inferences were not made. For future work, we recommend that the role of technology generation

be explicitly explored. Infrastructure must be laid to assure more robust and consistent collection based on technology generation.

Tradeoff between number of resolved activities and level of resolution

In light of the results of the ostensible activity analysis, our streamlined assessment included contextual information, as summarized in Table 4. Each activity was resolved as precisely as was considered currently or eminently possible given our understanding of data collection and measurement capabilities and infrastructure. To further inform such decisions, it would be interesting to have access to specification cost (fixed and variable expenses associated with infrastructure, manpower, energy, time) for each activity. With this information, tradeoffs could be made between the level of specificity and number of priority activities to specify. For example, a high-cost priority activity could be specified less stringently at the lesser expense of adding another activity to the priority list for resolution. A marginal cost threshold could be determined above which an activity is no longer attractive or cost-effective to resolve. With or without access to such cost information, such tradeoffs may be made between number of activities to resolve and level of resolution.

Among the attributes and activities in the LCD case study streamlined assessment, those presumed to have high specification costs include the fuel grid mixes for the cell, module and use. These mixes were specified to moderately wide ranges of five hundredths $kgCO_2e/kWh$ with the belief that this level of information granularity could be obtained, perhaps with high fixed infrastructure costs to locate and monitor facilities and use, but eventually low marginal cost. Other high-cost activities may include the bulb manufacturing energy demand and other activities associated with LCD sub-components upstream from OEMs in the supply chain, over which OEMs may have minimal control. Activities relating to PFC type and quantity may currently be expensive to measure and report, but may become more affordable over time as the industry adapts to greenhouse gas regulations targeted at semiconductor manufacturing. PFC emissions abatement and degradation rates for array and LED semiconductor manufacturing were specified at a moderately wide 10% range (e.g., between 80 and 90%). Based on LCD fabrication facility site visits by members of MSL, emissions abatement levels are currently specified as high, medium or non-existent and tight estimate ranges are probably not likely. Degradation rates may be calculated analytically and not directly measured, so a fairly tight range such as 10% may be a reasonable goal.

Activities deemed possible to specify precisely include LCD mass, for which there are both standard diagonal and area metrics. Bulb number and type were presumed to be straight forward to report and count before assembly.

Reasonableness of methodological assumptions

The analytically-derived false signal rate metric used in the self-test requires fitting stochastically-derived impact estimates to a common probability model. For the LCD case study, a normal model was applied because fairly normally distributed data were observed for the unresolved scenario and the first few levels of resolution, although the remainder of iterations were not assessed for normality.

4.2 Areas for future work

Potential propagation of data gaps and subjectivity

Because this methodology relies on existing data to inform targeted data collection, the quality and completeness of the analysis are reflected in the quality and completeness of those existing data. For our LCD case study, there was a dearth of manufacturing data, including specific process and materials information, as well as associated impacts. For this reason, proxy data for similar electronics processing were used and pieced together as comprehensively as possible. However, there are likely to have been gaps and it is difficult to know what they are. Such gaps may exist in any screening assessment which relies on existing research efforts.

Activities were therefore approximated as conservatively as possible. Efforts were made in the screening assessment to err towards conservative approximations for processes lacking data. An example of this is the cell manufacturing grid fuel mix. National-level proxy grids were applied at the screening level to account for geographic, spatial, and parameter uncertainty. However, it should be kept in mind that the specificity of mix proxy will determine the leverage of this parameter in the model. If highly specific information becomes available to modify the leverage, results may change. Unfortunately, information gaps due to underrepresentation of activities and impacts in existing literature are likely to be propagated in our method. Our approach of low-fidelity, high uncertainty reduces the cost of filling gaps and might encourage some assessment of issues using broad estimates that were previously omitted. Furthermore, subjectivity may be introduced in our methodology, especially at the data collection and screening stages, but subjectivity is inherent in any modeling process. We hope that despite such subjectivity, the methodology allows decisions to be defended quantitatively and results replicated, given access to the screening data.

Defining and identifying uncertainty

How uncertainty is defined and categorized may define how it is identified and processed. Uncertainty has been framed in many different ways, often depending on the analyst or decision maker. For the purposes of this thesis, uncertainty was dealt with in a uniform way—by assigning estimated probability distributions to one or more data points. Other methods of representing and evaluating uncertainty may be considered.

Metric quality

A number of approaches were possible to evaluate environmental performance hotspots, including the use of stochastic estimation methods to calculate the percentage of trials that an activity or life cycle phase contributes to a certain percentage of overall impact. Our method applied several other metrics to stochastic impact estimates to evaluate the ability to identify and leverage hotspots. These metrics included *average false signal rate* to evaluate the performance of the streamlined assessment model, *difference threshold* as a cutoff level of impact granularity, and the *number of priority activities to specify and level of specificity* as efficient uncertainty reduction measures.

Due to the large number of product scenarios under evaluation, the metric we chose to represent the performance of our model was the *average false signal rate*. It was defined as the average false signal rate for scenario comparisons that meet the FS criteria. For the purposes of this thesis, this average FS calculation weighted all scenario permutations equally, although in reality scenarios may have varying levels of occurrence and importance. This equal weighting gave undue emphasis to scenarios that matter less. Ideally, we would have used demographic data to weight scenarios to reflect realities such as location of production and use. One example is cell manufacturing electricity fuel mix, for which we had used equally-weighted proxy grids for Taiwan and Korea, the two primary countries in which manufacturing takes place for the four largest LCD manufacturers. In reality, manufacturing between the two countries is not evenly split. Market share or product volume data could be used to weight manufacturing impacts. For example, we could have estimated AUO and CMI, which manufacture in Taiwan, to have 23% and 16.8% of market share respectively, and LG and Samsung, which manufacture in Korea, to have 32.3% and 27.9% of market share. An amplifier of 39.8% could be used for Taiwanese scenarios and 60.2% for Korean scenarios, effectively emphasizing Korean grid impacts to reflect the reality of manufacturing location.

Another potential metric of performance would be the *environmental penalty* associated with the false signal rate of our modeling. In other words, we could calculate the impact difference between the false signal rate scenarios and perfect discrimination. This requires first knowing the false signal rate or the average false signal rate across multiple scenario comparisons, so false signal rate is a metric to be converged upon first.

The *difference threshold* is an impact measure below which we do not attempt to resolve. It is a decision to be converged upon by the modeler and stakeholders and will likely be based on the expense of measuring and reporting at very fine levels of granularity, as well as meaningful units to people, especially consumers evaluating this information on product labels. For the purposes of this research, the threshold was set to vary as a proportion of impact magnitude. However, in the future, this threshold may be set to a consistent, absolute value.

The *number of priority activities and level of specificity* is an implementable measure to reduce uncertainty and enable discrimination. This framing assigns activities and related uncertainty as decision variables. Other methods of framing may exist.

5. CONCLUSIONS

In today's marketplace, firms from every sector are facing significant pressure to evaluate the environmental performance of their operations and products. For the IT industry, this is no simple task. Complex and dynamic products and supply chains translate into high costs for pervasive and effective environmental evaluation. There is much interest in streamlining measures to improve the efficiency and effectiveness of evaluation. However, potentially high uncertainty associated with simplification measures may undermine the robustness of streamlining results. This thesis research sought to enable the identification of high-impact activities streamlining elements necessary for robust streamlining assessment.

Our methodology leveraged existing streamlining measures including secondary data and screening for hotspots. First, an activity model was built upon existing BOA and impact data, incorporating full ranges of uncertainty. Stochastic analysis was used to triage activities based on contribution to overall uncertainty. The priority activities were then targeted for specific data collection to the point where overall impact uncertainty distributions were sufficiently distinct from one another, enabling us to discriminate environmental performance. The goal of probabilistic triage is to identify those key drivers of impact so that data collection can be focused on the aspects of a product life-cycle "that matter" and thereby conserve limited resources for data collection. To accomplish this, the triage method relies on available data sources, but tries to accurately reflect the associated uncertainty that comes with the use of secondary data.

The case study for LCDs identified the key drivers of impact for LCDs as applied in laptop computers. The probabilistic triage identified 22 key activities that account for nearly all variation in impact. Resolving these strongest drivers of variability provided significant improvement in the fidelity of an estimate of LCD impact and allowed us to discriminate with high confidence—only 9 percent error. Our results demonstrated that triage is possible (and therefore much lower data collection burden is possible) even with highly uncertain data. In the end, this study represents just a piece in a larger effort to reduce the cost of impact assessment and to, therefore, allow it to be used throughout the IT industry. These initial results show promise for the probabilistic triage method.

The key drivers for LCD were related to high-tech manufacturing and use—attributes that relate to context rather than ostensible product attributes. In fact, the resolution of ostensible attributes alone, such as bulb type, number, and materials, did not provide enough leverage to reduce uncertainty and false signal rate to a meaningful extent.

Priority contextual attributes may currently be costly to measure and report. We hope the results of this research will motivate the development of reporting infrastructure and industry

collaboration. Measurement precision is a decision that will need to be converged upon to inform the difference threshold used this methodology. The difference threshold quantity should be granular enough not to mask meaningful impact differences, but not so granular that measurement is prohibitively costly. Future work to weight scenarios according to demographic realities will improve the accuracy of the average false signal rate. Ideally, an optimization algorithm will solve for the number of activities to resolve, and level of resolution for each, based not only on the average false signal metric but the costs associated with specification, which may vary widely by activity.

Although much work remains to identify the optimal streamlined LCA method, the results of this thesis show promise for the use of probabilistic streamlining methods for analyzing the environmental performance of IT products. For the case analyzed, the triage method identified that only a small set of attributes strongly determine product environmental performance. Such information should greatly reduce the cost of implementing environmental evaluation within IT supply chain. Additionally, by explicitly considering uncertainty and variability within the assessment process, the probabilistic triage approach enables broad, comprehensive assessment without undue increase in analytical cost. This comprehensiveness should improve confidence in the result and thereby increase "buy-in" or acceptance of conclusions by stakeholders inside and outside of the supply chain. These benefits should encourage the further exploration of probabilistic streamlining methods in the IT sector and beyond. Reducing the cost of generating environmental assessments and increasing the acceptance of their results should only help to move forward current debates about carbon labeling and footprint requirements. In the end, this is a necessary step towards lowering the footprint of industrial production and the consumption that drives it.

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7. APPENDICES

Appendix A: Acronyms

Acronym	Phrase or name
a:Si	Amorphous silicon
AM	Active matrix
BLU	Backlight unit
BOA	Bill of activities
BOM	Bill of materials
BSI	British Standards Institute
CCFL	Cold cathode fluorescent lamp
CFL	Compact fluorescent lamp
CMI	ChiMei-Innolux Corporation
CMO	ChiMei Optoelectronics
COV	Coefficient of variation
CRT	Cathode ray tube
CSR	Corporate social responsibility
DQI	Data quality indicator
EPD	Environmental product declaration
EPEAT	Electronic Product Environmental Assessment Tool
EuP	Energy Using Products
FPD	Flat panel display
FS	False signal rate
FU	Functional unit (as used in LCA)
GWP	Global warming potential
I/O	Input/output
IC	Integrated circuit
iNEMI	International Electronics Manufacturing Initiative
IPCC	Intergovernmental Panel on Climate Change
IPS	In-plane switching (light modulation)
ISO	International Organization for Standardization
IT	Information technology
kgCO$_2$e	Kilograms of carbon dioxide equivalents
LCA	Life cycle assessment
LCD	Liquid crystal display
LCI	Life cycle inventory
LED	Light emitting diode
LGP	Light guide plate

MJ	Megajoule
MSL	Materials Systems Laboratory
OEM	Original equipment manufacturer
PAIA	Product Attribute to Impact Algorithm
PCF	Product carbon footprint
PCR	Product category rules
PFC	Per-fluorinated compound
PM	Passive matrix
PMMA	Polymethyl methacrylate
PWB	Printed wiring board/Printed circuit board
SCM	Simplified characterization model
SKU	Stock-keeping unit
SMRS	Sustainability Measurement and Reporting System
TFT	Thin-film transistor
TN	Twisted-nematic (light modulation)
TSC	The Sustainability Consortium
WLICC	World LCD Industry Cooperation Committee
WRI/WBCSD	World Resources Institute/ World Business Council on Sustainable Development

Appendix B: Case study analysis data tables

The following tables contain data to support the LCD case study described in Chapter 3.

Table 5. LCD probabilistic screening model/bill of activities

Activity/ Material	Sub-Activity/ Material	Units	Proxy	Source	Assigned distri-bution	Min/Max or Mean/COV
LCD screen size	LCD screen area	m^2	10.1"-17" diagonal screen areas	HP & Lenovo specs	uniform	10.1": 0.0450-0.0451 11.6": 0.0589-0.0590 12.1": 0.0620-0.0621 13.3": 0.0734-0.0735 14": 0.0798-0.0799 15": 0.0939-0.0940 16": 0.1014-0.1015 17": 0.1271-0.1272
LCD mass	LCD mass	kg	LCD mass ranges	CMI data for sizes 10.1 to 17.3"	uniform	0.16 to 0.66
Materials Processing						
Glass	Glass/minerals mass	kg	Minerals	(MSL 2010b)	uniform	10 to 30% of LCD mass
	Glass/minerals emissions factors	kgCO$_2$e/kg	ecoinvent mineral arithmetic mean	(ecoinvent 2010)	lognormal	15, 439, 0.00744 (mean, SD, location)
Plastic	Polymer mass	kg	Polymers	(MSL 2010b)	uniform	20 to 50% of LCD mass
	Polymer emissions factors	kgCO$_2$e/kg	ecoinvent polymer arithmetic mean	(ecoinvent 2010)	lognormal	6.3, 9.1, 0.001939 (mean, SD, location)
Metal	Metals mass	kg	Non-precious metals	(MSL 2010b)	uniform	20 to 70% of LCD mass
	Metals emissions factors	kgCO$_2$e/kg	ecoinvent non-precious metals arithmetic mean	(ecoinvent 2010)	lognormal	11.7, 46.4, 0.00577 (mean, SD, location)
Machining	Energy demand	kWh/kg	Inj. molding, machining, finish machining	(Gutowski et al. 2009)	triangle	0.36, 0.48, 166.67 (min, mean, max)
	Grid emissions factors	kgCO$_2$e/kWh	Extreme geographic proxies for California and India	(PE International GmbH 2006; ecoinvent 2010)	uniform	0.28 to 1.58
Backlight bulbs	Bulb No.	#	Edge light design only	(Socolof et al. 2001b; Chien 2008; Myers 2011)	uniform	Unresolved: 1 to 30 LED: 15 to 30 CCFL: 1 to 4
	Energy	kWh/bulb	CFL lighting bulb kWh,	(Slocum 2005) and	uniform	Unresolved: 1.26 to 12.65

			LED-SSL lighting (DRAM proxy)	estimates		LED: 10.35 to 12.65 CCFL: 1.26 to 1.54

Manufacturing (high-tech)

Array PFC	Array PFC mass	kgPFC /m^2	IC semiconductor manufacturing	Lower limit: (IPCC 2006; MSL 2010b) Upper limit:(Krishnan et al. 2008)	uniform	SF$_6$: 0.004 to 0.5000 NF$_3$: 0.0003 to 0.4000
	Array PFC un- abated	%	Extremes	Estimated by modeler	uniform	1 to 100%
	Array PFC char factors	kgCO$_2$e/kg PFC	CF$_4$, SF$_6$, NF$_3$	(IPCC 2007)	uniform	17,200 to 22,800
	PFC degradation	%	Estimates for SF$_6$ and NF$_3$	Estimated by modeler	uniform	SF$_6$; 1 to 2% NF$_3$: 10 to 15%
Array energy	Deposition electricity	kWh/ kg	CVD and PECVD, sputtering	(Gutowski et al. 2009)	uniform (n=7)	325 to 66,389
	Deposition mass	kg	Deposition trace materials	(Socolof et al. 2001b) Tbls 2-56 and 2-57	uniform	0.02 to 0.16
	Lithography electricity	kWh/ kg	Process chain Si to wafer (kWh/kg Si out)	(Williams et al. 2002; Boyd et al. 2009)	uniform (n=1)	1,489 to 2,765 (based on mean 2,127 in literature)
	Lithography mass	kg	Lithography trace materials	(Socolof et al. 2001b) Tbls 2-56, 2-57	uniform	0.01 to 0.08
	Etching electricity	kWh/ kg	Dry etching of Si$_3$N$_4$/SiO$_2$	(Gutowski et al. 2009)	uniform (n=2)	5,305 to 8,639
	Etching mass	kg	Etching trace materials	(Socolof et al. 2001b) Tbls 2-56, 2-57	uniform	0.036 to 0.360
	Cleaning electricity	kWh/ kg	Etching electricity	(Gutowski et al. 2009)	uniform (n=2)	5,305 to 8,639
	Cleaning mass	kg	Cleaning materials	(Socolof et al. 2001b) Tbls 2-56, 2-57	uniform	0.0108 to 0.1077
	Array/cell grid mix	kgCO$_2$e/kWh	Ranges for Korea and Taiwan	(PE International GmbH 2006; ecoinvent 2010)	uniform	0.46 to 1.24
Module fuel	Module fuel energy	kWh/ kg LCD	Module fuels	(Socolof et al. 2001b) Table 2-58: fuels=elect + fuels - elect	uniform	82 to152
	Grid emissions	kgCO$_2$e/kWh	Extreme geographic proxies for California and India	(PE International GmbH 2006; ecoinvent 2010)	uniform	0.28 to 1.58

Backlight semicon-ductor	Area	mm^2	LED semiconductor chip area	(Slocum 2005), on the order	uniform	0.5 to 2.5
	PFC mass	kg PFCs/mm^2	IC DRAM manufacturing PFCs	(Williams et al. 2002)	uniform	LED: mean of 0.012 for a range of PFCs, range of 0.008 to 0.016 given CCFL: 0.0
	Char. factor	kgCO$_2$e/kg PFC	SF$_6$ and NF$_3$	(IPCC 2007)	uniform	17,200 to 22,800
	Abatement	%	Extremes	Estimated by modeler	uniform	0.01 to 1.00
	Degradation rate	%	Estimates for SF$_6$ and NF$_3$	Estimated by modeler	uniform	2 to 3 for SF$_6$; 12 to 20 for NF$_3$
IC PFCs	Die area	m^2	Measured package area * die factor	Disassemblies (12.1", 13", 14.5", 15")	triangle (n=4)	0.000031875; 0.0000511491; 0.00006763
	PFC emission factors	kgCO$_2$e/m^2	PFC emissions	(SIA 2008)	uniform (n=29)	400 to 34,000
IC energy	Die area	m^2	Measured package area * die factor	Disassemblies (12.1", 13", 14.5" and 15")	triangle (n=4)	0.000031875; 0.0000511491; 0.00006763
	IC electricity	kWh/m^2	kWh/area wafers out	(SIA 2008)	uniform (n=29)	2,000 to 48,000
PWB impacts	PWB Area	m^2	0.2 to 1.0 screen size	Based on various typical screen sizes	uniform	0.2*screen area to 1.0*screen area
	PWB emission factors	kgCO$_2$e/m^2		(PE International GmbH 2006; ecoinvent 2010)	uniform (n=14)	39 to 678

Transport

Transport (all legs)	Distance	km	Extreme scenarios	Estimated by modeler	uniform	40 to 20,000
	Mass	t	Extreme scenarios	Estimated by modeler	uniform	100 to 400% of LCD mass
	Mode emissions	kgCO$_2$e/kg	Tanker, air, van	(ecoinvent 2010)	uniform	0.01 to 1.90

Use

Consumer use	Energy demand	kW	Typical product, mod	(Slocum 2005; CMI 2011)	uniform	Unresolved: 0.022 to 0.0934 LED: 0.022 to 0.028; CCFL: 0.073 to 0.0934
	Lifetime	yrs	Extremes		uniform	1 to 5
	Duty cycle	hrs/yr	Extremes		uniform	1000 to 8760
	Grid Emissions	kgCO$_2$e/kWh	Averages for China and California	(PE International GmbH 2006; ecoinvent 2010)	uniform	0.27 to 1.58; average US grid used of 0.78

End of Life: not addressed

Sensitivity: TOTAL GHG

Assumptions	Contribution To Variance
Use Duty Cycle (hrs/yr)	0.219
Use Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.159
Use Lifetime range (MSL) (yr)	0.135
* Screen size (m2)	0.088
Cell Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.045
Array PFC mass (Krishnan 2008, CMO) (kg PFCs/m2 semiconductor)	0.039
deposition/sputtering electricity (kWh/kg)	0.037
PWB area (screen size) (m2)	0.033
* LCD mass (CMI) (kg)	0.033
Array PFC non-abatement (%)	0.032
deposition mass (kg/m2)	0.027
Polymer mass (kg)	0.023
Mineral mass (kg)	0.020
LED PFC abatement %	0.019
Transport mass (t)	0.018
Use Energy Demand (CMI, Slocum) (kW)	0.015
LED PFC degr rate	0.012
Bulb	0.011
Bulb manu energy (Slocum) (kWh/bulb)	0.007
etching mass (kg/m2)	0.006
LED semicond PFCs (kg PFCs/mm2)	0.006
LED semincond area (mm2)	0.002
* # Bulbs, LED or CCFL (manu-related only)	0.002
Module Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.002
Array PFC CF (IPCC) (kgCO2e/kg PFC)	0.001
Other	0.006

Figure 7. Contribution to variance parameters for the first set of trials. Use phase duty dycle had the highest contribution and was therefore resolved before the next set of trials

Sensitivity: TOTAL GHG

Assumptions	Contribution To Variance
Use Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.214
Use Lifetime range (MSL) (yr)	0.185
* Screen size (m2)	0.095
Cell Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.054
deposition/sputtering electricity (kWh/kg)	0.053
Array PFC mass (Krishnan 2008, CMO) (kg PFCs/m2 semiconductor)	0.050
Array PFC non-abatement (%)	0.040
* LCD mass (CMI) (kg)	0.037
PWB area (screen size) (m2)	0.032
deposition mass (kg/m2)	0.029
Use Energy Demand (CMI, Slocum) (kW)	0.028
Polymer mass (kg)	0.027
LED PFC abatement %	0.023
Mineral mass (kg)	0.021
LED PFC degr rate	0.019
Transport mass (t)	0.017
Bulb	0.017
Bulb manu energy (Slocum) (kWh/bulb)	0.017
LED semicond PFCs (kg PFCs/mm2)	0.013
etching mass (kg/m2)	0.008
* # Bulbs, LED or CCFL (manu-related only)	0.007
LED semincond area (mm2)	0.006
LED PFC CF (IPCC) (kgCO2e/kg PFC)	0.001
Module Grid EF (GaBi, Ecoinv) (kgCO2e/kWh)	0.001
Array PFC CF (IPCC) (kgCO2e/kg PFC)	0.001
Other	0.002

Figure 8. Contribution to variance parameters after duty cycle was resolved

Table 6. Activity priority list for LCDs

Run No.	Activity/ attribute resolved	Mean impact (kgCO$_2$e)	COV of impact (%)	FS rate (%)	Largest contributor to variance	Un-resolved values	Resolved values	Unit
1	Unresolved	1631	48.1	44.2	Duty cycle	1000-8670	4380-4380.001	hrs/year
2	Duty cycle	1557	37.7	42.6	Use grid	0.27-1.58	0.78-0.781	kgCO$_2$e/kWh
3	Use grid fuel mix	1451	31.1	40.1	Lifetime	1-5	3-3.001	yrs
4	Lifetime	1448	26.2	39.4	Screen size	0.045024 – 0.1271	0.07976-0.07986	m^2
5	Screen size	1411	22.4	37.6	Cell grid	0.46-1.24	0.5-0.50001	kgCO$_2$e/kWh
6	Cell grid	1233	23.0	37.9	Use energy demand (depends on bulb type)	Bulb: LED or CCFL	LED	type
7	LED	1133	25.2	38.9	LED PFC un-abated	0.01-1.00	0.08-0.0801	
8	LED PFC emissions	903	22.0	37.4	Array PFC mass (choose type of PFC)	SF$_6$: 0.004-0.5000 NF$_3$: 0.0003-0.4000	NF$_3$: 0.0003-0.4000	kg
9	PFC type: NF$_3$	840	18.4	35.0	Array PFC un-abated	0.01-1.00	0.98-0.98001	
10	Array PFC emissions	955	18.6	35.2	Deposition electricity	325-66,000	30,000-30.001	kWh/kg
11	Dep. elect	941	16.9	33.8	Array PFC mass	0.0003-0.4000	0.045-0.045001	kg
12	NF$_3$ mass	760	11.1	26.2	Deposition mass	0.02-0.16	0.15-0.15001	kg
13	Dep. mass	834	8.2	19.3	LCD mass	0.16-0.66	0.25-0.25001	kg
14	Mass	803	6.5	13.8	Bulb No.	LEDs:15-30	20-20.0001	#
15	20 LEDs	790	5.9	11.5	Etching mass	0.036-0.360	0.05-0.06	kg
16	Etching mass	750	4.8	7.2	LED semicond. area	0.5-2.5	0.5-0.6	mm^2
17	LED semicond. area	720	4.6	6.3	Use energy demand	LEDs: 0.022-0.028	LEDs: 0.022-0.02201	kW
18	Use energy demand	690	3.9	3.4	Module fuel mix	0.27-1.58	0.99-1.00	kgCO$_2$e/kWh
19	Module fuel mix	690	3.4	1.8	PWB emissions factor	39-678	50-51	kgCO$_2$e/m^2
20	PWB emissions factor	680	3.2	1.3	Machining energy			

Table 7. Activity priority list for LCDs—sensitivity of bulb type

Run No.	Resolution level	Mean impact (kgCO$_2$e)	COV of impact (%)	FS rate (%)	Largest contributor to variance	Un-resolved values	Resolved values	Unit
1	Unresolved	1631	48.1	44.2	Duty cycle	1000-8670	4380-4380.001	hrs/year
2	Duty cycle	1557	37.7	42.6	Use grid	0.27-1.58	0.78-0.781	kgCO$_2$e/kWh
3	Use grid fuel mix	1451	31.1	40.1	Lifetime	1-5	3-3.001	yrs
4	Lifetime	1448	26.2	39.4	Screen size	0.045024 – 0.1271	0.07976-0.07986	m^2
5	Screen size	1411	22.4	37.6	Cell grid	0.46-1.24	0.5-0.50001	kgCO$_2$e/kWh
6	Cell grid	1233	23.0	37.9	Use energy demand (depends on bulb type)	Bulb: LED or CCFL	CCFL	type
7	Bulb type (CCFL)	1334	15.4	32.3	Array PFC mass, choose PFC type	SF$_6$: 0.004-0.5000 NF$_3$: 0.0003-0.4000	NF$_3$: 0.0003-0.4000	kg
8	PFC type: NF$_3$	1270	12.8	29.0	Array NF$_3$ mass	NF$_3$:0.0003-0.4000	NF$_3$:0.045-0.045001	kg
9	NF$_3$ mass	1175	10.5	25.0	Deposition electricity	325-66,000	30,000-30,001	kWh/kg
10	Deposition electricity	1160	8.1	19.2	Use energy demand	CCFL: 0.07355-0.093352	CCFL: 0.07335-0.07336	kW
11	Energy demand	1060	7.1	15.9	Deposition mass	0.02-0.16	0.15-0.15001	kg
12	Deposition mass	1134	5.6	10.2	LCD mass	0.16-0.66	0.25-0.25001	kg
13	Mass	1103	3.6	2.6	Etching mass	0.036-0.360	0.05-0.06	kg
14	Etching mass	1064	2.7	0.5	Array PFC un-abated	0.01-1.00	0.98-0.98001	
15	Array PCF un-abated	1090	2.6	0.3	Module fuel mix	0.27-1.58	0.99-1.00	kgCO$_2$e/kWh
16	Module fuel mix	1090	1.9	0.0	PWB EF	39-678	50-51	kgCO$_2$e/m^2
17	PWB emissions factor	1080	1.7	0.0	Machining energy			

Table 8. Product attributes alone are insufficient to attain low false signal rate (full table)

Run No.	Activity/ attribute to resolve	Mean impact (kgCO$_2$e)	COV of impact (%)	FS rate (%)	Largest contributor to variance	Unresolved values	Resolved values	Unit
1	Unresolved	1345	36.5	42.3	Screen size	0.045024 – 0.1271	0.07976- 0.07986	m^2
2	Screen size	1300	34.0	41.8	Bulb type	CCFL, LED	LED	Type
3	Bulb	1434	31.0	41.0	Bulb no.	LEDs:15- 30	20- 20.0001	#
4	Bulb no.	1413	30.8	40.9	LCD mass	0.16- 0.66	0.25- 0.25001	kg
5	LCD mass	1383	31.6	41.1	LED semicond. area	0.5- 2.5	0.5- 0.6	mm^2
6	LED semiconductor area	1209	31.9	41.2	Materials proportions	Minerals: 10 to 30% of LCD mass; polymers: 20 to 50% of LCD mass; metals: 20 to 70% of LCD mass	Minerals = 20%, polymers = 30%, metals = 50%	%
7	Material proportions	1209	32.3	41.3	PWB area (less than 0.1 contribution to variance)			

Table 9. Sufficient false signal rate (9%) is attained in streamlined assessment (full table)

Run No.	Activity/ attribute to resolve	Resolution range	Scenario 1 range	Scenario 2 range
1	Duty cycle	One thousandth hrs/yr	4380-4380.001	N/A - correlated
2	Use grid fuel mix	One thousandth $kgCO_2e$/kWh	0.78-0.781	N/A - correlated
3	Lifetime	One thousandth yr	3-3.001	N/A - correlated
4	Screen size[12]	One ten-thousandth m^2	0.0798-0.0799	0.0939-0.0940
5	Cell manufacturing grid fuel mix	Five hundredths $kgCO_2e$/kWh	0.50-0.55	1.04-1.09
6	Bulb type[13]	Type	LED	CCFL
7	Bulb no.	One bulb	20	2
8	Bulb manufacturing energy	One kWh/bulb	10.35-11.35	1.26-2.26
9	LED PFC mass	Unresolved $kgPFC/mm^2$	0.0-0.026	N/A
10	LED PFC un-degraded	Ten %	0.80-0.90	0.90-1.00
11	Bulb electricity demand	One hundredth kW (ten watts)	0.022-0.032	0.074-0.084
12	LED semi-conductor area	Five tenths mm^2	2.0-2.5	0
13	LED PFC un-abated	Ten %	0.90-1.00	0.08-0.18
14	Array PFC un-abated	Ten %	0.90-1.00	0.01-0.11
15	Array PFC type		NF_3	SF_6
16	Array PFC char. factor	Ten CO_2 equivalents	17,200-17,210	22,800-22,810
17	Array PFC un-degraded	Ten %	0.80-0.90	0.90-1.00
18	Array PFC mass	Five hundredths kg PFC/m^2	0.05-0.10	0.10-0.15
19	Deposition electricity	One hundred kWh/kg	30,000-30,100	60,000-60,100
20	Deposition mass	One tenth kg/m^2	0.016-0.160	0.10-0.20
21	LCD mass	Five thousandths kg	0.25-0.255	0.45-0.455
22	Module manufacturing grid fuel mix	Five hundredths kWh/kg LCD	0.99-1.04	1.45-1.50

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[12] Approximate area of 14" and 15" LCDs (m^2)

[13] Bulb type was modeled to resolve variables 7-13 to the following extent: <u>LED</u> resolves to the following: 1-4 bulbs, bulb manufacture energy 1.26-1.54 kWh/bulb, LED PFC mass 0.014-0.026 $kgPFC/mm^2$, LED PFC degradation 1-20%, bulb energy demand 0.022-0.028 kW, LED semiconductor area 0.5-2.5mm^2, LED PFC abatement 0-99%. <u>CCFL</u> resolves to the following: 15-30 bulbs, bulb manufacture energy 10.35-12.65 kWh/bulb, bulb energy demand 0.07335-0.09335 kW, zero LED PFC mass, LED PFC degradation, LED semiconductor area, and LED PFC abatement.

Appendix C. Literature review of LCD global warming impacts

As stated in the case study chapter, the analysis performed for this thesis pertains to materials and manufacturing for a specific LCD module technology: twisted-nematic (TN) amorphous-silicon (a:Si) thin-film transistors (TFTs) within the active matrix (AM) LCD type. In this thesis, the generic term "LCD" refers to this specific technology because the available literature emphasizes this most commonly manufactured and purchased type of laptop display.

AM-LCDs have driver tabs along the rows and columns of the display glass. A matrix is formed across the glass by parallel electrical lines, where each intersection of the matrix forms a pixel (Socolof et al. 2001b). AM-LCDs which employ the TFT switch type have a transistor at each pixel which acts as a switch. It is this active technique which permits the strong contrast between a pixel's on and off states (Socolof et al. 2001b). Within the AM-LCD technology, switch types include not only TFT but diode matrix and metal insulator metal. Within TFT-AM-LCDs, there are various transistor technologies, including a:Si, polycrystalline silicon (p:Si), or non-silicon (such as CdSi). Within the a:Si transistor technology, TFT light modulating modes include TN and IPS. The majority of modules employ TN. The orientation of the liquid crystal (LC) molecules allows light to pass from a background source to the display cell. When a current is applied, the LCs turn perpendicular to the glass. The alignment layer, electrical charge, and polarizers on the glass panels work together resulting in the on or off state of the LCD cell. LCDs are considered non-emitting display technologies because the technology regulates passage of backlight through the display (Socolof et al. 2001b).

Materials Processing

With regard to the processing of display materials, natural gas is associated with 28% of the total LCD life cycle burden, followed by steel production (1.1%), polymethyl methacrylate (PMMA) sheet production (0.5%), polycarbonate production (0.5%) and several other process (<1%) (Socolof et al. 2001b). See Table 10 for this list.

Table 10. Materials processing GWP of LCDs (Socolof et al. 2001b)

Process Group	GWP (kgCO$_2$e)	% of total LCD
Natural gas production	166.3	28.0
Steel production, cold-rolled, semi-finished	6.8	1.1
PMMA sheet production	2.9	0.5
Polycarbonate production	2.8	0.5
Aluminum production	1.8	0.3
Styrene-butadiene Copolymer production	0.8	0.1
PET resin production	0.4	0.1
Total Materials Processing	**181.7**	**30.7**

EuP 2007 provides a BOM and associated GWP impact for an LCD monitor. The main drivers of impact from materials processing are identified as the LCD screen (16.83 kgCO$_2$e), ICs (5.44 kgCO$_2$e), galvanized steel sheet (5.24 kgCO$_2$e), polyamide 6 (3.61 kgCO$_2$e) and ABS (2.25 kgCO$_2$e).

Manufacturing

With regard to manufacturing impact, that of the monitor/module is associated with 29% of the total LCD life cycle burden, followed by the electric grid with 8.7%, and LPG production and natural gas production at 1.4 and 0.6%, respectively (Socolof et al. 2001b). The monitor/module manufacturing impact is driven by emission of perfluoro-compounds (PFCs) in array production, specifically NF$_3$ and SF$_6$, as well as the GHG emissions associated with the electricity grid. The complete list of manufacturing burdens is displayed in Table 11.

Table 11. Manufacturing GWP of LCDs (Socolof et al. 2001b)

Process Group	GWP (kgCO$_2$e)	% of total LCD
Monitor/module	174.0	29.4
Japanese electric grid	51.9	8.7
LPG production	8.3	1.4
Natural gas production	3.8	0.6
US electric grid	0.9	0.1
LCD glass manufacturing	0.1	0.0
Fuel Oil #4 production	0.1	0.0
Fuel Oil #6 production	0.0	0.0
Fuel Oil #2 production	0.0	0.0
Panel components	0.0	0.0
Total Manufacturing	**239.2**	**40.4**

As mentioned above, module manufacturing is the largest contributor to manufacturing GWP. Figure 9 shows the processes and components that contribute to module impact from materials processing and manufacturing, based on ecoinvent data using the IPCC 2007 GWP 100a impact assessment method (IPCC 2007; ecoinvent 2010). Under this scenario of non- or low-abatement of PFCs used in LCD assembly, the assembly process accounts for 98% of module materials and manufacturing impact. This is attributed primarily to the emissions of NF$_3$ and SF$_6$ used in LCD array and cell manufacture. However, a non-abatement scenario such as this is not realistic based on current industry abatement goals. A complete abatement scenario of assembly PFCs is shown in Figure 10. Under complete abatement, assembly burden shifts from PFCs to the electricity used in production, specifically for China and Japan (the assumed manufacturing locations, current production dominated by Taiwan, Korean and Chinese manufacturing). Other large impacts are from IC semiconductor product (Higgs et al. 2009), the PWB and the BLU.
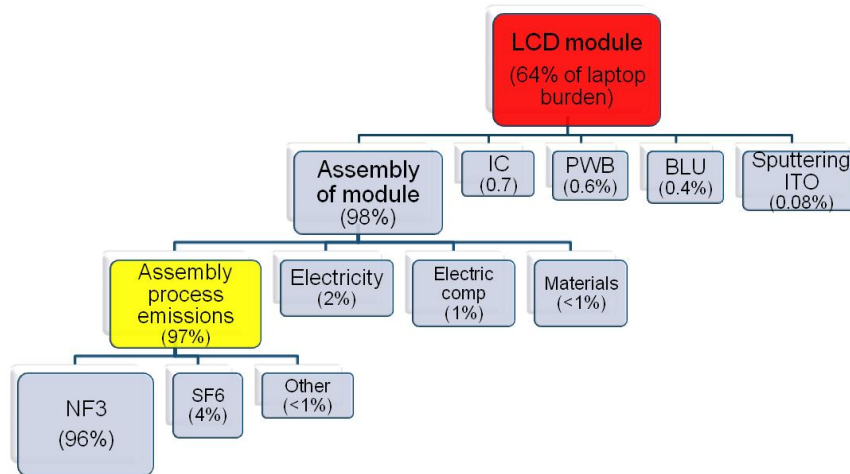
Figure 9. PFC emissions drive LCD module materials and manufacturing GWP under a non-abatement scenario of NF_3 and SF_6 used in LCD assembly (datasource: ecoinvent 2.2 2007 and IPCC 2007 GWP 100a)
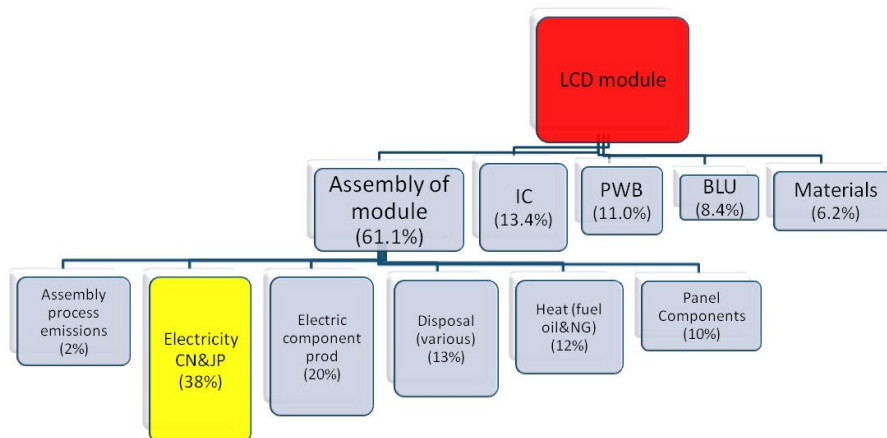

Figure 10. Electricity emissions drive LCD module materials and manufacturing GWP under a scenario where NF_3 and SF_6 are abated from array process emissions (datasource: ecoinvent 2.2 and IPCC 2007 GWP 100a)

The EuP 2007 study of LCD monitor impacts identified OEM plastics manufacturing (5.10 $kgCO_2e$), sheet metal manufacturing (1.59 $kgCO_2e$) and PWB manufacturing (1.35 $kgCO_2e$) to be the main drivers of manufacturing GWP (EuP 2007).

Use

The use-phase GWP burden of an LCD is comprised of the GHG emissions created as a result of the electricity consumed during laptop use, and is therefore a function of quantity of electricity used and grid mix of energy sources that produce the electricity. Socolof et al. 2001 estimates this use-phase burden as 29% of the total LCD burden. This burden will vary based on the duty

cycle, ability for laptop to reduce power to idle display, and energy efficiency of the specific laptop, and the grid mix for the region where the laptop is used.

End-of-life

The first known LCA case study for displays was performed by Ecobilan in 1995 to determine the most environmentally-favorable EoL fate for CRT displays. The study estimated VOC emissions, dust emissions, and energy consumption for landfilling, reuse and recycling (Epelly 1995).

The end-of-life (EoL) fate for LCDs varies widely, particularly by region and by local regulations and resources. Potential EoL fates for monitors and modules include incineration, landfilling, recycling, and reuse. Estimates of GWP for incineration and landfilling are shown in Table 12 (Socolof et al. 2001a). The GWP contributions from EoL are relatively minor (0.1%) relative to total life cycle impact, though this may not be the case for other impact categories, such as eco-toxicity or human health (Epelly 1995). According to this study, incineration is associated with a larger impact than landfilling (1.65 $kgCO_2e$ versus 0.03 $kgCO_2e$). This difference may be due to assumptions about the fate of embodied carbon. Presumably, incineration releases embodied carbon to the atmosphere, some of which goes unabated and contributes to GWP, whereas landfilled LCDs do not degrade during the timeframe considered (100 years) and therefore do not contribute to GWP. Contributions from indirect activities relating to incinerator and landfill infrastructure and operation are relatively minor (e.g., electricity grid, LPG production) or even negative (e.g., natural gas collected from landfill). As incinerator emissions abatement technology improves (and it likely has since the 2001 report) incineration GWP estimates will likely decrease.

Table 12. End-of-Life GWP for LCDs (Socolof et al. 2001b)

Process Group	GWP (kgCO$_2$e)	% of total LCD
LCD incineration	1.65	0.28
US electric grid	0.03	0.01
LCD landfilling	0.03	0.00
LPG production	0.00	0.00
Fuel Oil #4 production	-0.35	-0.06
Natural gas production.	-0.79	-0.13
Total EoL	**0.57**	**0.10**

Lee 2008 provided a thorough qualitative discussion of the EoL impacts of LCD monitors as well as LCD subcomponent masses. Lee identified commonly used materials for various subcomponents of an LCD and discussed potential impacts of these materials. These impacts are primarily around eco-toxicity and human health, and there is little discussion of GWP (Lee 2008).

Some EoL GWP can be abated with thoughtful LCD design. Shih 2007 evaluated recycling processes for LCD-type products, noting that parts were often soldered together instead of fastened, making them more difficult to disassemble and recycle effectively. The high cost of manual separation necessitated shredding for material recovery in many cases. This study investigated methods of optimizing disassembly and shredding based on cost/benefit parameters (Shih and Lee 2007).

Table 13 presents data from Socolof et al. for all life cycle stages, ranked in order of impact. From this we identified the following bundled drivers of impact:
- Level of abatement of PFCs
- Quantity of energy used for materials processing, manufacturing, and use
- Electricity grid mix for region of materials processing, manufacturing, and use

Table 13. LCD life cycle hotspots listed in order of significance (Socolof et al. 2001b)

Phase	Process Group	GWP (kgCO$_2$e)	% of total	Material	Details
Manu	Monitor/module	174.0	29.4	SF$_6$ (29.4%), CO$_2$ (<1%)	SF$_6$ used in etching stage of photolithography
Use	US electric grid	171.4	28.9	CO$_2$ (28%), CO$_2$ (<1%), N$_2$O (0.1%)	CO$_2$ bi-product of electricity grid mix
Mat proc	Natural gas production	166.3	28.0	CO$_2$ (15.6%), CH$_4$ (12.4%), N$_2$O (<0%)	CO$_2$ and CH$_4$ part of materials processing
Manu	Japanese electric grid	51.9	8.7	CO$_2$ (8.7%), N$_2$O (<1%), CH$_4$ (<1%)	CO$_2$ bi-product of electricity grid mix
Manu	Liquefied petroleum gas production	8.3	1.4	CO$_2$ (1.2%), CH$_4$ (0.1%), N$_2$O (<1%)	
Mat proc	Steel production, cold-rolled	6.8	1.1	CO$_2$ (1.1%), N$_2$O (<1%), CH$_4$ (<1%), C$_2$F$_6$ (<1%)	
Manu	Natural gas production	3.8	0.6	CO$_2$ (0.4%), CH$_4$ (0.3%), N$_2$O (<1%)	
Mat proc	PMMA sheet production	2.9	0.5	CO$_2$ (0.4%), CH$_4$ (<1%), N$_2$O (<1%)	
Mat proc	Polycarbonate production	2.8	0.5	CO$_2$ (0.4%), CH$_4$ (<1%), N$_2$O (<1%)	
Mat proc	Aluminum production	1.8	0.3	CO$_2$ (0.2%), CF$_4$ (0.1%), CH$_4$ (<1%), C$_2$F$_6$ (<1%), N$_2$O (<1%)	

Such data from Socolof et al. and ecoinvent comprise the base of our hotspot analysis, as there have been few other complete LCAs for LCD since then.

Based on the potential significance of LCDs in the overall footprint of laptops and the older data that are available within the LCA arena, this document presents a detailed description of the production process. The extent of this detail is illustrative of the possible levers to reduce impact

within displays. This description provides a framework over which changes in the LCD manufacturing process can be potentially outlined.

Appendix D: Analysis and discussion of LCD global warming impacts

In this section, LCD life cycle phases and associated global warming impacts are evaluated. This analysis helped inform the development of the screening model discussed in Section 3.1.

Production and Raw Materials

This section includes a description of the drivers of environmental impact during production. For the purposes of this thesis, production will be defined as cradle to gate, while the use is defined as use by the consumer at the laptop product-level (though LCD module-level use, including backlight bulb energy demand, will be included).

The LCD manufacturing process is typically framed in three stages as shown in Figure 11 below:
- Array: creation of color filter (CF) and thin-film transistor (TFT);
- Cell: spacers and liquid crystals (LCs) inserted in sealed array, polarizer added, diffuser film and light guide added behind the TFT side, drivers added along sides; and
- Module: backlight unit (BLU), power supply, PWBs, IC tabs and cables added to cell.
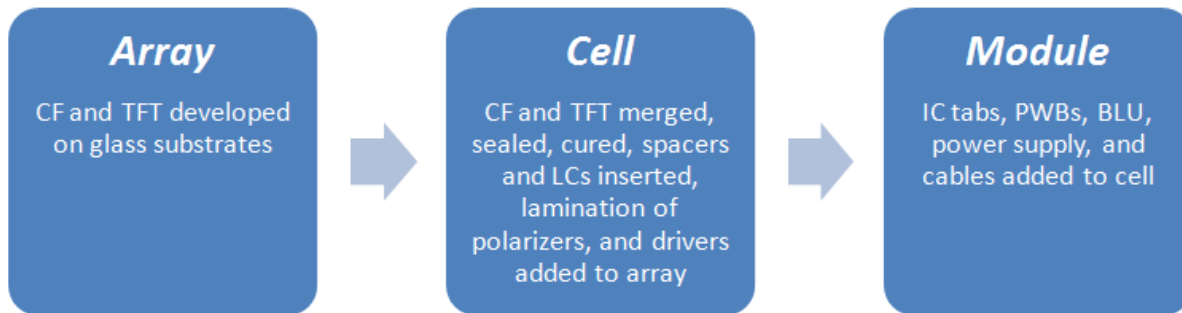

Array
CF and TFT developed on glass substrates

Cell
CF and TFT merged, sealed, cured, spacers and LCs inserted, lamination of polarizers, and drivers added to array

Module
IC tabs, PWBs, BLU, power supply, and cables added to cell

Figure 11. Stages of LCD production as described in literature

Array stage

In the array stage, a CF and a TFT are each created on a substrate (typically glass) through the following steps (Socolof et al. 2001b)
a) **deposition** of thin film materials (conductors or semiconductors) on the substrate using chemical vapor deposition (CVD) or physical vapor deposition (PVD). A typical low-pressure CVD (LPCVD) process will require chamber cleaning using NF_3. Deposition is preceded by an oxidation step.
b) **lithography** by coating the substrate with materials to transfer a pattern through a mask. This step is used multiple times in combination with different masks.
c) **etching** of the thin films through the pattern resulting in transfer of the pattern to the films. Etching can be wet or dry, though dry is most common for flat-panel displays. PFCs are often employed in this stage. AM-LCD etching involves amorphous silicon, silicon nitride, various oxides, and metals (Socolof et al. 2001b).

d) **cleaning** is necessary to minimize contamination preceding oxidation and deposition and following each lithography step. Cleaning traditionally uses large quantities of ultra-pure water.

Because these steps are relatively burdensome in terms of life cycle GWP for an LCD, the number of CF and TFT formation steps is directly related to impact. Conventionally there have been four CF formation steps (one for each of four color layers: black, red, green and blue) and eight TFT formation steps (for various layers including gate metal, SiO_2, and ITO) (Socolof et al. 2001b). According to a study which evaluated the environmental impacts of semiconductor photolithography, a change in the number of interconnect layers from six to eight increases fabrication energy consumption by 13% (Krishnan et al. 2008). Primary drivers of environmental performance are discussed below.

Glass substrates
The substrates on which the TFT and CFs are created are usually soda lime or non-alkali borosilicate glass (Socolof et al. 2001b; DisplaySearch 2006). However, research in past years has considered flexible materials such as plastic film substrates based on polymer-dispersed LC technology with molecular alignment control (Fujikake and Sato 2009). These and other potential flexible substrates are currently in research and development (CMO). Glass is widely used in LCDs, and there is growing demand for glass substrates free of arsenic and other heavy metals. The EAGLE XGTM glass substrate claims to be free of arsenic, antimony and barium while maintaining light, durable and advanced thermal properties (Lee 2008).

Gases
During deposition, etching and cleaning steps of array fabrication, gases similar to those in semiconductor manufacturing are used, though they are generally of lower purity requirements. Etching may be wet or dry, though dry appears to be most common (DisplaySearch 2006). The gases of global warming significance are PFCs including SF_6 used for dry etching/deposition and NF_3 used in the cleaning chambers of plasma-enhanced CVD to clear away undesired material (DisplaySearch 2006; AUO 2009; MSL 2010c)

Emissions abatement infrastructure may be of the point-of-use variety (process pumps, cold bed adsorption, combustion and water scrubbing, plasma abatement) or the facilities variety (house scrubber and acid waste neutralization, VOC exhaust, fluoride treatment, copper treatment, ultrapure water, process cooling, or HVAC).

Trends
- **Replacement of SF_6 with NF_3** (Samsung 2010; MSL 2010c). NF_3 is a less potent GHG than SF_6, with characterization factors of 17,200 and 22,800, respectively (IPCC 2007). In addition, NF_3 decomposes more rapidly than SF_6 and persists less in the atmosphere.

Sputter targets

Deposition methods may include LPCVD, PECVD, HDP-CVD, PVD evaporation, and PVD sputter. Sputter targets are used to deposit metal thin films for date, source/drain and pixel electrodes (DisplaySearch 2006). Sputtering is described as an inefficient process, with the percentage of useful material (utilization) typically only 30 to 40%. Indium-tin oxide (ITO) is the dominant material used for the pixel and color filter electrodes. If PVD sputter is used, it is environmentally significant to know if ITO is used for the electrode. PVD sputter can occur through direct current, radio frequency, or magnetron.

Trends
- **Rotatable targets with higher utilization** are under development (DisplaySearch 2006).

The IPS mode display employs the same front panel patterning process described above for TN, with the exception that no ITO electrode is formed. For the rear panel, the number of patterning layers is reduced from six or seven to around four (USEPA 1998) and the electrode on the rear glass is made of any number of other materials (e.g., Mo, Ta, Al/Cr, MoW). Therefore, ITO is not used in IPS manufacturing (Socolof et al. 2001b). Despite this environmental benefit of IPS production, IPS demands an increase in the number of backlights to meet the brightness requirements (for desktop applications) which carries its own environmental burden (DisplaySearch 1998).

Etching lasers

It may be environmentally significant to know what pulse-width laser technology is used in etching. State-of-the-art laser technology may apply very efficient lasers using pico-second pulse-width as opposed to nanosecond (Lee et al. 2009b). The pico-second laser provides high quality processing at slower speeds but at higher capital costs for the laser in relation to the nanosecond. It is believed that the pico-second is a 'sweet spot' in the pulse-width range with benefits for a wide range of materials (Lee et al. 2009b).

Facility energy demand

The facilities used to manufacture LCD arrays require significant environmental control. For instance, the ovens used to bake the CF and TFT require high energy demand, yet the facilities must be maintained at temperatures ideal for workers and machinery.

Trends

Cell stage

The cell stage is the term used to describe the creation of the cell, which typically includes the following activities: merging of front and rear substrates, sealing of substrates, curing of substrates, insertion of spacers between substrates, inspection of cell, application of UV-cured adhesive, insertion of LCs, application of UV or oven-cured sealant, and lamination of front and rear polarizers onto the substrates.

Later stages include the functional testing of the glass panel, cleaning and testing of circuit boards, attachment of column and row drivers, and system testing.

Liquid crystals

There are more than 400 varieties of LC compounds in use for displays, many of which are trade secret (USEPA 1998). Liquid crystals tend to be PAHs or halogenated aromatic hydrocarbons (USEPA 1998). Socolof et al. lists organic liquids, specifically phenylcyclohexane biphenyls, as examples. Because LCs comprise a small fraction of the total LCD mass, they are often left off the BOM and omitted from LCAs. The mass of LCs is only about 0.8 mg of LC per cm^2 of LCD screen (USEPA 1998).

Polarizers

Polarizers are typically made of PET and thin-crystal film (Ukai 2007). The polarizer and analyzer are formed using polymer plates with cellulose triacetate and polyvinyl alcohol with iodine (Tavares et al. 2009).

electrode and the LCD is driven by only the pixel circuit when displaying a still image. The result is only a small charging current to the pixel capacitor, resulting in ultra-low power operation (Ukai 2007).

Module stage
The module stage describes the addition of the BLU, the power supply, several PWBs (for driver input, controller, adjustment, BLU, and power supply) as well as ICs to the LCD cell.

Backlight unit
The BLU is comprised of the following: light sources, light guide plate (LGP), and optical sheets such as reflection sheets, diffusion sheets, and inverter for CCFL light sources (DiFeng 2005; Kobayashi et al. 2009). The BLU drives GWP during production, use, and disposal phases, though disposal is not well quantified. While use impact is driven by the amount of electricity consumed by the backlight bulbs, production impact is driven by the materials and manufacturing associated with backlight type, number of bulbs/diodes, arrangement of backlight, and LGP. The following paragraphs discuss the tradeoffs between bulb type, arrangements, and material requirements.

Light sources
Light sources include CCFL, hot cathode fluorescent lamps (HCFL), external electrode fluorescent lamps (EEFL), flat fluorescent lamps (FFL), magnetically coupled electrode-less lamps, mercury-free fluorescent lamps, inorganic EL, field emission, and inorganic and organic LEDs. Not all of these may be used currently for laptop applications. Traditionally, CCFLs were the most commonly used technology in laptops and monitors, though inorganic LEDs are rapidly replacing this technology and are now favored in laptop applications (DisplaySearch 2006; Kobayashi et al. 2009). LEDs are gaining market share over CCFL though the technology is not yet fully mature.

There are no known quantitative LCAs for laptop backlights, though various studies have investigated specific life cycle phases or investigated bulbs and diodes used for ambient lighting, which may be used as a proxy for backlight bulbs and diodes. In this case, it would be important to know how ambient lighting bulbs and diodes differ in production processes, materials, use, and disposal impacts. For instance, whether the semiconductor processing and substrate material the same for lighting LEDs as backlight LEDs.

Chien 2008 evaluated the environmental performance of CCFLs, noting the high efficiency of light output, contrasted with high operation voltages, fragility, lengthy wait for full flux (about 10 minutes) and the use of poisonous substances, such as mercury. This study noted that LED technology is replacing traditional CCFL in LCDs due to "large color gamut, color temperature adjustability, long durability, and environmental safety", i.e., mercury-free (Chien 2008).

One study of interest on lighting was performed through the EPA in 2005 (Slocum 2005). Due to lack of publicly available data and the multitude of materials choices and designs still being considered for LED-SSL backlight technology, this report evaluated LED ambient lighting technology compared with incandescent and CFL ambient lighting as proxies for BLU technologies. The study identified potential significant environmental impacts of LEDs, focusing on ecological and human health metrics (2005). The physical product of an LED is made of fewer primary materials than a CCFL. LEDs are compact sources of light and are made on chips on the order of 0.5 to 2.5 mm^2 (Slocum 2005). However, semiconductor manufacturing for LEDs is a highly energy-intensive process (Slocum 2005). Semiconductor substrates of silicon, used in the computer industry, can be grown as large-diameter wafers of 12 inches, but the substrate materials for LEDs are more difficult to grow while maintaining a low defect density, and are therefore two, four or six inches in diameter (Slocum 2005). LED chips are manufactured with compound semiconductor materials such as aluminum gallium indium nitride (AlGaInN) (Slocum 2005). The process requires highly controlled steps using techniques such as molecular beam epitaxy (MBE) and metal-organic chemical vapor deposition (MOCVD). The epitaxial growth of LEDs in MOCVD reactors is currently the most demanding and costly processing step, with much lower yields (~60%) than in the more mature silicon-chip industry (Slocum 2005). More information specific to LED chip manufacture can be found in Slocum 2005.

Since few data are available for semiconductor manufacturing energy requirements, Slocum approximated it using a 32 MB DRAM chip from the oft cited study by Eric Williams et al. (Williams et al. 2002). She compared its production and use impacts with those for CFL and incandescent lighting, as shown in Figure 12. The production energy for one SSL-LED lamp was much higher than that for the other lights. Though this analysis was for ambient lighting bulbs and DRAM was used as a proxy for LEDs, the results may inform our hotspot analysis for laptop backlights. For instance, the high-purity materials required for semiconductor processing should be evaluated, though it would be expected that on life-cycle basis, LEDs demand less energy than the other two lamps (Slocum 2005).

	CFL	Incandescent	LED-SSL
Input Power (W/lamp)	15.0	60.0	7.5
Flux (lm/lamp)	900	730	1500
Luminous Efficacy (lm/W)	60	12	200
Lifetime (hr)	8,000	1,000	20,000[1]
Required luminous service (lm-hr)	1,000,000	1,000,000	1,000,000
Number of hours lamp is used to provide required service (hr/lamp)	1,11	1,370	667
Number of lamps used to provide required service	0.14	1.37	0.03
Energy consumed in use, based on required service (kWh)	16.67	82.19	5.00
Production energy for 1 lamp unit (kWh)	1.4	0.15	11.5
Production energy of lamp, based on required service (kWh)	0.19	0.21	0.38
Total Energy (kWh)[2]	16.86	82.40	5.38

Source: (Gydesen, & Maimann, 1991); Author's calculations.

[1] A conservative estimate for the lifetime of SSL device is assumed, because of the uncertainty regarding the lifetime of lamp and luminaire components, besides the LED chip.

[2] The energy estimates do not imply these values are accurate to four significant digits. As discussed in the text, values should be considered to be order-of-magnitude only.

Figure 12. Energy demand of manufacturing and use for three lamp types (Reproduced from Slocum 2005)

An OSRAM study compared the life cycle performance of ambient lighting technologies, including a conventional light bulb (40W GLS), a CFL lamp (8W CFL Dulux Superstar), and an LED lamp (8W Parathom). The LED process inventory included the LED chip, housing, and necessary transports. These LED data were collected at OSRAM Opto Semiconductors, while data for the incandescent and CFL lamps were taken from two other studies on behalf of OSRAM. Other process and raw materials data were taken from the GaBi database, literature, or ecoinvent. Front-end LED process flows included epitaxial growth of the LED structures on a sapphire substrate via metal organic vapor phase epitaxy, various metallization and lithography steps, and the replacement of the initial substrate with a carrier substrate before chip separation. Backend processes included deposition of the LED chip into a leadframe, wire-bonding, and phosphor and lens deposition (OSRAM 2009). The functional unit was 25,000 hours of light and assumed 100% yield. Based on these assumptions and data, the study determined that LED lamps need less than 2% of their life cycle energy for their production and dismissed any concern over LED production being very energy-intensive, as shown in Figure 13 (OSRAM 2009). Results for GWP mirror those for energy demand, and are shown in Figure 14. The results for the LED lamp are driven by aluminum as a heat sink and the ballast, which are energy-intensive in production and use, respectively. Drivers of CFL impact are the PWB and power-consuming

processes (OSRAM 2009). Production of an OSRAM Golden Dragon Plus LED requires about 0.4 kWh of electricity, while a Parathom LED lamp that includes six LEDs requires 9.9 kWh. Because this study analyzed ambient lighting bulbs, not backlights, the semiconductor, heat sink, and ballast technology should be further investigated.
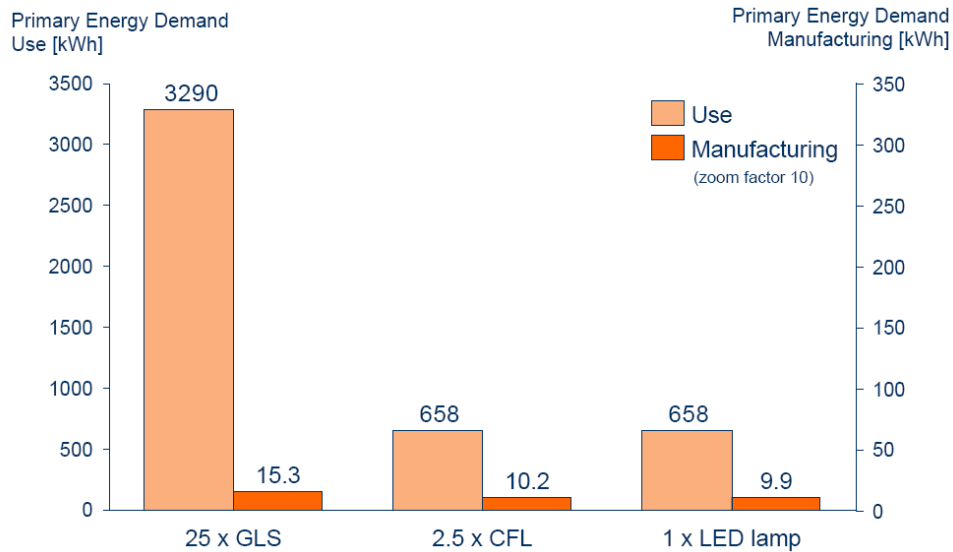

Figure 13. Primary energy demand of manufacturing and use for three lamp types (Reproduced from OSRAM 2009)
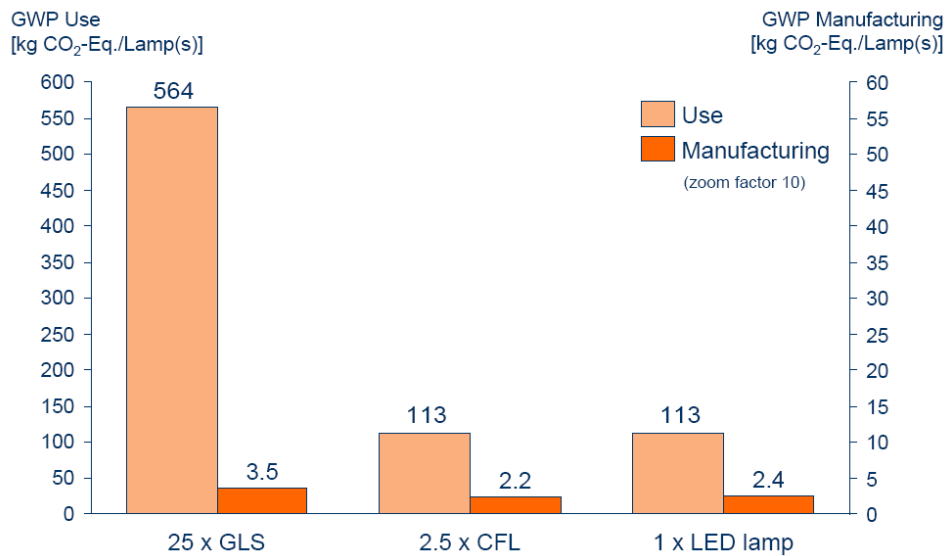

Figure 14. GWP of manufacturing and use for three lamp types (Reproduced from OSRAM 2009)

Because 100% yield is not realistic in semiconductor manufacturing, the OSRAM study performed a sensitivity analysis around yield assuming a worst case scenario (40% in frontend production and 80% in backend). This scenario increased the energy demand from 9.9 kWh to 12.6 kWh, which made no difference in the final outcome of the LCA (OSRAM 2009). Apart

from bulb type, another consideration for backlight environmental impact is the arrangement of the bulbs, usually chosen in conjunction with light-guide plate geometry. There are two ways LED components tend to be arranged:

- Edge light "indirect" arrangement generates a very thin and uniform BLU (1 to 10 mm); LEDs are located at the side edges of the LGP. Edge type is the most common arrangement for laptops and monitors.
- Array backlight "direct" arrangement results in a thicker BLU (25 to 40 mm) and is practically unlimited in terms of diagonal because LEDs are arranged in a dense array behind the display.

The IPS TFT structure requires more backlights to meet brightness requirements (e.g., eight CCFL bulbs instead of four for TN) (USEPA 1998; DisplaySearch 2006).

To retrofit a CCFL-lit BLU with LEDs, the BLU architecture can remain almost identical, with the addition of a PWB strip for the diode base. Up to 154 diodes may be used (Kobayashi et al. 2009). For the edge light arrangement, twenty (for screens less than 7") or more (for screens greater than 12") LEDs are used to provide uniform luminance for LCD (Chien 2008). LEDs have the advantage that if consistent LED packing density is maintained, the luminance remains constant for all backlight unit sizes (Kobayashi et al. 2009). Socolof et al. estimated that a typical CCFL backlight contains four bulbs.

Trends

- **LEDs are replacing CCFLs in laptop backlights** LEDs can achieve the same luminance with less power (Kobayashi et al. 2009). It is unclear whether the direct or the indirect LED arrangement is environmentally favorable. LEDs are replacing CCFLs in laptops because of heat issues (MSL LCD site visit, August 2010). AUO plans to introduce LED backlights to 100% of laptops by 2011 (AUO 2009).
- **Improved technology is allowing the reduction of bulb quantity** for certain varieties of screens (AUO 2009)
- **CCFLs will evolve to be longer to accommodate larger diameter displays**. They will also evolve with a wider color-gamut, higher luminance and higher luminous efficiency (Kobayashi et al. 2009).

Optical components

The optical components of backlights include the lamp reflector, the LGP, and the optional diffuser (Kobayashi et al. 2009). The light guide plate and diffuser will be discussed in greater detail below because they are typically made of PMMA which has a high material production GWP.

Light guide plate

Market demand for thinner, lighter and brighter BLUs has spurred innovation of LGPs which distribute a light source to the full screen area (DiFeng 2005). The LGP is often paired with a brightness enhancement film, or prism sheet, to enhance luminance (DisplaySearch 2006).

For these thin, edge-lit arranged BLUs, the LGP functions as an optical device that converts a linear light source (from CCFLs) or some point sources (from LEDs) into an area of uniform light. The light rays are incident on one side of the LGP and reflect internally. An array of etched or ink-printed white spots at the bottom of the LGP causes the rays to reflect and refract. Once the light is emanated from the top surface of the LGP, the diffusion sheet disperses and evens out the light. LGP research is underway to maximize these performance criteria with minimal LGP material. LGPs are produced in both flat- and wedge-type varieties (Kobayashi et al. 2009). Laptops mostly use wedge type.

Research has proposed a uniform LGP for LCDs with the goal to overcome heat, shadow and illuminative uniformity problems. It would enable incident light to be distributed uniformly to the BLU and enhance optical efficiency of output. This design could decrease the required number of LEDs and achieve demand for illuminative uniformity (Chien 2008).

The LGP is the heaviest part of the BLU, accounting for 15-20% of the weight (DisplaySearch 2006). They are typically made by injection molding or cast molding PMMA, which has a high GWP associated with high energy of production (Kobayashi et al. 2009; ecoinvent 2010). Injection molding is a highly productive method, whereas cast molding is less productive (Kobayashi et al. 2009). Plastics Europe has been unable to collect sufficient current plant data and therefore no longer has a PMMA profile online (Schanssema 2010). Additional data collection is needed on PMMA production impacts. Compared with PC, PS and COP, PMMA has superior optical properties (93% optical transmission) and is by far the favored material for performance (Kobayashi et al. 2009). PMMA is also highly durable against UV exposure and is cited to have reasonable lifetime (Kobayashi et al. 2009).

DiFeng proposes a LGP made of PMMA based on micro-prism structures designed to control the illumination angle, which results in a thinner and brighter backlight system because other optical sheets are not required (DiFeng 2005).

The choice to design with a LGP is coupled with arrangement of the light source. For edge arrangements, a light guide is necessary. A direct backlight arrangement may not use a LGP but requires diffusive sheets between the light source and the LC panel (Kobayashi et al. 2009). An alternative to a LGP is a cavity to produce vertical uniformity when LEDs are placed at both the top and bottom sides of the display.

Diffuser plates

Diffuser plates are necessary in many laptop BLUs to convert point light sources or line light sources into a flat light source. Diffusers are often made of PMMA, like the LGP, and therefore face the same high GWP of production. Other potential materials include MS, MMA, PS, PC and COP, but like the LGP, PMMA is the favored material due to its high optical qualities (Kobayashi et al. 2009).

Printed wiring boards in LCDs

An LCD requires at least one PWB to function. Socolof et al. identified six PWBs for an LCD, including controller, row driver, column driver, power supply, backlight, and adjustment knob PWBs (Socolof et al. 2001b). The major PWBs, by size and function, are the controller and backlight PWBs. The column and row PWBs are relatively small.

Energy used to manufacture PWBs has a significant impact on the GWP of the entire life cycle. In terms of estimating the GWP of PWBs, it will be important to know the quantity of PWBs (probably between 1 and 6), the total area of PWB, the number of layers, and the surface type.

Integrated circuits in LCDs

The ICs in LCDs supply voltage levels that control the liquid crystals. They are categorized as:
- **gate** (or **row**) driver IC: switches the TFT on and off, thereby activating the rows of the display (DisplaySearch 2006).
- **source** (or data or **column**) driver IC: provides voltages that control gray scale levels (DisplaySearch 2006) in the activated row. Source drivers supply video data signals to data lines connected to the source of TFTs at each pixel of an LCD (Patentdocs).
- **controller** IC: used to coordinate the timing of the row and column drivers and provide a constant stream of display data to the column drivers. The controller may also modify the display data to enhance the image quality (EEtimes.com).

The number of ICs used in a LCD may vary. There is a relationship between the resolution/screen size and the number of ICs (DisplaySearch 2006). Larger displays require several row driver ICs, several column driver ICs, and a controller IC. Small displays may accommodate all three on a single chip, such as the Isron device (EEtimes.com). The IS2341 IC is an example of combining row and column drivers in a single component at a small process mode. ICs may be mounted directly onto the glass of the display to reduce the complexity of manufacturing and reduce display. This eliminates the need for a surrounding IC package (EEtimes.com).

A list of major components for a disassembled 15" laptop manufactured in 2005 is shown in Table 14. The identification number had been removed from the board. The housing size was measured using a caliper. The die-to-package area ratio was calculated by the research team (Environmental Assessment of ICT Products, Display Data) for a series of logic and memory ICs. The research team calculated the die area based on the aforementioned ratio. The potential function of each IC was researched on IC manufacturer websites and in academic literature. The pin count was based on observation and the mask count was based on pin count, using mask count ratios provided in GaBi documentation (PE International GmbH 2006).

Table 14. Components identified from disassembled Dell Latitude D600 from 2005

ID #	Estimated Housing type	Housing area (mm^2)	Die area: package area	Die area (mm^2)	Possible function	# pins	# masks (GaBi)
Board with LCD inverter							
U2	SO	18.80	20%	3.76	CCFL brightness control	8	2
U1	SSOP	27.50	20%	5.50	CCFL backlight driver	20	3
T1			20%		LCD inverter		
Board running across length of screen drivers							
IC3	SSOP	21.60	20%	4.32	Driver IC	16	2
IC4	TSOP	13.42	20%	2.68	Driver IC	8	2
IC6	SSOP	64.45	20%	12.89	Driver IC	14	2
	TQFP	192.38	20%	38.48	Controller IC	100	13

Metal frame

The metal frame (or bezel) of the LCD is of low priority in terms of GWP. If we were to quantify its GWP, it would be important to know whether the material quality is high, medium or low; whether steel is used (steel production, cold-rolled, semi finished is relatively burdensome) and where the steel and frame were produced to resolve uncertainty around the electricity grid mix.

Use

The display subsystem accounts for 30% of the power consumed in a laptop (Horowitz 2003). The backlight is responsible for high power dissipation, accounting for 90% of LCD power consumption (EuP 2007; Kobayashi et al. 2009). This high power demand motivates the push for modern and efficient technology, including use of LED backlights over other lighting options.

Some LCDs almost always have a backlight running. To create a black screen, the display may simply block pixels to prevent light from getting through (EuP 2007). Therefore, the notion that power consumption is linked to resolution may have been true for CRTs, but may not be true for LCDs. Rather, power consumption is correlated to screen size because of the way the picture is delivered to the screen (EuP 2007).

Horowitz 2003 considers laptop displays fundamentally inefficient. He estimates that perhaps only 1% of energy drawn from an outlet in the wall is actually available as information on the display. Horowitz proposes the use of the metric *pixels per watt* to evaluate monitor efficiency. A wide range of monitor efficiencies is found among laptops, from 27,000 pixels per watt to 186,000 pixels per watt (Horowitz 2003). Power consumption estimates by LCD screen size for from a TCO study are provided in Table 16 (EuP 2007).

When comparing CCFL and LED backlights for LCDs, it is generally understood that LEDs consume less energy than CCFLs (Slocum 2005). In addition, LEDs deliver light more efficiently to small areas, result in less 'overglow' than CCFLs, and are considered more rugged and durable (Slocum 2005). In an experiment evaluating energy consumption, two identical 15.4" laptops equipped with either LEDs or CCFLs were compared. Both achieved a maximum luminance of 180 cd/m^2, with uniformity of 80%. The color gamut was comparable at about 40% of NTSC. However, the LED outperformed CCFL, using 1.5W versus 3.37W at 60 cd/m^2. The implications of this are extended battery life and energy savings for the consumer, as well as reduced GWP (Kobayashi et al. 2009). Slocum determined that as of 2005, LEDs had the potential to provide up to 200 lm/W, though in their current state provided 25-40 lm/W, which is less efficient than fluorescent technology at 55-90 lm/W, see Figure 15 (2005). Increasing use of LED technology will drive its efficacy.

Lighting Technology		Efficacy (lm/W)
Incandescent		13-25
Fluorescent		55-90
HID		25-124
SSL	Current	25-40
	Potential	150-200

Figure 15. Lighting technology efficacies (Reproduced from Slocum 2005)

An important consideration for LEDs is that the luminous output gradually depreciates over time. Therefore, end-of-life tends to be when the LED reaches 50% of its initial luminous output (Slocum 2005). There are minimum luminance requirements, of course, depending on the display function. Luminance may be at least 1900 cd/m^2 with a single CCFL bulb. If DVDs or other visuals are to be enjoyed, at least two bulbs are necessary to produce 3600 cd/m^2 (DisplaySearch 2006). For an LED BLU, it is recommended that the luminance level on an LCD screen be between 200 cd/m^2 for monitor applications, with a brightness uniformity of at least 85%. A color gamut greater than 100% NTSC must be achieved (Kobayashi et al. 2009). For the LED backlight of a 32-inch LCD panel, 150W ought to be the maximum power consumption, comparable to a CCFL LCD. The key is to minimize the number of LEDs to minimize failures in time and reduce power consumption. LED lifetime may well exceed CCFL, reaching 50,000 hours. One experiment reported LED power consumption of 190mW (and 30W for all 154 LEDs) for a retrofitted 19-inch LED LCD monitor.

The power mode categories defined by ECMA 2009 for integrated computers are listed below. It is not necessarily the case that LCD power consumption will adjust proportionally to overall laptop power consumption. For example, during laptop idle mode when overall laptop power consumption decreases, the backlight is probably still producing light although the pixels are blocking the light from being emitted. For this reason, it is likely that LCD power consumption stays fairly consistent through the laptop's active and idle modes. Further research in this area is needed. Laptop power mode categories are listed below.

- Disconnect: no power sources
- Off: lowest power mode that cannot be switched off; correlates to ACPI system level S5 state (ECMA 2009)
- Sleep: reduced power state; lowest mode entered automatically after a period of inactivity or manual selection; computer returns to on-mode with full operational capacity upon sensing a request from the user/computer (EuP 2007); correlates to ACPI system level S3 or S4; Wake on LAN capability disabled (ECMA 2009)
- Wake on LAN Sleep: same as Sleep mode (above) but with the Wake on LAN capability enabled.

- On: when not in Sleep, Off or Disconnect modes; has several sub-modes including Long Idle, Short Idle, and Active mode.
- Idle: operating system and software have loaded and product is not in Sleep mode. Includes:
  - Short Idle: 5 minutes after OS boot, screen is on and set to as-shipped; brightness and long idle power management features should not have engaged.
  - Long Idle: 15 minutes after OS boot, screen has just blanked but remains in working mode (ACPI G0/S0). Power management features should have engaged but product is prevented from entering sleep mode (ECMA 2009).
- Active: product is carrying out work, including active processing, seeking data from storage, memory or cache; connected to a power source and producing image on screen, producing brightness as set to.

For on-mode power for LCDs of various screen sizes, see the Energystar 2007 database (EuP 2007). Table 15 shows approximate maximum, average and minimum power consumption for LCD monitors. It should be noted that this probably refers to stand-alone monitors with CCFL backlights.

Table 15. Power consumption for displays in on-mode (Reproduced from EuP 2007)

		Power [W/m^2]		Power [W/MPx]	
		CRT	LCD	CRT	LCD
Max		1087	617	92	214
Average		760	290	52	23
Min		281	184	20	12

Table 16 shows power demand for best-selling LCDs in 2005. We assume that these LCDs are stand-alone displays and not integrated modules. This distinction is important if we consider that stand-alone displays often use CCFL backlights and may be built to be more robust than an integrated display, which is designed for portability and commonly houses LED backlights. For this reason, the power consumptions listed below are likely to be higher than those for an integrated LCD. The large range of values across these studies for various power modes motivates further resolution into the drivers of this demand and the role of the LCD.

Table 16. LCD power consumption estimates (Reproduced from EuP 2007)

Data Sources		IVF summer survey			Product Case Data Sets			TCO 2005 data 17" LCD			TCO 2005 data 15" LCD		
Operation -al Modes (W)	**FU**	**Ave**	**Max**	**Min**	**Ave**	**Max**	**Min**	**Ave**	**Max**	**Min**	**Ave**	**Max**	**Min**
Active	Display	39.9	70	30	31.4	N/A	N/A	25.9	47	17.1	16.4	21.3	12.9

Active	m^2	415	604	330	345	N/A	N/A	285	526	191	236	306	185
Active	Mpixel	28.5	39.7	22.9	23.9	N/A	N/A	21.5	59.8	13.7	20.9	27.1	16.4
Sleep	Display	1.2	2	0.7	0.9	N/A	N/A	1.1	4	0.5	1.0	2.1	0.7
Sleep	m^2	13.2	22	7.1	10.3	N/A	N/A	12.4	44	5.3	14	30.1	9.6
Sleep	Mpixel	0.9	1.5	0.5	0.7	N/A	N/A	0.9	3.1	0.4	1.2	2.7	0.9
Off	Display	1.1	2	0.7	0.8	N/A	N/A	1.0	3.0	0.5	0.9	1.2	0.6
Off	m^2	11.7	22	7.1	9.2	N/A	N/A	11.4	33.6	5.2	12.2	17.5	8.6
Off	Mpixel	0.8	1.5	0.5	0.6	N/A	N/A	0.9	3.8	0.4	1.1	1.6	0.8

Trends
- **Use of organic light emitting diodes** (OLEDs) may bypass [inorganic] LEDs and CCFLs altogether. OLEDs create light efficiently and directly from each pixel instead of lighting a crystal. They did not have the operating lifetime to be marketable in laptops at the time of the Horowitz 2003 report
- **A potential energy saving strategy** may be to design the backlight unit to reduce standby power draw of the backlight (Samsung 2010)

EoL

Laptop (and therefore LCD) EoL varies by geographic region and policy. EoL options include reclamation for refurbishing and reuse, reclamation for recycling of materials, landfilling, and incineration.

Some members of the laptop industry have instated take-back programs, such as Samsung's Global take-back program (Samsung 2010). Changes in processing requirements may begin to influence the way laptops are disposed of and recovered (Lee 2008). The European Union's Waste Electrical and Electronic Equipment (WEEE) Directive and Restriction of Hazardous Substances (RoHS) Directive are two existing and influential policies that increase recycling of e-waste and encourage green design (Lee 2008). Also, the USEPA and the American Plastics Council define or regulate electronics waste in the United States (Noon 2009). Efforts are underway to design LCDs with EoL impact in mind. Such efforts include research to relate the dimensions of an LCD to its impacts so that designers can facilitate recycling and reuse of products (Lee 2008).

For the most part, laptops have not been designed with reuse/recycling in mind (KCSWD 2007). One LCD recycler reported that there was no method to recover glass and liquid crystals from LCDs so the entire module must be shredded. Another recycler reported sending screens to a primary smelter in Canada for materials recovery (KCSWD 2007). Tavares et al. discuss LCD separation aimed at recycling and point out that it is the plastic between the glass substrates which makes it difficult to recycle the glass. In fact, separation requires a grinding process, which includes coil, disk, balls and hammer mills. However, coil and disk mills cannot complete this separation and are therefore not viable processes for recycling. Only a hammer mill has an

efficiency of around 98% completion. Lee also cites panel glass recyclability as a key area requiring improvement (Lee et al. 2009a). In addition, the King County Literature Review describes the small and inaccessible fasteners on a typical FPD, including clips, screws and adhesives, making disassembly challenging. The design and location of these fasteners differs by manufacturer and makes it difficult to create a standard disassembly method (KCSWD 2007).

Due to concerns over impacts, reuse and recycling are the preferred EoL management strategies in Washington State (KCSWD 2007). Figure 16 shows LCD monitor EoL processing based on a study in Seattle, WA (Lee et al. 2009a). At the time of this study, the LCDs collected at EoL as part of Seattle's 'Take it Back' Network were not disassembled, though 40-70% were refurbished for reuse/resale. The remaining 30-60% were sent by the handler to a processor (along with the majority of CRTs, for which there is little demand for reuse) (Lee et al. 2009a). For the LCDs that were processed, PWBs were reused or smelted overseas, CCFLs were recovered on site, the LCD panels were sent to a plastics recycler or metal smelter, aluminum was sent to a local broker, mixed plastics were sent to a plastics recycler locally or in China, ferrous metals were sent to a local steel mill, copper was sent to an overseas smelter, and removable plastic components were sent to a local plastics recycler or to one in China.

End-of-life impact of backlight bulbs is considered extremely small (~0.1% of the primary energy demand over the life cycle) (OSRAM 2009).
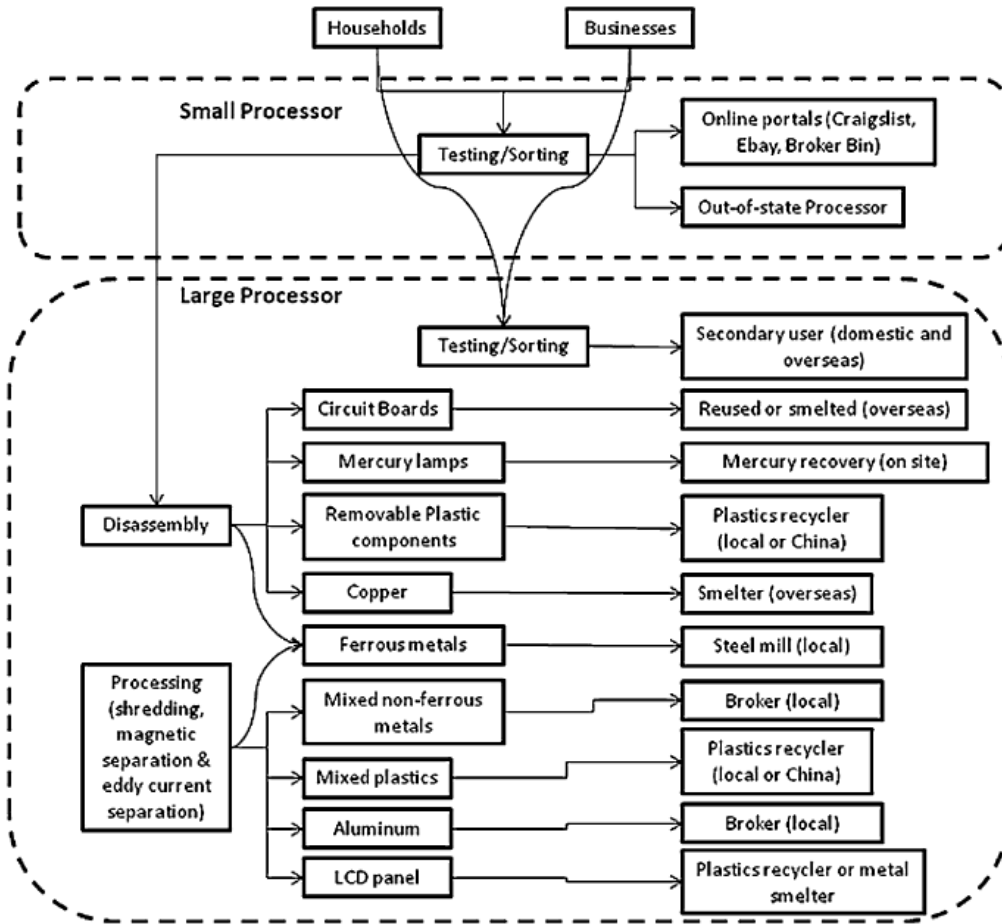
Figure 16. LCD monitor processing in Seattle, WA (Reproduced from Lee 2009a)

The King County Solid Waste Decision (2007) evaluated EoL management of FPD devices, including laptop LCDs. For AM-LCDs, the components most likely to fail and limit the lifetime of the machine are the display, LCs, TFT, backlight, driver IC, tabs and other small components. Failure of LCs and transistors would require replacement of the entire display panel, while the BLU and IC tabs could be replaced readily. It is estimated that LCD monitors have a lifespan 3.6 times that of a CRT.

EoL considerations for backlights include whether LED or CCFL lighting technology is used. For instance, the projected longevity of LEDs (up to 100,000 hours) could extend the lifetime of the lighting system and reduce the quantity of spent lamps (and therefore materials) entering the waste stream (Slocum 2005). In addition, LEDs simply require less physical product using fewer materials, and therefore could be expected to reduce the waste stream of spent lamps (Slocum 2005).

Summary of Future Trends in LCDs

Anticipated changes to process or product materials include (MSL 2010a):

- Slim and light design: cascade, polished glass, glass center turn-key solution
- Power saving total solution: ambient light sensor, dynamic blight control, dynamic refresh rate, fly-cut LGP
- Style: slim border cell technology, a:Si gate
- Touch panel: integrated TP, external TP
- Advanced technology: three-dimensional display, MEMC, display port

Anticipated/occurring environmentally significant changes in process materials:

- None (MSL 2010a)
- To reduce PCF and SF_6 emissions, the member nations of the World LCD Industry Cooperation Committee (WLICC) are investing effort into emissions reduction. Member companies, including, AUO, started designing plants in 2003 to install a PFC abatement tool with a removal rate of over 90% (MSL 2010b)
- Encouragement of suppliers to use renewable energy (AUO 2009)
- GHG emissions and water per substrate quantity reduced (AUO 2009)
- Increase of the recycle and reuse rate of the packaging materials for semi-finished products (AUO 2009)
- Production weight reduction
- Product disassembly time improvement

Anticipated system-level technology changes (e.g. integrated technologies):

- Development of carbon footprint verification e-system to collect supplier data to improve verification efficiency (AUO 2009).