Environmental Assessment of Information Technology Products Using a Triage Approach

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Abstract
There is growing need for effective and efficient environmental assessment tools for information technology (IT) products. This paper presents a streamlined life cycle analysis (LCA) methodology using a screening and triage approach. The methodology is applied to the case study of liquid crystal displays (LCDs). Global warming potential uncertainty is reduced by identifying and resolving uncertainty around key drivers of impact. The resolution of impact continues until a meaningful level of reduction of uncertainty is achieved, such as the ability to discriminate one class of LCD from another.

Problem addressed
Information Technology (IT) product design decisions have traditionally been driven by market demands and performance criteria and have not directly considered environmental performance. Recent and increasing external pressures on original equipment manufacturers (OEMs) have led to extensive corporate interest in "carbon footprinting" or life cycle assessment (LCA) of products for consumer-facing indices. These pressures generate interest, on the part of OEMs, to create a platform that provides a "level playing field" from which products can be measured. Developing such tools to assess the environmental performance of IT is critical to address the impact of these products and to inform design improvements.

The environmental assessment of IT is challenged by the complexity of the products (i.e., thousands of components), the specialization of the processes, as well as the high turnover rate of manufacturing process flows and supply chains. These factors lead to significant uncertainty and variability in environmental assessments or, conversely, drive high costs to address these uncertainties. These issues have motivated more streamlined or flexible methodologies in order to reduce cost compared to traditionally resource-intensive LCA. This paper discusses ongoing work of a consortium of IT industry, academia and governmental/non-governmental organizations, convened to develop methods that reduce the cost of environmental assessment for IT products. These cost-reducing goals include reduced data collection, reduced analytical effort by using a tool, and reducing reporting requirements by harmonizing disparate standards.

Knowledge of prior work
The relevant prior literature and work in the field on this topic is several fold. Providing convergence or harmonization among existing and emerging standards provides one primary motivation for the participating companies in this effort. Therefore, the methodology development is informed by standards in this area such as those from the British Standards Institute, the International Standards Organization, and the World Resources Institute/World Business Council on Sustainable Development [1-3].

Due to the resource intensity of LCA and the dynamics of IT, streamlining the environmental assessment process is of great interest to participants in this project. Numerous approaches have been proposed to streamlining that reduce the information burden of data collection. One class of simplifications is the use of qualitative information to rank the impacts of each life cycle (LC) activity (generally against some benchmark) demonstrated by the Environmentally Responsible Product Assessment [4] which employed a matrix approach to streamlining. Other authors have proposed the use of publically available data, pay-for-use databases, expert opinion to eliminate or reduce the data collection for specific life-cycle stages, or screening assessments [5-7]. The method described herein attempts to fill the gaps left by these approaches: 1.) qualitative methods do not seem satisfactory to meet labelling requirements; 2.) use of proxy data introduces uncertainty and previous discussions do not comment on whether the uncertainty is too great, undermining the purpose of the analysis; and 3.) previous studies have not specifically explored the extent to which secondary data is acceptable.

Project undertaken

The approach developed here (described in more detail subsequently) uses a high level analysis, based on existing data and its uncertainty, to triage life cycle phases and product components for further data collection and refinement. Therefore literature describing uncertainty and variation methodology provides further foundation for methodology development. The approach aggregates comparable, relevant data [8-9] with temporal and spatial uncertainty and variation.

This work aims to develop a near term, quantitative approach for labeling/environmental performance evaluation that resolves the global warming potential (GWP) among product types (as opposed to SKU level specificity) for IT products. The initial case focus has been laptops and, therefore, the major subsystems of a laptop. This paper focuses on the methods used to identify and target key drivers, and thereby minimize data collection, through a triaged approach that incorporates uncertainty. The results of the triage are then used to develop algorithms that determine changes in environmental performance based on relevant attributes. The method will be demonstrated with a case study on liquid crystal displays (LCDs), a key contributor to overall laptop environmental performance.

Research methods

Our streamlining methodology for laptops includes two major steps that serve to prioritize the data collection process and minimize the inputs of the user: a.) probabilistic triage of all drivers followed by targeted refinement, to inform b.) the creation of regressive relationships between key characteristics of the product mapped to environmental impact [8]. This paper focuses on our research approach for the probabilistic triage step.

A triage begins with a screening assessment, leveraging existing LCAs, commercial LCA databases, published academic literature, and existing data within industry, to create the best available estimate of environmental impact for the product of interest – laptop LCD. Three types of information are essential: a.) data on processes associated with LCDs, b.) a bill of activities (BOA) for LCDs, and c.) uncertainty of both. With this information we create a Monte Carlo simulation model of the impact of the product. A targeted refinement of the uncertainty around the most impactful drivers is then performed through focused, strategic data collection. This step results in reduction of the coefficient of variation (the mean-normalized standard deviation or COV) by determining those factors where data improvement provides the greatest leverage in resolving impact. These factors are identified and prioritized by magnitude of the Rank Order Coefficient (ROC) assigned by the Monte Carlo model, which is based on the sensitivity of the overall impact to changes in the activity. Factors are also selected for targeted refinement based on the practical feasibility of data gathering for that activity. Figure 1 is a schematic representation of the progression from high uncertainty associated with initial screening results to reduced uncertainty through targeted data collection and information provided by the user.

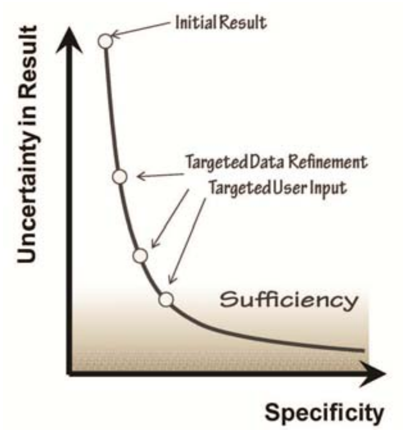


Figure 1. Targeting data and input around hotspots efficiently reduces uncertainty of result

We resolve areas of uncertainty until we are able to discriminate with a meaningful level of accuracy the alternatives that are being considered. The pertinent alternatives will depend on the question being asked of the assessment. The theory of this analysis can be represented with probability density functions of GWP for LCD options, *A* and *B*, which represent, for example, the impacts of a 13.3” LCD and a 14” LCD, where μ_B is greater than μ_A based on our model results. We can infer that *A* is the environmentally preferred option over *B* a majority of the time, though with some error rate because the two populations are not completely distinct. This error rate, or false signal (FS) rate, is represented by the area of overlap, indicated by *FS* in Figure 2.

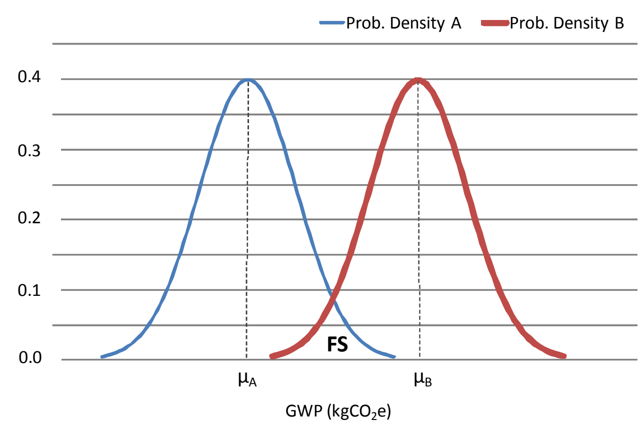


Figure 2. False signal rate represented by area of overlap for two LCD probability density functions

The formulation for this false signal rate is expressed in Equation (1). A low FS rate is necessary if we wish to accurately discriminate products based on environmental performance. The research team has set a target threshold of 10%.

$$false\ signal\ rate\ (FS) = P(B < A) \quad (1)$$

The false signal rate can be derived directly from the Monte Carlo simulation results by comparing scenario pairs *A* and *B* where μ_B is greater than μ_A and calculating *P*(*B*<*A*). With some simplifying assumptions, an analytical solution can be derived. There is a body of literature to calculate *P*(*B*<*A*) given probability models with normal, beta, exponential, gamma, couchy, and Weibull distribution [10-11]. Based on the mean and COV of *A* (μ_A and COV_A), the necessary distance between μ_A and the other population's mean, μ_B, can be derived, given that the distributions resemble, or can be transformed to resemble, these common probability models.

For example, if *B* is the product against which we are comparing *A*, μ_B is greater than μ_A, the standard deviation of *A* is equal to that of *B* ($\sigma_A = \sigma_B$), and the probability density functions resemble normal functions, we can derive the distance μ_B must be from μ_A in order to discriminate the two populations with false signal rate *FS**. This distance is denoted $k(\mu_A)$. The formulations to calculate *k* based on normal density functions are presented in Equations (2) and (3).

$$FS^* = P(Z = B - A < 0) \tag{2}$$

$$k = \left(\left(\left(\Phi \left(\frac{\left(\frac{(2FS^* - 1) + 1}{2} \right)}{\sqrt{2}} \right) \right) \times -2 \right) \times COV_A \right) + 1 \tag{3}$$

Capital phi (Φ) represents the inverse of the normal cumulative distribution function. The analytical solution is less accurate than direct comparison of scenario pairs, but provides insights into what drives this type of result. In particular, we can see that spacing $k(\mu_A)$ grows linearly with COV and is directly related to *FS**.

Results

We demonstrate this methodology by evaluating simulations for LCDs. For the screening assessment, data was collected from Ecoinvent, PE International, a survey of LCD manufacturers carried out by the research team in 2010, as well as publicly available data from the USEPA and others [9, 12-18]. In our literature review of existing LCD LCA results, we identified environmental hotspot activities to thoroughly evaluate in the model, such as perfluorocompounds (PFCs) used and emitted during LCD array production. Careful consideration of this driver revealed large variability of impact, based on levels of abatement within particular fabrication facilities, as well as the particular PFC gas used. In addition to use and emission of PFCs, attributes and activities identified as key drivers of environmental performance (based on rank order coefficient magnitude) include screen size, number of ICs and area of PWBs, as well as location of production and energy intensity of production. Where uncertainty was not explicitly estimated in our data sources, we estimated it to reflect a realistic range of possibilities.

Using these data and associated uncertainty parameters, we evaluated LCD classes differentiated initially by size: 10.1", 13.3", 14" and 17", where $\mu_{10.1} < \mu_{13.3} < \mu_{14} < \mu_{17}$. We evaluated them in strategic pairs: 10.1" and 17" as the lower bound of resolution required; 13.3" and 14" to demonstrate the higher bound of resolution required; and a middle pair, 10.1" and 14". Figure 3 presents false signal rate results for all pairings of LCD size classes, with the selected LCD size (informed by our modeling results) along the vertical axis and the alternative sizes listed on the horizontal axis. These false signal results do not meet the target threshold of 10% set by the research team as the lowest false signal rate is 24%, for the extreme pair 10.1" and 17". Further resolution of additional impact drivers is needed.

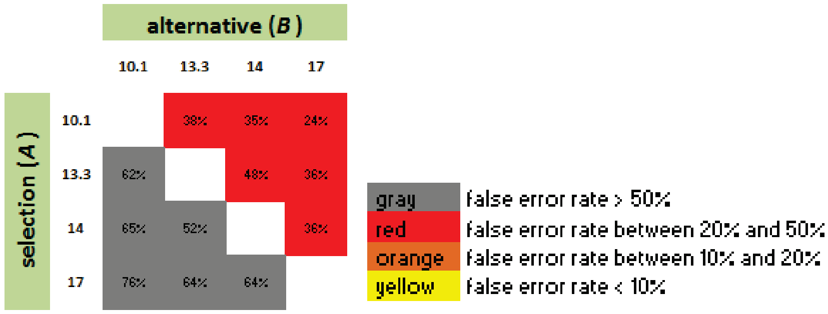


Figure 3. Resolution at screen size alone does not achieve a 10% false signal rate under any scenario

Based on the rank order results of the Monte Carlo simulations, the next key driver to resolve is PFC abatement level in the fabrication facility. We resolve PFC abatement efforts into three levels of granularity: low, medium or high. This level of resolution, in addition to screen size, improves the ability to discriminate with high confidence only for some classes (see Figures 4, 5, and 6). For example, we are able select a highly abated (HA) 10.1" over a medium- or low-abated 14" or 17" LCD, with very high confidence of choosing the environmentally preferred product (<4% *FS**). However, further resolution is required in order to discriminate other scenarios. We will proceed by focusing on the similar pair (13.3" versus 14") as it is the pairing that will require the highest level of resolution (see the circled scenarios in Figure 6).

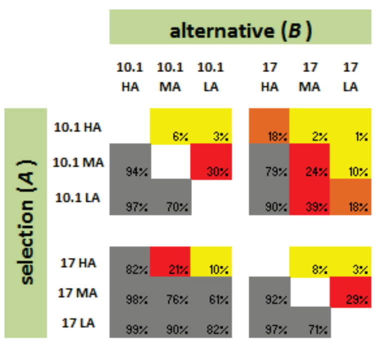


Figure 4. 10.1" versus 17"

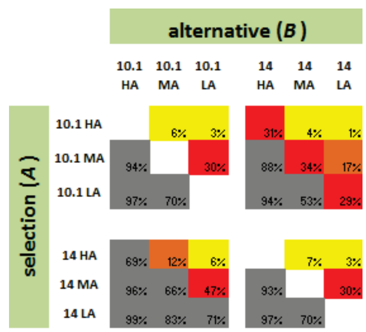


Figure 5. 10.1" versus 14"

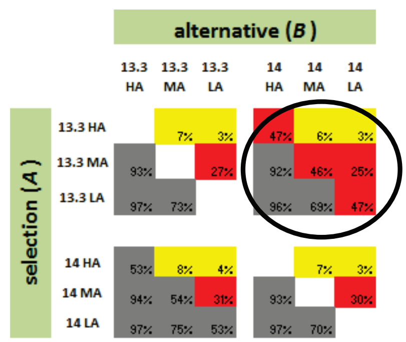
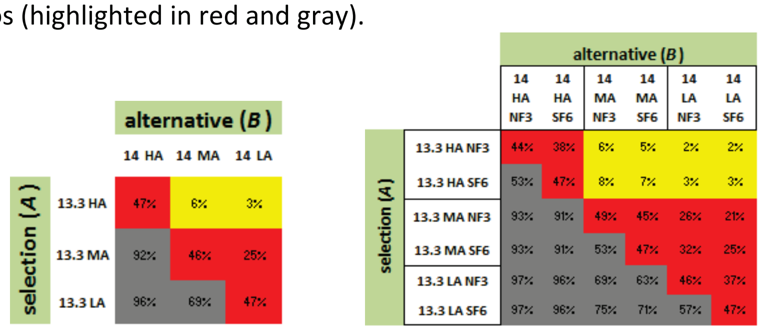


Figure 6. 13.3" versus 14"

We now focus on the 13.3" (*A*) and 14" (*B*) scenarios from Figure 6 and resolve by another key driver which is once again informed by the rank order coefficients provided by the Monte Carlo model. This next driver is PFC type used in manufacturing the LCD array, specifically whether NF_3 is substituted for SF_6, in deposition and etching activities. Figures 7 and 8 demonstrate the progression of resolution from size and abatement level to the addition of PFC type. At this additional level of resolution for the 13.3" and 14" pair under high, medium and low abatement scenarios, we are able to discriminate with high accuracy a 13.3" highly abated LCD from 14" low abated ones (highlighted in yellow), but not under any other scenario. We would need to continue to resolve attributes in order to reduce the false signal for these other scenarios (highlighted in red and gray).



Figures 7 and 8. The false signal rate continues to decrease with the addition of PFC type

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. This paper discusses one element of a larger project to reduce that cost. Specifically, this paper has described the application of probabilistic triage to identify the drivers of impact for LCDs as applied in laptop computers. 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. For the case of the LCD, a probabilistic triage was able to identify several attributes that appear to account for the majority of the variation in the impact that derives from LCD products. Resolving just the three strongest drivers of variance, namely, screen size, manufacturing PFC abatement level, and PFC type, begins to provide significant improvement in the fidelity of an estimate of LCD impact. Further resolution of additional key drivers, such as location of manufacture and use, energy demand of use, and number of ICs and area of PWBs will be needed to discriminate with higher confidence. Clearly, more work needs to be done to determine how many more attributes need to be resolved to lead to an acceptably accurate estimate, but this preliminary result provides promise 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.

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