

# Accepted Manuscript

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PII: S0959-6526(18)31763-3

DOI: [10.1016/j.jclepro.2018.06.113](https://doi.org/10.1016/j.jclepro.2018.06.113)

Reference: JCLP 13259

To appear in: *Journal of Cleaner Production*

Received Date: 20 November 2017

Revised Date: 23 April 2018

Accepted Date: 11 June 2018

Please cite this article as: Marchese DC, Bates ME, Keisler JM, Alcaraz ML, Linkov I, Olivetti EA, Value of information analysis for life cycle assessment: Uncertain emissions in the green manufacturing of electronic tablets, *Journal of Cleaner Production* (2018), doi: 10.1016/j.jclepro.2018.06.113.

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## Value of Information Analysis for Life Cycle Assessment: Uncertain Emissions in the Green Manufacturing of Electronic Tablets

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### ABSTRACT

Optimization of manufacturing processes and practices requires multiple tradeoffs among often competing priorities. This is especially the case for green manufacturing, where meeting sustainability goals often requires the use of more expensive materials and technologies with uncertain effects on product performance. Not only are decisions regarding such trade-offs difficult to make, these decisions often need to be made with incomplete and uncertain information. These scenarios often result in requests for more information, some of which may be irrelevant for the decision at hand. Value of information (VoI), a decision analytic method for quantifying the expected benefit of acquiring additional information, can be used to improve a wide range of manufacturing decisions. By identifying the contribution of specific model parameter uncertainty to total product or decision uncertainty, VoI can prioritize additional data collection and research strategies to optimally reduce uncertainty and support decisions, i.e., those with the greatest “bang for the buck.” VoI has been used in many fields including medicine, ecology, and economics, but is rarely used in manufacturing and has never been applied within life cycle assessment (LCA), e.g., to address uncertainty in product development decisions. This paper discusses the use of VoI with LCA in manufacturing and details a case study in which we calculate VoI related to the lifecycle environmental impact of electronic tablet production. We found that LCA-VoI can be successfully used to triage the data gathering process in electronic tablets, to more accurately describe lifecycle environmental impact. We anticipate future applications of LCA-VoI to lead to more cost-effective and sustainable production.

**Keywords:** value of information analysis, life cycle assessment, green manufacturing, decision analysis

### 1. INTRODUCTION

Due to increasing consumer pressure to be more sustainable, companies are constantly seeking ways to reduce the greenhouse gas (GHG) emissions associated with the material sourcing, manufacturing, transportation, use, and other lifecycle stages of their products (Cheah et al., 2013). Market pressures continue to spur identification of sustainable, or *green* manufacturing processes (Bocken et al., 2011), based on concerns over environmental degradation in the form of biospheric pollution, resource depletion, and overflowing waste sites (Srivastava, 2007; Wang et al., 2016; Su et al., 2016). Although green manufacturing presents a path for industry to overcome some environmental challenges, it is not without hard choices such as balancing profitability against the higher costs of sustainable materials and emissions controls.

The challenges of green manufacturing are especially prevalent in electronics production (Jaber et al., 2013; Teehan and Kandlikar, 2013). Here, GHGs are emitted during material procurement, product manufacturing, product delivery, customer use, and end-of-life processes. Reducing the GHG emissions associated with electronic device production requires a holistic understanding of how each product component and manufacturing process contributes to the total emissions for the device. Life cycle assessment (LCA) includes a suite of methods and databases that can be used to identify the GHG emissions associated with each lifecycle stage of a product. LCA is supported by a strong community of researchers and practitioners and is becoming increasingly important for manufacturers as their products and processes are subjected to stricter emissions regulations and increasing stakeholder concern. Moreover, LCA methods can identify the relative GHG-emission contributions of each component or process of a product (Lankey and McMichael, 2000), and be used in prospective as well as retrospective product-design decisions (Wender et al., 2014). However, few LCA applications directly account for or operate on the uncertainty in the supporting data, and error propagation is often ignored (Gregory et al., 2016).

Value of information (VoI) analysis is a separate technique, with its own community of researchers and practitioners, that evaluates the benefit of obtaining additional information to reduce uncertainty in a specific decision-making context (Lawrence, 2012). These techniques are rooted in statistical decision theory (Howard, 1966; Raiffa, 1993), and are present in applications such as healthcare (Tuffaha et al., 2014; Yokota and Thompson, 2004b), environmental risk management (Bates et al., 2016; Yokota and Thompson, 2004a), oil and gas (Bratvold et al., 2009), earth science (Eidsvik et al., 2015) and engineering, agriculture, and economics (Keisler et al., 2014). VoI compares the anticipated value of making a decision with present information relative to the anticipated value of making that same decision with the benefit of gathering additional information, and pairs those findings with the differing expected costs of information gathering. Among the results of VoI analysis is an identification of additional data (e.g., model parameters) for which resolving uncertainty would lead to the most efficient increase in expected value for the decision maker. VoI results also help decision makers identify when additional information is needed vs. when a decision can be made confidently under the current uncertainty. By performing this analysis, engineers, product and technology developers, risk managers, and research planners can strategically buy down uncertainty for many applications, resolving uncertainties about those parameter values most likely to change outcomes while accepting

lingering uncertainties whenever expected costs of resolving uncertainty outweigh expected benefits.

Implementations of LCA methods to model green manufacturing are common in practice and research (Seuring and Müller, 2008), but lack integration with VoI techniques. The few implementations of VoI related to manufacturing have been focused on supply chain management (e.g., Gavirneni et al., 1999; Lee et al., 2000) and applications of VoI outside manufacturing have at most used LCA results alongside other economic and operational factors in product selection decisions (Bates et al., 2014; Linkov et al., 2011). None of these applications have incorporated the uncertainties within LCA models, leaving a knowledge gap regarding the complementarity of LCA and VoI as approaches for production optimization. In discussing the intersection of LCA with decision analytic techniques, Elghali et al. (2007) call for the future integration of VoI and LCA. The VoI and LCA communities each have their own rich literature, research, and practice that can be integrated to better prioritize research in green manufacturing.

This paper introduces LCA-VoI analysis and presents a case study that integrates VoI analysis with an LCA model for the total lifecycle GHG emissions of an electronic tablet. This novel analysis includes modeling of the relationships between uncertainties in emissions from device components and the differing costs of reducing those uncertainties. The objective of VoI in this context is to identify the most cost-effective means of increasing precision (i.e., reducing error) in device GHG emissions estimates by gathering information to reduce select uncertainties about interacting components modeled in the LCA. Note that the objective here is not to reduce GHG emissions by altering the life-cycle flow, but rather to identify an optimal (Pareto-efficient) frontier of the most cost-effective strategies for improving accuracy in reported emissions for the existing processes. This can be helpful to manufacturers seeking to woo sustainability-conscious customers because reducing uncertainty in their emission estimates will allow them to report a lower top boundary for their GHG emissions and thus better convey their sustainability without increasing production costs. As LCA-VoI enables a more accurate understanding of component contributions to GHG emissions, other applications could easily extend this to allow interested decision makers to better identify future means for reducing the actual carbon emissions from their devices.

## 2. METHODS

VoI analysis is applied in an electronic tablet LCA case study to identify the most cost-effective means, if any, of reducing uncertainty in GHG emissions estimates. This more refined estimate of GHG emissions can be used to improve reporting and/or to direct mitigation efforts towards reduced manufacturing impact. As an electronic tablet is made using many component materials and resources (e.g., ferrous metals, thermoplastics, electricity), GHG emission estimates are first developed for each component and then aggregated to collectively estimate the GHG footprint of the total device. These estimates include both an expected value and a probability density for each of two or three underlying parameters for each component of the LCA model for the device. Relative cost estimates for reducing parameter uncertainty are also included. The VoI analysis simulates uncertainty reduction for different combinations of

parameters and compares the corresponding expected gain in precision (reduction in error) of GHG emission estimates with the expected cost of acquiring that information. By comparing the cost of gathering information with the expected reduction in uncertainty, the results provide a ranked list of key components for further study. Obtaining this information is expected to lead to the most cost-effective reductions in total tablet GHG emissions uncertainty. The LCA-VoI approach is demonstrated extending a case study with an LCA model and data developed and summarized by Alcaraz et al. (2018) with VoI analysis, and represents, to our knowledge, the first known integration of LCA and VoI methods.

## 2.1. Greenhouse Gas Emissions

Identifying cost-effective strategies for reducing uncertainty in total tablet emissions requires knowledge of emissions estimates for each device component. Alcaraz et al. (2018) present an LCA model for electronic tablets and report component parameter values across the raw-materials sourcing, manufacturing, transportation, and use phases of the device's life cycle (details found in supporting information). For each product component, there are up to three parameters involved in its GHG estimate. A quantity parameter identifies the mass, area, or duration of each component used in the device's life cycle. An intensity parameter describes a corresponding resource use associated with inclusion of some quantities (e.g., identifying the energy associated with one square centimeter of integrated circuit fabrication). An impact factor parameter identifies GHG emissions per unit quantity of each component (or associated resource) in mass units of carbon dioxide equivalents (CO<sub>2</sub>e). Carbon dioxide equivalents describe the aggregated impacts of CO<sub>2</sub> and other GHGs (e.g., methane, nitrous oxide, chlorofluorocarbons) released during the product life cycle in terms of an equivalent mass of CO<sub>2</sub> that would produce similar impacts. These data are for industry-average tablets, derived from published studies, industry input, available data, life cycle inventory databases, and tablet teardowns (Alcaraz et al., 2018).

GHG emissions per component are calculated by multiplying the material quantity,  $Q$ , by the use intensity,  $I$ , if applicable, and by the impact factor,  $F$ . The total GHG emissions (kg CO<sub>2</sub>e.),  $E$ , for an electronic tablet are then calculated by summing across all  $n$  components (Equation 1).

$$E = \sum_{i=1}^n Q_i I_i F_i \quad (1)$$

If  $Q_i$ ,  $I_i$ , and  $F_i$  are set at industry averages from the detailed data in the supporting information, the equation above gives the base-case level of emissions. When these values are treated as uncertain with probability distributions reflecting the prevalence of individual parameter values in the industry, a probability distribution over  $E$  can then be derived and used to calculate the expected value for GHG emissions of an industry average electronic tablet. Alcaraz et al. (2018) summarize the range of possible values for each of these component parameter based on a thorough review of the academic literature, life cycle inventory databases, teardown information and industry input. These values and distributions are shown in the supporting information.

The contribution of any parameter's uncertainty to total GHG emissions uncertainty depends on the distributions and magnitudes of both that parameter's value and the values of other emissions parameters for the same component. Parameters with larger magnitudes, with greater uncertainty, and representing components with higher inclusion rates in the device will be the most influential contributors to uncertainty in total GHG emissions. Conversely, parameters with lower magnitudes, less uncertainty, and/or representing components with lower inclusion rates in the total device will have smaller influences on total emissions uncertainty.

## ***2.2. Relative Costs of Obtaining Information to Improve Emissions Estimates***

Uncertainty in GHG emissions estimates for a specific tablet can, of course, be reduced by identifying the actual (deterministic) parameter values for that tablet instead of relying on generic industry averages and distributions. This type of device-specific information is largely obtainable, but comes at differing time, money, effort, and other resource costs. VoI requires knowledge about these relative costs for resolving different parameter uncertainties so that those uncertainties can be ranked in terms of their cost effectiveness for improving total device emissions estimates, if investigated. Without these relative costs, it is possible to determine whether it would be more effective to obtain information about one set of parameters or another, i.e., which would lead to greater reduction of uncertainty, but it is not possible to say which focus of information gathering represents a more efficient use of resources.

In order to gauge the cost of acquiring additional information about the GHG footprint, a survey (available in the supporting information) was sent to several industry partners and eight responses were obtained. These respondents provided judgments about the relative cost among the different activities present in the footprint. Here, cost included both monetary costs and effort. Effort was defined as the time spent identifying individuals in a company or supply chain for input, hiring outside consultants to gather data or other potential ways of gathering data. The question asked in the survey was: "What would be the relative cost of reducing the uncertainty of the \_\_\_\_\_ from [X] to [Y]." For example, "what would be the relative cost of reducing the uncertainty of the scope 1 and the scope 2 emissions for integrated circuits packaging from an industry average to the specific fab emissions?" The respondents were first asked to identify the most expensive task on the questionnaire (in other words, the task associated with the parameter for which acquiring uncertainty requires the most effort) and assign it a score of 1.0. In the next step, they were asked to score the cost of reducing uncertainties for the other parameters relative to the cost for the most expensive parameter. The resulting average cost was treated as a deterministic value in our analysis, although in general (with some added complexity) LCA-VoI could also treat cost as uncertain.

Table 1 shows the compiled data as used in the LCA-VoI analysis. We define a *package* of information (first column) to be a group of individual component parameters (second column) for which information would be obtained simultaneously. The relative cost of each package is listed in the third column. Across the packages of information, the mean expert values for relative cost differ by a factor of four. Subsets of the full LCA parameters are included in



packages as candidates for future information acquisition, but all parameters remain included in the calculations of GHG emissions.

Table 1. Relative cost to obtain additional information about different types of parameters for electronic tablet components; IC = integrated circuit; FE = front end; PFC = perfluorocompound; LCD = liquid crystal display

Information Package	Description	Relative Cost
1 Electronics Quantities	<i>Quantity of capacitors, resistors and transistors</i>	0.52
2 IC Scope 3 Intensity and Impact Factor	<i>Integrated circuit assembly and test materials and carbon intensity</i>	0.62
3 IC Scope 2 Intensity	<i>Wafer manufacturing electricity</i>	0.58
4 IC PFC Intensity and Impact Factor	<i>Integrated circuit area and carbon intensity of fugitive emissions</i>	0.53
5 LCD Intensity and Impact Factor	<i>Display area and carbon intensity of fugitive emissions</i>	0.40
6 Use Impact Factor	<i>Carbon intensity of the grid mix for use</i>	0.47
7 Material Impact Factors	<i>Carbon intensity of materials</i>	0.83
8 IC Scope 2 Impact Factor	<i>Carbon intensity of the grid mix for IC fabrication</i>	0.44
9 IC Fabrication Impact Factor	<i>Carbon intensity of IC fabrication</i>	0.32
10 IC FE Scope 3 Impact Factor	<i>Carbon intensity of materials in IC fabrication</i>	0.55
11 PWB Impact Factor	<i>Carbon intensity of PWB manufacture</i>	0.29
12 LCD Chemical Impact Factor	<i>Carbon intensity of chemicals used in LCD manufacture</i>	0.54
13 LCD Fabrication Impact Factor	<i>Carbon intensity of LCD manufacture</i>	0.23
14 Electronics Impact Factors	<i>Carbon intensity of capacitors, resistors and transistors</i>	0.92
15 Assembly Impact Factor	<i>Carbon intensity of the grid mix for assembly electricity</i>	0.27

### 2.3. Value of Information (VoI) Analysis

In the LCA-VoI tablet case study, we simulate the effect of reducing uncertainty for different sets of parameters and compare the relative cost associated with their information packages with the average resulting improvements in device emissions estimates. To do this, Equation 1 is applied using LCA parameter values sampled from the distributions mentioned in Table 1 (and described in the supporting information) over many Monte Carlo iterations, producing distributions and average values for GHG error reduction. Note that not all uncertainties need to be resolved simultaneously and that the inputs to Equation 1 can be a mix of values for parameters estimated with industry averages or values sampled probabilistically from their associated distributions. To evaluate the value of improved emissions estimation, we assume consumer demand is linear in reported emissions.

To set up the VoI analysis, we define jagged array  $p = [p_1, p_2, \dots, p_m]$  to be the  $m$  packages of information listed in order in Table 1, where  $m = 15$  and  $p_j$  refers to the  $j$ th package of information. Within each  $p_j$  are values associated with a subset of parameters  $Q_i$ ,  $I_i$ , and  $F_i$ , grouped as described in Table 1. Associated with each  $Q_i$ ,  $I_i$ , and  $F_i$  is a probability density function given by  $f(Q_i)$ ,  $f(I_i)$  and  $f(F_i)$ , respectively. In this analysis, resolving uncertainty in  $p_j$  is presumed to mean learning the actual values of all parameters contained in  $p_j$ . We define a possible research strategy,  $R$ , to be a binary vector with  $m$  elements, where  $R = [r_1, r_2, \dots, r_m]$ . Then,  $R_k$  denotes the *research strategy*, or portfolio, which acquires information about the  $k^{\text{th}}$  of the  $2^m$  possible combinations of information packages. We say  $r_{kj} = 1$  if  $R_k$  obtains information about the  $j$ th row of  $p$ , and  $r_{kj} = 0$  otherwise. We define the no-research strategy  $R_o$  as the case in which all  $r_{kj} = 0$ , and define the complete research case  $R_c$  as the case in which all  $r_{kj} = 1$ . Efforts to obtain information about the packages in a research strategy are funded as a block.

To estimate the effectiveness of each research strategy for reducing total device uncertainty within an individual Monte Carlo iteration, we first make a single draw from all probability density functions in each  $p_j$  that we call the “true” set of packaged parameter values for that iteration,  $t = [t_1, t_2, \dots, t_m]$ . I.e.,  $t_j$  represents one possible realization of parameter values in  $p_j$ . For each research strategy,  $R_k$ , we initialize an array of “estimates” for parameters in  $p_j$  labeled  $e_k$ , where  $e_k = [e_{k1}, e_{k2}, \dots, e_{km}]$  with  $e_{kj} = t_j$  for all  $r_{kj} = 1$ , and  $e_{kj} = p_j$  (expected values) for all  $r_{kj} = 0$ . We then use the parameter values in  $e_k$  and  $t$  to generate total estimated and true GHG emissions using

$$\hat{E}_k = \sum_{i=1}^n (Q_i I_i F_i)_k \in e_k \quad (2)$$

$$T = \sum_{i=1}^n (Q_i I_i F_i) \in t \quad (3)$$

where  $\hat{E}_k$  is the estimated GHG emissions calculated using the information contained in  $e_k$ , and  $T$  is the true GHG emissions sampled using the probability density functions in  $t$  for that iteration. The effectiveness of each research strategy is described by the absolute estimation error, given by



$$error_k = |\hat{E}_k - T| \quad (4)$$

To approximate the mean absolute estimation error of each research strategy, we executed a 100,000-iteration Monte Carlo simulation, repeating the process of generating a true array of component parameters, and comparing that true array to estimated arrays in Equations 2 through 4. We compare the mean absolute error across all iterations for all  $2^{15}$ , or 32,768 different potential research strategies. We then evaluate the reduction in uncertainty that results, on average, from funding each strategy.

To calculate the cost-effectiveness of each research strategy for reducing GHG emission uncertainty, total relative costs were assigned for each strategy based on the information in Table 1. The costs to obtain additional information were treated as independent, such that the cost of a portfolio that contains packages 1 and 2 is equal to the sum of the costs of obtaining information packages 1 and 2 separately. We then identify which portfolios offer the most cost-effective mechanisms for buying down uncertainty by comparing relative costs with the mean results of Equation 4.

### 3. RESULTS AND DISCUSSION

The mean absolute error in GHG emission reports after simulating research strategies was found to range between 11 and 37 kg CO<sub>2e</sub> (Figure 1). This equates to between about 7 and 25% of the total greenhouse gas emissions per average tablet of 150 kg CO<sub>2e</sub> (Alcaraz et al., 2018). The mean errors shown in Figure 1 are absolute values, with some errors being positive and some negative. The relative costs in Figure 1 represent comparative units of estimated resource expenditure, where the cost of gathering information on any given parameter is bounded between 0 and 1 and the combined costs for gathering information on all parameters in any research portfolio range between 0 and 8. The mean absolute error does not equal 0 kg CO<sub>2e</sub> for the most expensive portfolio (i.e., where all evaluated information is obtained) because not all information that contributes to tablet emissions uncertainty is included in the VoI analysis. Of the 64 parameter variables in the supporting information, 47 were included in the information packages listed in Table 1.

The dashed red line in Figure 1 highlights the optimal portfolios on the Pareto-efficient frontier (i.e., portfolios that are most cost-effective at reducing GHG emission uncertainty at a given cost). Note that the vertical depth of potential portfolios above the efficient frontier is quite large relative to the magnitude of values on the frontier. This means that choosing a wise research strategy for refining tablet LCA studies, and potentially LCA studies in general (e.g., on the basis of VoI estimates) can result in vastly improved outcomes over unoptimized strategies. For example, a decision to reduce uncertainty by spending 4 resource units on an optimum portfolio would yield a GHG emission report with a mean absolute error of approximately 13 kg CO<sub>2e</sub>, down from a base case mean absolute error of 37 kg CO<sub>2e</sub>, whereas selection of any of the least efficient portfolios for that expenditure level could result in little or no error reduction whatsoever. This large range of resulting mean absolute error from similar investments in

different packages exists because some information is relatively expensive to acquire but contributes little to a reduction in uncertainty, whereas other information is relatively inexpensive and highly effective at reducing error.

In general, as the relative cost of portfolios increases, the mean error decreases. This is because the more expensive portfolios generally contain information about greater numbers of packages of parameters. Note that there are also diminishing marginal returns in terms of mean absolute error from continued investment in information gathering, as shown by the non-linearity of the efficient frontier of optimized portfolios. In other words, there are some research strategies that represent relatively “low hanging fruit,” where limited investments can produce substantial gains, but eventually achieving continued gains requires greater and greater unit costs. Though the efficient frontier is non-linear overall, there is a relatively large span from about 0 to 4 relative cost units where it is roughly linear; beyond 4 relative cost units, the marginal benefits of additional research diminish quickly. This implies that manufacturer investments to reduce tablet emissions uncertainty should be pursued as budgets allow in the 0-4 unit relative cost range, but only pursued beyond this range if a very strong business case remains.

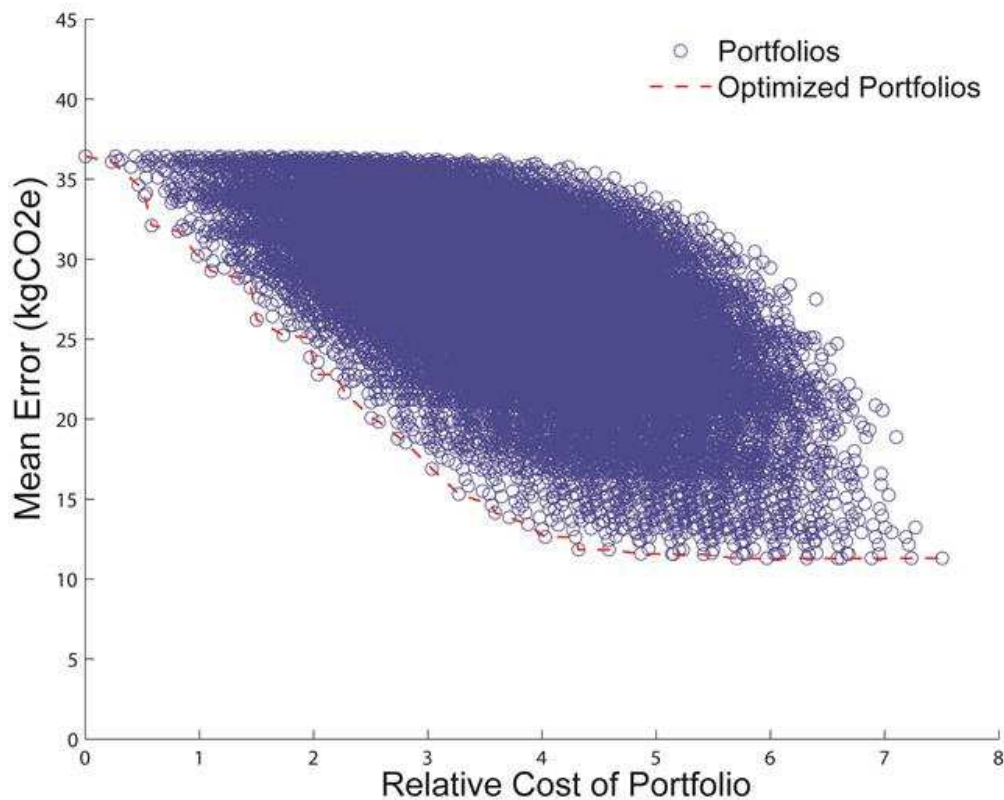


Figure 1. Mean absolute error in GHG emissions (kg CO<sub>2e</sub>) and relative cost for each portfolio of additional information. Blue circles represent the 32,768 portfolios. Optimized portfolios (red line) identify a Pareto-efficient frontier of the most cost-effective strategies for reducing uncertainty in GHG emissions.

To summarize which specific packages of information are expected to be most cost-effective at reducing uncertainty, we analyze the contents of each portfolio on the Pareto-efficient frontier (on the “optimized” red line in Figure 1). The frequency of each of the 15 packages’ inclusion in an optimal portfolio is shown in Figure 2. The packages near the left side of Figure 2 represent the most cost-effective approaches to buying down uncertainty in total GHG emissions, and are included in almost all packages. The package most frequently included across all efficient portfolios is the “IC Scope 3 Intensity and Impact Factor” package, followed by the “Electronics Quantities” package and the “IC PFC Intensity and Impact Factor” package. This is consistent with the results found by previous work by others showing that the impact of integrated circuits contributes significantly to total impact and uncertainty (Boyd et al., 2006). Pragmatically, if one were to strategically construct a strategy for pursuing additional information about component parameters in the tablet LCA model, the aforementioned parameters should be the first ones sought. This research strategy could continue to grow, adding packages of information from the left toward the right side of Figure 2, until the budget for additional information is reached or until a satisfactory level of uncertainty (GHG emissions reporting error) is achieved.

It is worth noting that this summarized cost-efficiency ranking can be quite different from a ranking based only on information package acquisition cost (which might naively be viewed as a proxy for value). In our results, three of the four cheapest packages (LCD Fabrication Impact Factor, Assembly Impact Factor, and IC Fabrication Impact Factor) are ranked last in efficiency and one of the four most expensive packages (IC Scope 3 Intensity and Impact Factor) is ranked most efficient, which seems to make intuitive sense. However, one of the four cheapest packages (PWB Impact Factor) is ranked fourth most efficient, the most expensive package (Electronics Impact Factors) is ranked fourth from last, and two other of the four most expensive packages (Material Impact Factors and IC Scope 2 Intensity) are middling, intricacies that would be hard to intuit without this analysis. Summarizing the results this way, based on rank order for frequency of inclusion in efficient portfolios, provides a simple and understandable take-home message for decision makers, and smooths over potential sensitivities to modeling choices and methods that might be encountered in individual portfolios.

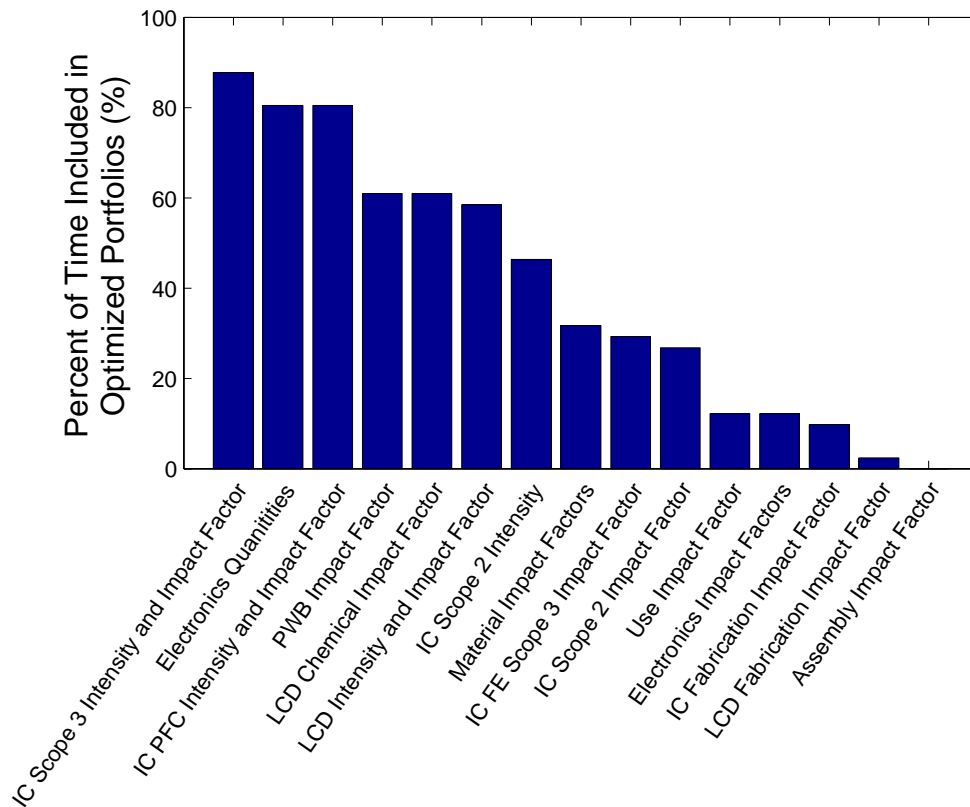


Figure 2. Percent of optimized portfolios that include each potential packages of additional information. These packages all include one or more related component parameters from the tablet LCA model. The package names correspond entries in Table 1.

#### 4. CONCLUSION

The uncertainty in lifecycle GHG emissions for electronic tablets can be reduced by acquiring information about LCA model parameters for components of those tablets (Alcaraz et al., 2018). Understanding and reducing GHG emissions uncertainty is important for manufacturers of all kinds, because it can reveal greater existing sustainability as well as drive operational decisions to improve future sustainable (Gardner and Colwill, 2016). Data collection and analysis are resource-intensive, however, requiring detailed investigations into many facets of the material procurement, manufacturing, transportation, use, and end-of-life processes for a product. Analytic methods are needed to prioritize data collection and research strategies based on their expected costs and benefits.

VoI is a decision analytic method that quantifies the expected benefit of acquiring additional information in uncertain problems (Keisler et al., 2014). When applied within LCA models, LCA-VoI reveals the most cost-effective research strategies for buying down uncertainty in life-cycle emissions and impacts. This is important whenever the potential to engage in information gathering is limited, as LCA-VoI both identifies research strategies expected to have

the “best bang for the buck” in terms of investment payoff and also helps identify stopping points beyond which additional effort is unlikely to substantially increase value. In addition to identifying efficient resource allocation, LCA-VoI can be used to more transparently communicate R&D strategies to stakeholders. The electronic tablet case study in this article is, to our knowledge, the first known application of LCA-VoI. It identifies groups of model parameters (i.e., IC Score 3 Intensity and Impact Factor; Electronics Quantities; IC PFC Intensity and Impact Factor, etc.) for which additional information gathering is expected to most increase the precision of tablet emissions estimates at lowest cost. It also identifies Pareto-Efficient portfolios of research efforts that are expected to dominate all other research strategies within this context. This demonstrates that LCA-VoI can be successfully applied to advance green manufacturing.

Although VoI is a useful technique for prioritizing LCA research strategies, the necessary data collection and model instantiation can be limiting factors for decisions in which no extensive statistical analysis has been executed. Performing VoI analysis requires some knowledge of the uncertainty distributions for the underlying data, which may be impractical for models where most or all parameters are treated as deterministic. However, for cases in which the probability distributions for model parameters are observable or can be estimated, LCA-VoI provides powerful insights. We anticipate that future applications of LCA-VoI will lead to more cost-effective and sustainable production.

## FUNDING SOURCES

This research was supported by the U.S. Army Engineer Research and Development Center and the Massachusetts Institute of Technology. No specific grants were received from funding agencies in the public, commercial, or not-for-profit sectors. We would like to acknowledge the participation of the responding companies.

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Manuscript Number: JCLEPRO-D-17-08365

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### Highlights

- Green manufacturing requires tradeoffs between sustainability goals, cost, and performance.
- Decisions need to be made under uncertainty, often leading to requests for new information.
- Not all information is equally costly to acquire or illuminating for the decision.
- Here we apply value of information (VoI) analysis within life-cycle assessment (LCA) for the first time.
- LCA-VoI identifies optimal data acquisition strategies and can lead to more cost-effective and sustainable production.