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ASSESSING THE IMPACT OF PRODUCT USE VARIATION ON ENVIRONMENTAL SUSTAINABILITY

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ABSTRACT

The goal of this research is to characterize the effects of use patterns on the environmental sustainability of consumer products, and to enable decision making throughout design processes that encourages product sustainability. Life Cycle Assessments (LCA) are currently used to evaluate the environmental impact of a product, but there can be considerable uncertainty in these analyses, especially relating to the use phase of the product. To better understand this uncertainty, we conducted environmental impact assessments of 20 household products, and employed two uncertainty quantification approaches to accommodate variation in the use phase of these products. The results from each product were then compared to products with similar attributes to find generalizations. This knowledge was integrated into decision trees so designers can better understand the degree to which use-phase uncertainty can affect quantitative measures of environmental impact before performing LCAs. This work enables designers to make more informed decisions about the intended use and use lifetimes of consumer products, potentially leading to a reduced environmental impact of this life cycle phase.

INTRODUCTION

As the worldwide human population continues to grow and become more affluent, there is a greater need for consumer goods. Despite increased product efficiencies, this demand for consumer products has a substantial impact on the environment and has resulted in the depletion of natural resources. The environmental impact of products can be quantified using Life Cycle Analysis (LCA). These approaches use product data, including component material and manufacturing data, assembly data, transportation data, use-phase data, and disposal methods. While LCAs have been used in engineering design processes to reduce the environmental impact of products, there are elements of these analyses that are often overlooked, such as how users interact with the product.

Products with use phases have consumables like electricity, water, or other products (for example, the K-Cups necessary to make a cup of coffee using a Keurig coffee maker) and have higher environmental impacts than products without a use phase. For products with a use phase, the use-phase environmental impact can account for 50-80% of the total environmental impact of the product [1]. Therefore, accurately representing user interaction with products is critical. We want to understand the effect to which use behavior affects the environmental impact of products and find means of representing accurate use behavior in LCAs.

In using LCA to determine the environmental impact of products, there are inherent uncertainties not only due to the necessary estimation of input values, but also within the LCA methods themselves. While accurately characterizing and representing the use phase in LCA is important, it is also crucial to understand how uncertainty propagates throughout the entire analysis. While there has been substantial previous research in uncertainty quantification, there is a need to characterize existing, vetted uncertainty quantification methods in measuring the use-phase impact of common consumer products. This approach will lead to more accurate use-phase estimation and increased LCA reliability, clarifying the link between design, use, and environmental impact of products.

The characterization of uncertainty in the product life cycle—specifically uncertainty introduced by heterogeneous product users [2]—can inform a framework for accommodating such heterogeneity throughout the design process. Existing uncertainty quantification methods can be applied to more accurately model life cycle impacts; however, in order to ensure that error is reduced in the analysis, objective true values must be attained and used in direct comparison. In this study, we compare three uncertainty quantification approaches for measuring the variation in environmental impact due to heterogeneous product consumers, and we compare those values against a *functional unit* approach [3], defined as "*a quantified description of the performance of the product systems, for use as a reference unit*" [4]. Traditionally, LCA practitioners use an average use phase—two cups of coffee a day; vacuum use of 45 minutes twice per month, etc.—as part of the functional unit. However, this single point approach does not account for potentially wide-ranging use behaviors. Our hypothesis is that use behaviors can be more accurately represented and included in LCA through using uncertainty quantification methods.

LITERATURE REVIEW

In the design of consumer products, design engineers can make design decisions in relation to the product's environmental impact; this is referred to as *Design for the Environment*. According to the United Nations, economic, social and environmental systems are the three co-dependent aspects of sustainability [5], though in this study we primarily focus on environmental sustainability. This desire to design products that are less environmentally damaging is becoming more prevalent as interest in sustainability increases. Researchers have found that 80% of the decisions relating to the environmental impact of products are made during the early design phases, reflecting the importance of understanding DfE in traditional engineering design processes [6]. However, most engineers need more education and awareness on how their decisions will affect the environmental impact of products and systems [7]. Companies are also interested in hiring engineers who can design products that are more environmentally sustainable [8]. The research presented in this paper builds on previous literature in Design for the Environment (DfE), including the use of LCAs in design, uncertainty quantification and decision making in sustainable design, and existing design processes and tools for DfE.

Many studies have been completed focusing on LCA's and a variety of products. It has been found that the environmental impact from the use phase can be twice as much as production for products like PDP televisions [9]. Modifications to minimize the consumables during the use phase can reduce the environmental impact up to 36% as found with domestic cooker hoods in France [10]. A study on domestic induction hobs found that the components create up to 85% of the environmental impact, illustrating that the use phase is not always an important aspect [11] . All of these studies determined a single functional unit for analysis of the use phase.

Use of LCA in Engineering Design

LCAs encompass a product's entire life cycle to quantify the environmental impact of the product. The life cycle of these products is analyzed using a cradle-to-grave approach, considering a product's preliminary material acquisition through to disposal. To conduct a cradle-to-grave LCA, the practitioner considers all the materials and manufacturing processes necessary for component generation, assembly, transport, use, and disposal of a product [12]. Focusing on the product life cycle enables designers to understand the entire environmental impact of products [13]. This analysis is especially useful when comparing the environmental impact of dissimilar products or for new technologies. For example, in the 1990's, electric vehicles (EV) were assumed to be better for the environment than traditional gas cars because there were no emissions during the use phase. However, when the entire life cycle was taken into account including the manufacturing and disposal of the battery, it was found that these early electric vehicle designs were not better for the environment in all aspects [14]. More analysis has been done and found that the country's electric mix and the use of the car changes the environmental impact [15] [16]. Other analysis has found that the total environmental impact is similar for both types of vehicles, but the categories differ with eutrophication and human toxicity increasing in with EV's [17].

Many case studies on single products have been completed. Some evaluate a product, such as a tv remote, then compare the environmental product as the power source is changed from a battery to a solar panel and the product itself is redesigned to reduce the in environmental impact [18]. Others focus on the type of LCA performed as different types can lead to different results and uncertainties [19]. There are many ways to represent information, including in a purely statistical representation or in probability distributions. The best one depends on the richness of the data [20]. This study decided to use the more traditional purely statistical representation.

When trying to quantify the environmental impact during the use phase, designers use a functional unit that represents the average use of the product. In traditional LCA practice, use phases are defined through designer intuition, assumptions, and/or available data [21]. A superior way to define a functional unit is to survey and directly observe people who use the product. However, these methods can be costly and impossible when the product has not yet completely been designed or prototyped [22]. To date, there is no public repository of consumer product use data that is applicable in LCA. It is difficult, especially with new technologies, to establish functional units for new products that because it is not really known how people will use them [23].

Uncertainty Quantification in LCA and DfE

Even for common products, many assumptions are made about how users actually use a product. For example, a cradle-to-grave study on refrigerators found that the use phase was responsible for the highest contributions to the environmental impact of the refrigerator. To quantify the use, many assumptions about how people use their fridges were made, including how often people turn it off, and how long the refrigerator lasts before consumers purchase a new one [24]. Some of these assumptions can have reduced uncertainty for a product that has a uniform daily use (like a refrigerator) but can be difficult for a product that can be used in a variety of settings. The more information that is known the more adequate a statistical representation is, but for these products

Every aspect of LCA has inherent uncertainty that compounds through assessing all of the life cycle stages [25]. It is difficult to discern how uncertainty present in the inputs to an LCA propagate and affect the resulting environmental impacts. A study in Australia looked at how nominal uncertainty quantification would affect LCA results. For multiple types of diapers, they estimated how often people would change their babies, how often they would wash diapers, and the environmental impact of the washing to find the low, average, and high use impacts. This led to graphs with overlapping use, but still illustrated the product with the lowest environmental impact. Essentially, this helped illustrate that there were more efficient ways to use a product and how that depended on the frequency of the use [26]. While the nominal uncertainty quantification method worked well in the research about diapers, it may not be appropriate for all products, as different methods work better for different product families [27]. Another method to quantify uncertainty is a Monte Carlo simulation [28].

Existing Tools and Design Processes for DfE

As interest in DfE has increased, so has the interest in making tools that enable designers to consider environmental impact. One of the most valuable DfE tools is the LCA [29], though LCA is typically only applicable after concept generation is completed. As decisions made in the early design phases have the largest impact on the overall environmental impact [30], skeletal LCAs and sustainable design guidelines have been created to be used prior to and during concept generation [31,32]. Early design decisions are often not given the proper environmental considerations as designers do not have the tools to be able to evaluate and compare options quickly and without established input information. Most design tools are only available for the later stages of the product development cycle, which means most tools are not there to help when making decisions that have the largest impact on the overall environmental impact [6].

It has been found that designers need more tools to be able to quickly evaluate the environmental impact of potential products [33]. One example of this is the “Ten Golden Rules”, which are ten generic rules for designers to follow to minimize the environmental impact of their products. Out of these ten rules, only one relates to use (designers should minimize energy and resource consumption). This is a general rule that can be applied to almost all products, but it does not quantify the resources use or compare the environmental impact of using different resources. In this study, we want to better understand how variation in product use affects the life-cycle environmental impact of products, and to see if there are better means to representing this use heterogeneity in LCA. This will lead to more accurate prediction of environmental impact and will encourage the consideration of use-phase variation during the design of environmentally sustainable products.

METHODOLOGY

For this study, 20 consumer products were chosen for their variation in use. An LCA was conducted for each product using different use profiles developed through traditional uncertainty quantification methods. The goal is to assess how the modeled environmental impact of the products change as we attempt to more accurately represent use behavior. These products were only studied for one year.

Functional Unit and Uncertainty Quantification Methods

In this study, we use the functional unit as a baseline average against which we compare two uncertainty quantification methods. To develop the functional unit average for the use of each product in Figure 1, a middle value was found empirically and using use information found online. For example, it was assumed the average washing machine would be used approximately 3 times a week and each load uses about 40 gallons of water and 700 watts of energy for 0.5 hours per use [34]. This estimate was used as the functional unit for the use phase. This process was repeated for each product in order to have a unique functional unit for each.

The first uncertainty quantification technique we used is a Nominal Analysis. In this approach, minimum, average, and maximum values are used to clarify the use phase of each product. The average is the value found for the functional unit. The minimum and maximum value were found by extrapolating minimum and maximum scenarios around the average. For example, with the coffee maker, it is assumed that the primary owner of a coffee maker would at least use it about once a month, perhaps if the primary owner is not themselves a coffee drinker but keeps the product to make coffee for company. The maximum use would be in a high-capacity setting like an office, where coffee could be made almost nonstop for eight hours on weekdays. These three values are estimated and then integrated into the Sustainable Minds analysis.

The second uncertainty quantification technique used was a Monte Carlo method. In this approach, we assume that use has a normal distribution, so all of the inputs are normal distributions, and the Monte Carlo method randomly generates use scenarios that align with this distribution. It was assumed that 99.5% of the use would be between the minimum and maximum value using the 68-95-99.5 rule for normal distributions. A Monte Carlo simulation was created in MATLAB to produce 15 points with the probability based off of the normal distribution. These values for the use phase were then integrated into Sustainable Minds for each product.

Case Study Product Selection and Rationale

From Oregon State University’s Sustainable Design Repository [35], 20 products were selected for use-phase variation case study. These products were chosen to have a variety of consumables and use duration. As shown in Figure 1, of the 20 products, 8 only use electricity, 8 use electricity and other consumables, and 4 use only other consumables (such as fuel). These three categories were chosen as electricity is the most common consumable during products use phase. The second category was chosen to see how the environmental impact of a product changes when electricity interacts with other consumables, and the final set of products were selected to see how not using electricity would affect the results. The products were also selected to ensure that there is variety in the average amount of time that users use these products. As shown in Figure 1, these products vary from being constantly operational (refrigerator) to being used just a few hours a year (electric toothbrush). These products also can exhibit variation in how they are used, ranging from use by just one person to products being used in communal settings.

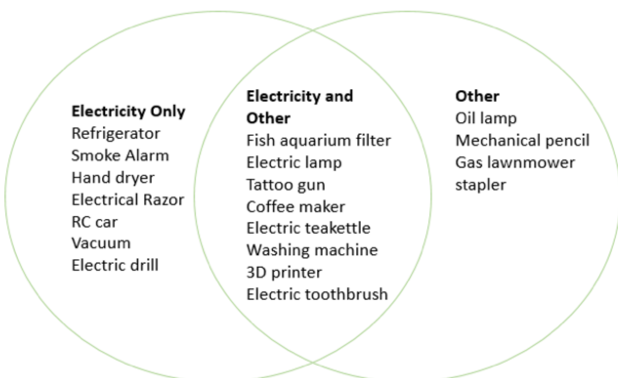

Figure 1: CASE STUDY PRODUCTS SELECTED FOR VARIATION IN USE PHASE: ELECTRICITY, ELECTRICITY AND CONSUMABLES, AND OTHER CONSUMABLES

Case Study LCA

The LCA software used in this study is Sustainable Minds, a web-based LCA tool. It was chosen because it is inexpensive and therefore accessible to practitioners of varied skill and interest; industries and universities who do not have the resources for training and purchasing other LCA software are more likely to use Sustainable Minds. This application takes in a bill of materials for a product, including the materials and manufacturing processes for each component. Transportation, use, and end of life data are also required for this analysis. These input data are used to calculated environmental impacts via the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) and normalization factors from the National Institute of Science and Technology (NIST). It uses Eco-Indicator 99 (Egalitarian Approach).

Sustainable Minds shows the total impact in millipoints, where one point is equal to the annual environmental load divided by the total American population. It is then broken down in to three main categories: ecological damage, resource depletion and human health damage, as shown in Figure 2. Each impact area is displayed as a percent of the total impact. From these percentages, the total impact of a product in millipoints can be identified.

The results that are exported from Sustainable Minds are in these categories:

- acidification (kg So2)
- ecotoxicity (CTUe)
- Eutrophication (kg N)
- global warming potential (kg CO2)
- ozone depletion (kg CFC-11)
- carcinogenics (CTUh)
- non-carcinogenics (CTUh)
- respiratory effects (kg PM2.5)
- smog (kg O2)
- fossil fuel depletion (MJ)

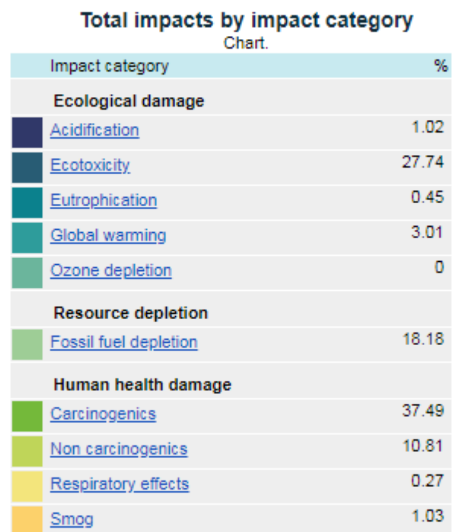

Figure 2: EXAMPLE OUTPUT FROM SUSTAINABLE MINDS, INDICATING VARIOUS TYPES OF ENVIRONMENTAL IMPACT

RESULTS

Table 1 shows the analyzed products, the average environmental impact over one year due to use in millipoints, the standard deviation from this average in millipoints, and the normalized (unitless) variance (maximum impact – minimum impact, divided by the average impact). All values shown are only the environmental impacts due to the use of the products, neglecting production and disposal impacts. All values are also developed for a year-long analysis. The normalized variance enables a comparison of products to others; this value is essentially the percentage of variation introduced by heterogeneity in use patterns.

Table 1: AVERAGE USE-PHASE ENVIRONMENTAL IMPACT, STANDARD DEVIATION, AND NORMALIZED VARIATION

Product	Average (mPts)	Standard Deviation (mPts)	(max-min)/ avg
Washing machine	4.59	1.76	1.66
Vacuum	2.32	6.80	13.02

3D printer	8.11	16.58	9.24
Tattoo gun	26.80	18.05	2.59
Stapler	0.02	0.01	3.21
Refrigerator	2.09	0.03	0.01
RC car	0.06	0.04	3.59
Mechanical pencil	0.00	0.00	15.28
Laptop	27.57	8.43	1.49
Hand dryer	28.13	9.82	1.49
Gas lawnmower	8.53	3.91	2.01
Fish tank filter	0.21	0.01	0.25
Electric toothbrush	0.01	0.00	1.14
Electric teakettle	4.77	6.23	6.25
Electric Razor	0.02	0.01	2.42
Electric drill	0.92	0.47	2.37
Electric lamp	5.99	2.72	2.19
Coffee maker	12.02	10.76	2.65

While our primary goal was to understand the variation in environmental impact due to heterogeneous product users, we also wanted to extend our study to include "best practices" for understanding the relationship between design and environmental impacts due to use. To better identify correlations between the use-phase impacts of these products, we created a set of 18 attribute bins in which the products can be grouped by similar characteristics. These bins were created by starting to look at similar characteristics in consumables, how often it is used, function, and users. It is from these areas that the 18 bins were created. Table 2 illustrates the 18 bins and the products in each of these bins. Through completing this analysis, we wanted to identify any relationships between product attributes and use-phase environmental impacts.

The bins were developed to expose variation in the amount of time it takes to use the product, the frequency of use, and the types of consumables used, and whether the product would traditionally be used by a single user/owner or by potentially multiple users. These bins are indicated in Table 2:

Table 2: PRODUCT ATTRIBUTE BINS AND CASE STUDY PRODUCTS

Bin Description	Products
Set amount of time to run	Hand dryer, Coffee maker, Washing machine,
Produces another product	Coffee maker, electric teakettle, 3D printer
Used in an office setting	Stapler, laptop, coffee maker,
Used with food	Coffee maker, electric teakettle, refrigerator
Potentially multiple users	Refrigerator, hand dryer, washing machine, vacuum, 3D printer, stapler, smoke alarm, RC car, gas lawnmower, fish tank, electric teakettle, electric lamp, electric drill, coffee maker
Single user	Electric razor, mechanical pencil, tattoo gun, laptop, electronic toothbrush
Has motor	Electric drill, gas lawnmower, washing machine, vacuum, RC car, electric razor, electric toothbrush
Heats water	Electric teakettle, coffee maker
Metal consumable	Tattoo gun, stapler
Plastic consumable	Fish tank filter
Electricity and water consumables	Coffee maker, electric teakettle,
Electricity and other consumables	Fish tank filter, electric lamp,
Used 1 to 12 times a year	Electric drill
Used 1-3 times a month	RC car, vacuum, electric teakettle, electric razor
Used 1-3 times a week	RC car, vacuum, electric teakettle, electric razor
Used 4-6 times a week	Washing machine, mechanical pencil, coffee maker, tattoo gun, hand dryer, laptop
Used every day	Electric toothbrush, electric lamp, fish tank filter, smoke alarm, refrigerator
Electricity is only consumable	Electric drill, vacuum, RC car, electric razor, hand dryer, laptop, refrigerator

Patterns identified from the uncertainty in the products were then used to make Figure 3. This chart is to assist designers or LCA practitioners in estimating the amount of uncertainty in the environmental impact analysis of their product based on characteristics of the product's use. The characteristics that have the largest influence on the amount uncertainty are the number of people that use it, the number of times it is used a month, and if it is on all the time. Based on these characteristics, the product will have almost no uncertainty, a moderate amount, or a large amount of uncertainty. If the product has high associated uncertainty, it is recommended that designers investigate the use phase more, and potentially explore use case studies throughout the design process.

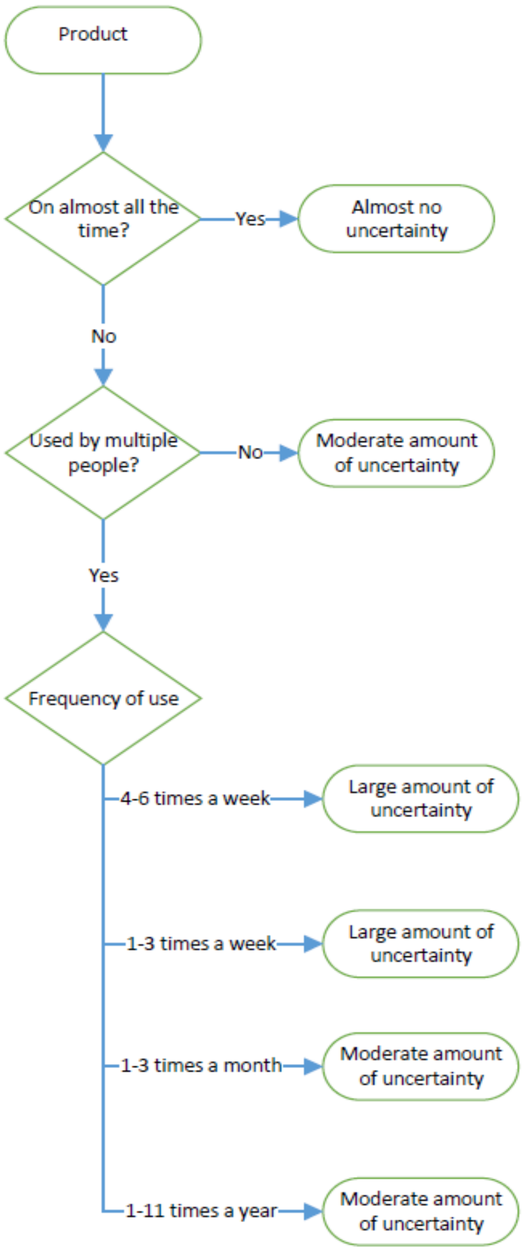

Figure 3: DECISION TREE DEPICTING RELATIVE AMOUNT OF UNCERTAINTY DUE TO VARIATION IN USE DURATION, USE FREQUENCY, AND NUMBER OF USERS

Figure 4 was created to isolate and identify the patterns relating the environmental impact categories to the product attribute bins. The goal is for designers to be able to quickly visualize how changing their consumables during the use phase will affect the type of environmental impact. This is useful as it negates the need to use LCA software to understand the type of environmental impact associated with certain use parameters. For example, if a designer is designing a product or system that consumes water, electricity, and a disposable housing, the material for the housing could be determined by which area of the environmental impact they want to minimize.

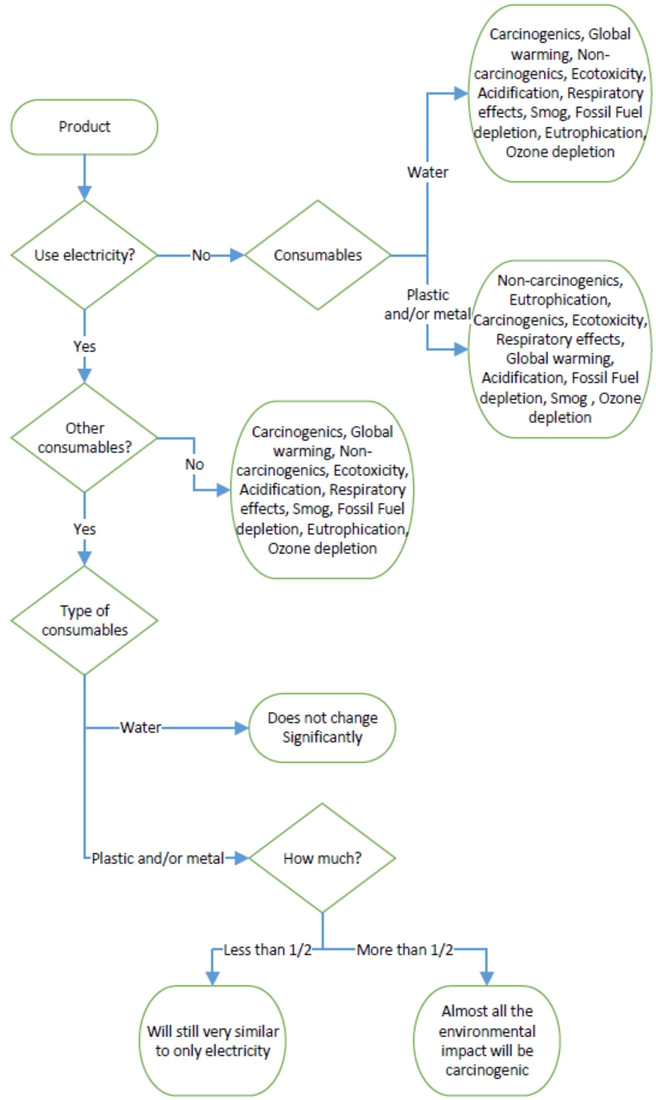

Figure 4: DECISION TREE DEPICTING THE MOST LIKELY TYPE OF ENVIRONMENTAL IMPACT PER CONSUMABLE TYPE

Assumptions

There are some key assumptions made as part of this research that have the potential to affect the conclusions. The most significant assumption is that the use of the case study products follows a normal distribution. It may be that some of the use phases of these products may be more accurately represented by, for example, a binomial distribution. This is particularly relevant for products that may be used in the home or in a communal setting, such as a coffee maker or tea kettle.

Another limitation is that the functional unit (which also served as the average assumptions for the nominal and Monte Carlo uncertainty analyses), the minimum use scenario, and the maximum use scenario were all determined empirically. Future work will explore surveying consumer product users to establish more validated values for these analyses.

The lifespan of the products was not considered. This is because that depends on the quality of the material and manufacturing, which is an assumption we did not want to make so these results could be applied to a wider variety of products. A final assumption is that the disposal of any wastes produced during the use of the products is not considered. An example of this is the filter from the aquarium pump that needs to be replaced multiple times a year. Because there is large variation in how people and cities dispose of waste, the disposal was intentionally omitted.

Table 1 illustrates that the environmental impact due to the use phase of products is widely varying. Many of these are intuitive, such as the refrigerator having very small uncertainty, because most people have their refrigerators on constantly, resulting in very little variation in use. This could change as other products are on all the time yet can have use be affected by other variables, such as temperature for an air conditioner. Other products have more variation, such as the tattoo gun and 3D printer. This is potentially because of the variety of use scenarios in which these products can be employed. For example, a tattoo gun could be used by a professional artist multiple times a day during most days, or by a livestock owner who uses it just a few times a year.

Table 2 shows our chosen attribute groups for the case study products. It illustrates certain use-phase characteristics by which the products can be grouped. These groups can then allow designers to limit the amount of analysis they need to perform based on use characteristics. Some of the bins had stronger relationships between the product's design and the environmental impacts and/or the uncertainty. These bins facilitated the creation of the decision trees, as we wanted to assess how products with consistent characteristics trended toward certain environmental impacts. More analysis can be performed to see if there are additional characteristics of use that should be considered.

The first decision tree is useful to provide a general idea of what type of uncertainty there might be present in LCA due to variation in the product's use phase. This information can then be used as a deciding factor to see if additional computation needs to be performed to quantify the uncertainty of the product. This could save engineering designers time and money when conducting DfE on products that have complex use phases.

The two use-phase uncertainty quantification methods performed on the selected products illustrates (1) which method is more appropriate for different use characteristics, and (2) whether uncertainty quantification is necessary to more accurately represent the use phase. For example, it is not necessary to perform a Monte Carlo analysis on products that are almost always running, such as a refrigerator or smoke alarm. If the nominal is reflective of the use, it should be representative. Products that are not used very frequently, like a drill, can be quantified with the nominal quantification approach. Monte Carlo is more expensive computationally, so if it is not going to provide significantly more data, it does not need to be done and instead the nominal quantification will provide adequate results.

The second decision tree illustrates how the impact categories change based on the consumables used. To make this decision tree, we looked at a few critical product attribute bins that had the strongest correlation to certain environmental impacts. This does not tell the designer the quantity of the total environmental impact, but it discusses the potential design decisions and resulting product attributes that will be result in potentially hazardous environmental impacts, for only the use phase. This decision tree also identifies some previously unexplored aspects about product consumables, for example: if a product uses electricity and a primarily metal consumable, almost all of the environmental impact due to the use of that product is carcinogenic impact.

Also, we identified that the use of water during a product's use phase is not a significant contributor to the total environmental impact of a product. This does not mean that designers should ignore this, especially when designing products for certain areas that have intense droughts, like Southern California. In addition, for products that use electricity, this use is the primary contributor to environmental impact.

Electricity is one of the best predictors for the environmental impact of a product because most products use significantly more of it then they do any other consumable. For example, the fish tank filter uses a variety of consumables, such as plastic, activated charcoal, cloth, and electricity. The electricity is the largest consumable and the other three just slightly change the weight of the environmental impacts and the total impact. For most practical purposes, the impact just due to the electricity is a suitable proxy for the environmental impact of the use phase. This saves computational resources as practitioners do not need to spend time calculating the amount additional resources that are used. These helpful tricks can lead to more, easy to access information about the environmental impact, that are almost as accurate as a full LCA, but cheaper computationally.

CONCLUSIONS

From this study, conclusions can be drawn about the environmental impact due to the use phase of products. First, there is little known about the environmental impact during the use phase, except that it can vary greatly and be a significant contributor to the total impact. This study grouped products and identified which attributes correlate to the largest variance in environmental impact. For example, it was found that if a product is almost constantly running, it has very little uncertainty in resulting environmental impact.

From this, decision trees were made so engineering designers can see how their decisions about the use phase can potentially affect the environmental impact of their product. These approaches also can inform engineering designers about the potential uncertainty during the use phase. This enables designers to understand if further potentially costly analyses or surveying is necessary to better represent the use of their product in environmental impact assessment.

This can also be integrated with functional modeling during product design. This means that as functions of a product are realized, the uncertainty and the amount of environmental impacts can be tied together, leading to a more environmentally conscious decision. Preliminary designs can then be based off of the functional modeling with the environmental impact and the uncertainty.

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