Framework for Modeling the Uncertainty of Future Events in Life Cycle Assessment

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Abstract

One limitation of Life Cycle Assessment is that it relies on the expectation of what will happen to a product as predicted at the point of creation. However, changes in technology, the economy, and end-of-life treatment practices may alter future emissions. This paper describes a study done to develop a model to improve the accuracy of estimated emissions by incorporating uncertainty into the expected impacts of a product by considering events that alter the phases that have not occurred. A case study using this model on a laptop shows use phase GHG emissions reduced by up to 55% in one scenario.

Keywords:

Life Cycle Engineering; Uncertainty

1 INTRODUCTION

Life Cycle Assessment (LCA) is a leading technique used to determine the environmental impacts of a product or process. Results from LCA evaluations are presented with an assumed level of accuracy. However, the methodology relies heavily on the predictions of events that have not yet occurred. Specifically, it is up to the organization conducting the LCA to make assumptions about the future frequency and duration of product use and what will happen to the product at the end of its useful life. These expected events are not guaranteed to occur, yet very little research has been dedicated to incorporating their uncertainty into assessments.

Assumptions made about the use phase are significant, and for many products this phase accounts for the majority of impacts. For instance, the dominant contributor to the CO2 emissions of a Volkswagen Golf A4 is the fuel consumed during the use phase, which makes up around 77% of the life cycle emissions [1]. For a cotton t-shirt, the use phase laundering is responsible for 78% of the energy that is required, and 82% of the greenhouse effect that is created for the product [2]. Dell reports that the energy needed for the use phase results in 65% of the product carbon footprint of a laptop used in China [3], and 90% of a server operated in United States [4].

However, there are events that can occur which disrupt the assumed useful life of the average product. The estimated lifetime of many products is based on the average time before the next technology is released rather than when the product will no longer be useful. However, technological disruptions can occur that are beyond the scope of the average evolution of technology. Substitutive technologies may cause people to buy new products before old products have reached the end of their expected life. For instance, in the transition from videocassettes tapes to DVDs many consumers purchased a DVD player despite the fact that their VCR continued to work. As a result of the proliferation of the new standard, consumers that wanted to continue using VCRs would have increasing trouble using the old technology, as supporting industries, like tape manufacturers, died off. In other cases, complementary technologies alter the way consumers are expected to use existing products, and hence the impacts associated with them. Netbooks, smartphones, and tablets, such as Apple's iPad, do not fully replace laptop and desktop computers, but they have altered the purpose and frequency with which consumers use them [5,6].

Policies can also cut the useful time of a product short. For example, in the state of California, statue SB 33 was passed in 1984 as the standard under which cars must qualify to pass a smog check. If a car cannot meet this standard, the state offers an incentive to retire the gross polluting vehicle through its Voluntary Accelerated Vehicle Retirement program [7]. This retirement program can cut the life time of the car short, reducing the expected use time and emissions down from original estimates. Another example of policies that impact expected emissions is the sourcing of energy. Most LCAs rely on the current "energy mix," or the proportion of the energy being generated by various energy producing technologies, to estimate the expected emissions from energy demand over the use phase of the product at an assumed location. The proportion of renewable energy sources in the energy mix is largely dictated by legislation. Over time new means of power production with different associated emission will go online, and change the actual emissions that were projected for the use phase.

Other events can prolong the average use phase of products. In many instances, it is not economically feasible for consumers and companies to invest in new equipment. In slow economic times, companies may not have the capital to upgrade equipment, even if it is operationally and financially advantageous to do so; instead they will get along with the available devices on hand that are still operational. For instance, with the post-2008 recession, businesses may not have the financial resources available to refresh their computer hardware at the rate that they had anticipated when they first modeled the expected life time of the computers they purchased years ago.

In this paper we aim to improve the accuracy of the estimated emissions of a Life Cycle Assessment by including predictable disruptions to the life cycle, thereby increasing the meaningfulness of LCA results. First we provide a framework to incorporate the uncertainty associated with such events into the LCA of any given product sold at a certain point in time. Then, we present a case study which applies this theoretical framework to empirical data from existing LCAs. Specifically, the possibility of a recession and the release of a complementary product are incorporated into previous studies conducted on a laptop. Finally, we discuss results and draw some main conclusions.

2 PROPOSED METHODOLOGY

For this study, we consider future uncertainty by incorporating specific events that may disrupt the expected course of the average product. The impacts of such events are determined by evaluating their likelihood and consequences over the duration of the lifecycle phase in which they occur. We begin by assessing the estimated time that any of these products are expected to be in use. This period spans from when the product is first released on the market until the last product sold reaches its end of the life. In other words, it includes not just the estimated lifetime of the product but, also, the amount of time that the products are on the market.

Once we have established the period of consideration, we next identify events that could change the expected use or disposal of products over this span of time. These events will be referred to as lifecycle disturbances. Disturbances can either increase or decrease the expected impacts of a product. Examples of disturbance events include: a recession; a change in policy; the introduction of, or change to, a complementary technology which alters how consumers use the product; the development of a substitutive technology which displaces the product; and the development, or proliferation, of an end of life processing technique. Additional events beyond these examples could exist, and are dependent on the individual product. The example we use in this study will focus on disturbances during the use phase.

For each event, data is needed to determine the likelihood that it will take place and its impact if it does occur. Historic Data is used to model the probability that an event will occur over time. This data may be complex to obtain or estimate. If the historic data needed to model an event is not available, it is suggested that either the definition of the event is expanded to include other occurrence of a similar type or correlated data is used as a proxy. The case study that follows discusses some possible source for this data. However, determining the most suitable data for all possible events is beyond the scope of this paper, and we will reserve this task for future work.

The future uncertainty of the use phase can be modeled in a scenario-based framework. Let $A=\{\alpha_{1,}\ \alpha_{2,}\ \alpha_{3\ldots}\ \alpha_n\}$ be the set of all events that could affect the use time of the initial product and $U(\beta)$ be the use time when a set of events $\boldsymbol{\beta} \in \boldsymbol{P}(\boldsymbol{A})$occurs, where $\boldsymbol{P}(\boldsymbol{A})$ is the power set of A, which includes all of the subsets of A. Then, with an estimation of the probability that β occurs, $\mathbf{Pr}(\boldsymbol{\beta})$, we can calculated the expected duration of use during the use phase with the following equation:

$$\mathbf{E}[\mathbf{use\ time}] = \sum_{\boldsymbol{\beta}\in\boldsymbol{P}(\boldsymbol{A})} \boldsymbol{U}(\boldsymbol{\beta}) * \mathbf{Pr}\,(\boldsymbol{\beta}) \qquad (1)$$

3 LAPTOP CASE STUDY

3.1 Introduction

Laptops serve as a good illustration for some of the potential unexpected disturbances that can take place over the life span of a product. There are several external events that can affect the rate at which consumers replace their laptops. Compared to other items, the obsolescence of high tech products is determined by the developments within the industry, rather than the functional life of a device. Also, the electronics industry in particular has recently been subjected to an increasing number of regulatory and voluntary market standards, including EPEAT, WEEE, Energy Star, and RoHS, which has intensified the generational differences between products.

3.2 Determining the Factors of Unexpected Disturbances

Period of Consideration

There are many estimates for the average duration of the use time of a laptop in LCA studies. IVF [8] estimates that a laptop lasts 5.6 years, Deng et al. [9] assumes that it is used for 2.9 years based on a survey, while O'Connell, and Stutz [3] evaluate the replacement time to be 4 years. For this study, the Dell figure of 4 years is used. This number is based on Energy Star's Typical Energy Consumption (TEC), which is also used to approximate the average use of the laptop. According to this standard, we assume that a laptop spends 60% of the time turned off, 30% being used, and 10% in sleep mode.

Meanwhile, we assume that the sales period, or the amount of time a laptop is on the market, is one and a half years. This is based on the assumption that laptop models are updated annually, though in actuality it can be less frequent. We add another six months to account for the fact that models are sold beyond the release date of the next version, until the remaining inventory is sold. With this figure, the sales period and the refresh rate combine to 5.5 years.

Identify Events

Given the scale of this study, we limit the disruptive events considered for a laptop to a recession and the release of a complementary technology. These two events have actually taken place in recent years and serve to illustrate the potential effects of disruptive events on impacts.

Predicting the Possibility of a Recession

Several factors make it difficult to predict when a recession will occur. The incidence of a recession is determined largely by changes in the gross domestic product (GDP). Yet, GDP serves as a poor predictor of the turning points of economic cycles [10]. Data from common economic indicators, like the GDP, lags months or even quarters behind the present day, making it difficult to determine even the current economic conditions. In addition, because recessions are rare, the corresponding data needed to adequately forecast them is limited [11].

When assessing the various recession forecast models that are currently available, several researchers have found them to be insufficient [10–12]. To our knowledge none of the existing models have been able to identify the start date of every recession correctly, without also providing false signals for downturns that do not come about. While researchers continue to refine the existing models [13–15] and explore alternative variables [16–18], Harding [12] notes that the unconditional probability would often serve as a better predictor than some of the models that have been proposed.

For this study, we must develop a method to determine the likelihood that a recession will occur at the point when laptop owners first begin to purchase newer replacement products to the point when the last customer is expected to refresh their hardware. The limitations of existing models, as well as their focus on shorter horizons, presently make them a poor candidate for estimating the probability of a recession many years into the future. However, with the correct variables, existing recession forecasting techniques, such as the differences in yield curves, and linear probability, univariate, and multivariate models, may later prove to be suitable methods to predict recessions farther on the horizon.

Instead we utilized data points from the National Bureau of Economic Research (NBER) to obtain the length of time between recessions in the United States, in order to determine the parameters of a probability distribution. We estimated the probability of a recession occurring from the third year of the period of consideration onward, as devices begin to reach the end of their life, using the Weibull distribution with fitted parameters. We define the time between recessions as the duration from the end of previous recession to the beginning of the next recession. These time intervals between events can be fitted to Weibull distribution. The shape parameter of the Weibull distribution represents whether the hazard rate function is increasing, decreasing, or constant over time. Changes in the hazard rates function over time indicate whether the next event will be more or less likely to occur as time goes on. The parameters of the Weibull distribution are estimated using Maximum-Likelihood Estimation (MLE). Despite the small amount of data points, we obtained a near 45% line in Q-Q plot, as shown in Figure 1, where the Q-Q plot is used to measure if two distribution are similar to each other or not. With the MLE estimator of the distribution, we can then calculate the probability that a recession will occur during a certain period of time, given the end time of the previous period.

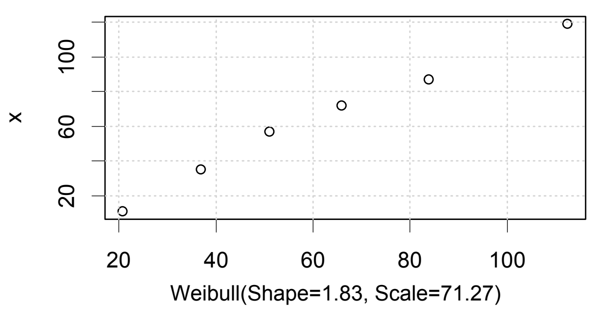

Figure 1: Q-Q Plot of the Fitted Weibull Distribution and the History Recession Data.

While the traditional definition of a recession is two consecutive quarters of shrinking GDP [19], NBER identifies recessions based on business cycles that begin the first day of a period following a peak through the last day of the period of the trough. More specifically, NBER defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales [20]." Only data from the most recent decades was used, as researchers have suggested that the economy has become less volatile and that recessions have become less frequent and severe in recent decades [21–23].

Predicting the Impact of a Recession

We assume that if a recession occurs at the time when laptop owners are expected to begin purchasing new replacement devices, they will put off their purchase for a year on average. Under this assumption, the laptop is assumed to be in use for 5 years. Using data from Deng et al., the effects of an additional year of use will be another 34.76 CO_2e (kg) provided no other disturbance events take place.

Predicting the Possibility of a Complementary Product

The continuous development of technology leads to better and more functional products. Over the course of this development, complementary products are introduced. Eventually these products may evolve to replace the initial product. This phenomenon has been observed in various technologies, such as computers and video playing and recording devices. At any point in time the reduction in the use of the initial product due to the new complementary product can be modeled for period t as shown in the equation below: The proportional reduction in period *t* is:

$$R(t) * \min\{a(t)/S(t), 1\}, \quad (2)$$

where for period *t*, *R*(*t*) is the proportion reduction in the use of the initial product amongst those who purchase the complementary product, *a*(*t*) is the number of people who adopt the complementary product, and *S*(*t*) is the number of people who own the original product.

The number of people who adopt the new product, denoted *a*(t), may be small initially, before it becomes successful and is purchased at a much faster rate. Bass [24] developed a model to estimate the adoption of new technologies. His model describes the diffusion process of new products based on communication theory and the spread of word of mouth. According to the Bass diffusion model, a small group of people are innovators, who like to try new products, while others are imitators that only purchase a new product when they hear positive reviews from others that own it. Over time, the whole potential market gradually adopts the new product as more and more imitators hear about it. Since the development of the model, the diffusion of word of mouth has accelerated, due to the development of the internet and the use of technology in social interactions.

Many researchers have extended upon the Bass diffusion model and developed methods to estimate the parameters of those models using sale data. Readers are referred to [25,26] for more details and extensions of the Bass model. In general, the model consists of three parameters: the coefficient of innovation, *p*, the coefficient of imitation, *q*, and the potential market size, *m*. For this study, we utilize the nonlinear least squares (NLLS) approach proposed by [27] to estimate the parameters.

Note that the parameter *m* can be estimated using either previous sales data or a specific number based on an educated estimate. For the tablet, we use both initial sales data for the nascent product, as well as diffusion data on other technologies to estimate *m*. In the United States there is a large difference between the number of people who have adopted various technologies. It was estimated that that 52% of adults owned a laptop in 2010, while 77% owned either a laptop or a desktop in 2012 [28]. These figures equate to 40% and 58% of the overall populations in 2010 and 2012, respectively. Given their price point and ease of use, we believe that tablets are more accessible products than traditional PCs, and as a result will become more popular. Since tablets require very little technical know-how, they could potentially become devices owned by children and the elderly—a group who have traditionally been the most reluctant to adoption new technologies. In fact, tablet manufacturers, such as Apple [29], Samsung [30], Acer [31], and Amazon [32] have already started pilot programs for testing tablets in classrooms. Cellular phones, which have previously been a product with a high rate of penetration, can give an idea of the potential adoption rate of tablets. In 2010, 85% of adults in the United States owned a cell phone. Given this information, we will assume that the potential market size for tablets is 65% of the overall national population that is expected in 2017.

In our study, tablet PCs are viewed as new complementary product to laptops. The nonlinear least square method is used to estimate the adoption rate of tablet PCs using sales data of tablets from 2010 to 2012. Due to the availability of sales data of the whole tablet market, we estimated the 2010 sales according to [33] and the 2011 and 2012 sales using a combination of the sales number and the market share of Apple ipad and Samsung galaxy [34,35]. The 2012 Q4 ipad sales are estimated from global data and scaled to a figure for the U.S. [36]. We assume that this data is an accurate measure of adoption for tablets. The adoption curve of tablet PCs is shown in Figure 2.

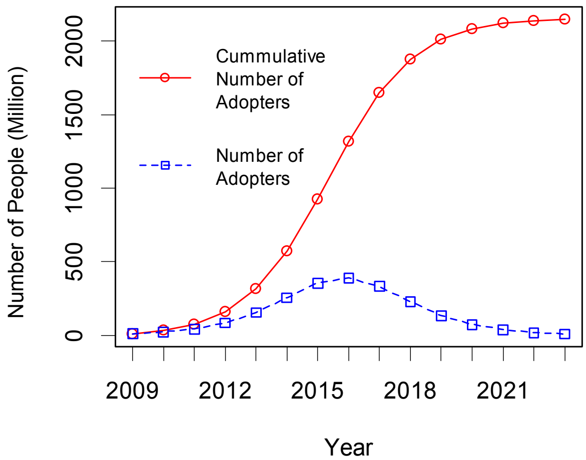

Figure 2: Estimated Adoption Curve for Tablet PC.

Surveys have shown that more than 30% of people who own both a tablet and a PC have reduced their usage of traditional devices [5]. However, these surveys do not indicate the amount of time by which these individuals have reduced their use. According to a report by Morgan Stanley [5], consumer PC usage decreased by 20% from 2008 to 2010. The report also suggests that, at present, tablet use is still limited to content consumption, such as web browsing, photo viewing, and music listening, while working, producing, and communicating, or creating content such as writing, spreadsheets, and edited photos, is still reserved for the PC. They calculate that around 75% of PC usage consists of content consumption. As a result, we assume that an increasing amount of desktop and laptop usage will be replaced by tablets, especially as more powerful hardware and software is developed. However, because of their small screen size and lack of a keyboard, PCs will still continue to be used for certain types of activities.

For the sake of simplicity, we will assume $R(t)$ to be a simple linear function with an upper bound:

$$R(t) = \min\{0.1*t, 0.8\}. \quad (3)$$

For the number of people who own laptops at time t, denoted $S(t)$, we assume 52% is the saturate rate of laptop for U.S. adults, which is the actual total proportion of adults who owned the device in 2010 [37]. We assume that this rate will continue into the future, and we can estimate the exact number for $S(t)$ based on projections for the U.S. adult population [38].

3.3 Total Impacts of Events

We considered three scenarios to investigate how lifecycle disturbances can affect the use phase impacts of an LCA. First, impacts are benchmarked without the inclusion of any of these events using U.S. greenhouse gas emissions factors [39] and the LCA results of [3] and [9]. Then, impacts that incorporate future uncertainty are assessed for products that are released at two respective points in time: the years 2009, prior to the release of the iPad and the subsequent adoption of tablets, when the possibility of this event was still uncertain; and the present year, 2012, when the release of tablet is no longer being a possible uncertainty. Since the likelihood that a disruptive event will occur changes over time, the impacts for a single product will differ based on when it is released. As a result, the inclusion of this type of uncertainty differentiates competing products based on a temporal aspect.

In the second scenario, we consider a new laptop that was launched on the market in August 2009, from the perspective of that point in time. In 2009, there were indications within the industry that a new product category was coming in the near future. In general, the history of innovations within the computer industry shows that fundamentally different technologies take on average about 10 years of development before they matures into a successful format that a large number of consumers can afford. In 2009, the personal computer industry had gone about that long, since the last big technology, laptops, had taken off. Additionally, for the two decades leading up to this point, the computer industry had been developing new mobility products, and had released technologies such as personal digital assistants (PDA) and netbooks. The iPhone and subsequent smartphones had been hugely successful, offering users increased access to some of the functions of a PC in a mobile device. Similarly, an iPod with Wi-Fi and multi-touch interface had hit the market in 2007. Rumors of the iPad were escalating [40]. All of this evidence suggested that there was going to be a new mobile product, and this product could displace some the functional uses of desktops and laptops.

For the 2009 scenario, we assume that the probability of a new product being introduced in 2010, 2011, or 2012 is each 30%. There is also 10% chance that there would be no new complementary product coming during the planning periods. Once the new product is launched on the market, we assume the reduced use time of the laptop depends on the adoption rate of the new product.

In the third scenario, we consider an LCA study that would be conducted in 2012 for a new laptop that is going to be launched in January 2013. For this scenario, the tablet has already been introduced, so the risk is low that there will be another complementary product coming on the market that will potentially displace the PC in the short term. Then the only uncertain event in this scenario is the recession. Note that the use time of laptops here requires an adjustment due to the adoption of tablet PC as well.

As mentioned earlier, a recession only affects the use time of a product when it happens in the last portion of the period of consideration. Hence, we assume that if there is a recession during the time between the third year and the fifth and a half year, the actual use time of a laptop increases for one year on average. The probability of a recession during a certain period can be estimated using the Weibull distribution with fitted parameters.

To simplify the analysis, we assume that the events we considering are independent of each other. In real life, with more information available, such as the correlation between the technology development and recession, the joint probability of dependent events can be estimated. With the assumption of independence, we calculate the probability and the corresponding use time of each event and obtain the expected greenhouse gas emissions using the U.S. energy mix [39] for the three scenarios, as are shown in Figure 3. The one standard deviation error bars for the 2009 and 2010 scenarios are also in the figure.

Our results show that the expected carbon footprint for the scenarios that consider future events differs from the benchmark scenario significantly. In our case study, due to the high probability of new complementary technology, we observe a much lower use phase energy consumption and GHG emissions compared with the benchmark scenario. Use phase greenhouse gas emissions are 24-55% lower than the benchmark scenario, contributing 20-33% to the overall LCA emissions reported by O'Connell and Stutz [3], as opposed to their estimates of 47%. Also, we observe that the standard deviation for the 2012 scenario is smaller than that of 2009 scenario because there are fewer uncertain events in the 2012 scenario.

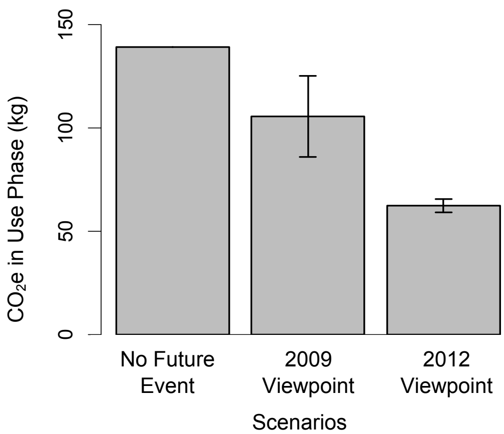

Figure 3: Expected CO2e for Scenarios.

For products that consume energy during the use phase, the energy consumption is usually a significant proportion of the total life cycle energy consumption. As demonstrated in our case study, future event scenarios could alter LCA result.

4 CONCLUSIONS

The uncertainty of Life Cycle Assessment is a very important factor to consider in order to ensure the accuracy of estimated emissions and meaningfulness of LCA results. However the uncertainty associated with expected events, including the use phase, which is known to be an important part of many products, has not been discussed. In this paper, we propose a model to incorporate uncertainty into the expected impacts of a product by considering disturbance events that may alter the phases that have not yet occurred. A case study using this model was performed on a Dell Laptop computer, based on the LCA results of [3] and [9]. We considered the impacts of two possible disturbance events, a recession, and the release of a new technology, and how such events affect the use of the average laptop.

The impacts of including such uncertainty were shown to alter results significantly, reducing use phase greenhouse gas emissions by 55% in one scenario. They also illustrate that the impacts of a single product can change significantly based on temporal aspects. While data and parameter uncertainty is commonly incorporated into LCAs, through statistical techniques such as sensitivity and Monte Carlo analysis, discussions about contextual or choice uncertainty, which deals with the definitions, system boundaries, and assumptions made while conducting the LCA are less prevalent [41]. Our results show that the assumptions made about the impacts of expected events, which have not yet occurred, are significant and can lead to an inaccurate assessment.

Given the scope and time constraints of this paper, we were only able to consider two events and provide a basic estimation of their probabilities. The proposed methodology would provide the most accurate results if all possible disturbance events that could impact the results of a LCA were considered. This illustrates that one drawback of the methodology is that there are no readily available resources for companies to identify such events, or obtain an easy estimates of their likelihood. Companies may be limited in the time and resources they can dedicate to exhaustively and accurately conduct such research. On the other hand firms have access to additional forecasting reports of their industry, which may provide better data for estimating the probability of events.

The case study presented in this work represents only two possible events that can disturb the expected lifecycle. The impacts of other events that might affect the use time of a product need to be explored in forthcoming work to substantiate the validity of our proposed model. In addition, the application of the model to other products will be attempted, to see if findings also hold true. Work dedicated to finding the most appropriate resources to estimate the possibility of events would also improve our confidence in the validity of these results. A possible prospect for future study includes a database constructed for identifying events and their probabilities which would aid others in incorporating the uncertainty of expected emissions into future LCA studies.

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