A Methodology for Robust Comparative Life Cycle Assessments Incorporating Uncertainty

A Methodology for Robust Comparative Life Cycle Assessments Incorporating Uncertainty

Jeremy R. Gregory, Arash Noshadravan, Elsa A. Olivetti, Randolph E. Kirchain*

Materials Systems Laboratory, Massachusetts Institute of Technology, 77 Massachusetts Ave, Rm. 1-276, Cambridge, MA 02139

*Corresponding author: jgregory@mit.edu, +1 617 324 5639

ABSTRACT.

We propose a methodology for conducting robust comparative life cycle assessments (LCA) by leveraging uncertainty. The method evaluates a broad range of the possible scenario space in a probabilistic fashion while simultaneously considering uncertainty in input data. The method is intended to ascertain which scenarios have a definitive environmentally preferable choice among the alternatives being compared and the significance of the differences given uncertainty in the parameters, which parameters have the most influence on this difference, and how we can identify the resolvable scenarios (where one alternative in the comparison has a clearly lower environmental impact). This is accomplished via an aggregated probabilistic scenario-aware analysis, followed by an assessment of which scenarios have resolvable alternatives. Decision-tree partitioning algorithms are used to isolate meaningful scenario groups. In instances where the alternatives cannot be resolved for scenarios of interest, influential parameters are identified using sensitivity analysis. If those parameters can be refined, the process can be iterated using the refined parameters. We also present definitions of uncertainty quantities that have not been applied in the field of LCA and approaches for characterizing uncertainty in those quantities. We then demonstrate the methodology through a case study of pavements.

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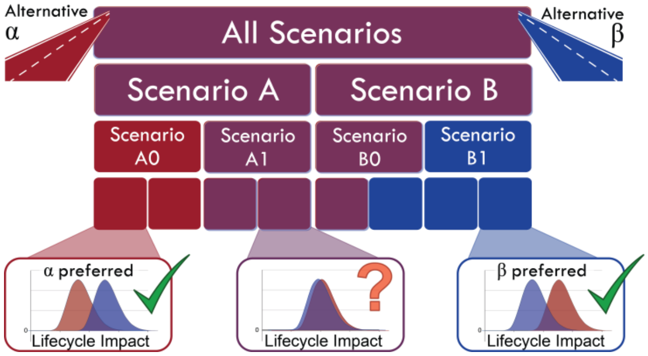

INTRODUCTION

As the application of life cycle assessment (LCA) expands, the importance of achieving meaningful and robust comparisons of the environmental performance of alternatives has increased. Indeed, the stakes are high for firms selling products and executing processes under consideration in LCAs. For instance, a European Union biofuels policy requires biofuels producers to demonstrate that the life cycle greenhouse gas emissions of a fuel are 35% below the baseline footprint of a fossil-derived fuel (this will increase to 50% in 2017 and starting in 2018 new installations will be subject to a 60% reduction).[1]

LCAs have often included the comparison of products or processes because relative impacts bring meaning to what is otherwise an abstract concept (e.g., mass of carbon dioxide in the air or disability adjusted life years). Practitioners have long understood the importance of standards to enable meaningful comparison including the broad ISO 14040/14044 standards[2] and product-focused standards such as the Publicly Available Specification (PAS) 2050 from the British Standards Institute,[3] the Product Life Cycle Accounting and Reporting Standard from the Greenhouse Gas (GHG) Protocol,[4] and the ISO 14067 standard.[5] However, to date, there is limited attention paid in the standards on how to investigate and comment on the significance of the difference between products' environmental impacts.

Analyzing uncertainty in LCA calculations is one way to evaluate the significance of calculated differences and this is recognized in the ISO 14044 standard: "An analysis of results for sensitivity and uncertainty shall be conducted for studies intended to be used in comparative assertions intended to be disclosed to the public."[2] While this statement is important, there is no guidance in the ISO 14044 standard on how to conduct uncertainty analyses to support assertions of the difference of impact between products. Indeed, there have been calls for such guidance in standards from the literature[6] and encouragingly the PAS 2050 and the Product Life Cycle Accounting and Reporting Standard from the GHG Protocol each have sections discussing uncertainty. However, the guidance is limited in that the focus is solely on qualitative characterizations of data quality and quantitative calculations of uncertainty in input data (often referred to as *parameter uncertainty*).

We note four challenges that are endemic to the assessment of uncertainty in comparative LCA and which deserve further guidance. The first challenge is that LCA uncertainty does *not* solely derive from conventional sources of data variation; instead it derives from the choices available for the framing of an LCA and the unique characteristics of individual decision-makers. Collectively these are often referred to as *scenario uncertainty*. Second, at present, there is little published guidance on how to combine analyses of scenario uncertainty with more conventional parameter uncertainty, particularly within comparative assessments. Third, while parameter and scenario uncertainty are typically analyzed together, their implications must be assessed distinctly. When scenario uncertainty is analyzed in a manner like conventional empirical parameters, information about the decision can be lost and the robustness of a given comparison becomes more ambiguous. Because the scenario/uncertainty space is large, analytical methods are important to efficiently synthesize the implications of scenarios. Finally, we note that life cycle (LC) data, especially data on uncertainty and variation, are costly to collect. Methods to assess comparative performance should accommodate efforts to reduce this cost through informed triage.

Given these challenges, we build upon previous work reported in the literature to address aspects of the gap in current LCA literature and practice by describing (and executing) a methodology for conducting comparative LCAs that 1) improves the definition and characterization of uncertain quantities in LCAs analyzed in both parameter and scenario analysis, 2) evaluates a broad range of the possible scenario space while simultaneously considering uncertainty in input data, and 3) efficiently synthesizes the implications of those results across the scenario space through the use of a categorization and regression tree analysis. The objective is to comment on the robustness of an assertion of difference among multiple products or processes. In particular, we ascertain 1) which scenarios have a statistically definitive environmentally preferable choice, 2) which parameters have the most influence on this difference, and 3) how we can identify the resolvable scenarios.

Our work represents a methodological contribution for uncertainty analyses in comparative LCAs and highlights the importance of analyzing scenario-related uncertainties in a proper manner. Specifically, we demonstrate that results are obscured when these scenario-related uncertainties are evaluated in a strictly probabilistic fashion. We use a case study of pavements throughout the document to illustrate concepts and demonstrate the methodology. Details on the models and data used in the case study are presented first, followed by definitions of quantities used in LCAs and approaches for characterizing uncertainty in those quantities. The comparative assessment methodology is then described and demonstrated using the pavements case study.

PAVEMENT LIFE CYCLE ASSESSMENT MODELS AND DATA

We consider two alternative pavements for an urban interstate highway in Missouri in a comparative LCA. The two alternatives are a hot-mix asphalt concrete (AC) pavement, representing a flexible pavement, and a jointed plain portland cement concrete (PCC) pavement, representing a rigid pavement. More technical details about the designs specifications are presented in Section 3 of the supporting information (SI).

Pavement LCAs usually comprise five phases: material extraction, construction of the pavement, use phase, maintenance and rehabilitation, and end-of-life.[7, 8] Figure S1 in the SI depicts the five phases and the major subcomponents associated with these phases. A detailed description of the life cycle model is presented in Noshadravan, et al [9]; here we focus on defining the terms and concepts that are of particular importance to the comparative assessment: analysis period, design life, and particularly the elements that contribute to the use phase of the pavement.

The first noteworthy elements in pavement LCA are the analysis period and design life of the pavement. The analysis period is the time boundary of the study and the design life is the life time of the pavement. The design life defines how frequently maintenance will be considered within the analysis period for the

LCA. Details on the models used in the use phase portion of the LCA are provided in Section S4 of the SI, but key elements are summarized here. The use phase could be significant in a comparative life cycle assessment, especially for high-volume roads, due to the effect of pavement-vehicle interaction (PVI).[9, 10] Two major sources of PVI include fuel losses due to changes in roughness and fuel losses due to deflection of pavements. The LCA model applied in this study accounts for both roughness and deflection components. The deflection losses are calculated based on the model developed by Akbarian et al.[10] Roughness is characterized by the international roughness index (IRI). The prediction of roughness over time is extracted from output of a pavement design software tool (Pavement-ME), which implements the calculations specified by the industry design guide. There is an underlying probabilistic model associated with the prediction of roughness over time using this model. Although the pavement is designed for a prescribed level of reliability, the uncertainty in the roughness evolution over time can be significant. We account for this uncertainty in our LCA and propagate it into the estimation of roughness-induced emissions in pavement LCA.[11, 12] The progressive change in the roughness over time relative to its value at initial construction is calculated and translated to the excess fuel consumption (i.e., fuel consumption due to pavement roughness beyond the fuel required to move the vehicle) using the empirical model presented by Zaabar and Chatti.[13]

Other parameters related to the use phase burden include the fuel economy and traffic growth of both cars and trucks on pavement, the albedo and carbonation resulting from the pavement material, and the lighting used to illuminate the pavement. Further details on the data sources for the remainder of the life cycle inventory are included in the Section S5 of the SI.

We use global warming potential (GWP) as the impact assessment metric in this case study and calculate it based on the guidelines put forward by the Intergovernmental Panel on Climate Change.[14] It should be emphasized that GWP is only one of many measures of environmental burden and a complete LCA would calculate multiple measures. Furthermore, our analysis focuses on uncertainty in life cycle inventory parameters and thus, we do not include uncertainty in the GWP factors, as has been done elsewhere.[15]

DEFINITIONS OF QUANTITIES IN LIFE CYCLE ASSESSMENTS

There is an extensive literature characterizing sources and types of uncertainty in life cycle assessment and methods for analyzing the impact of uncertainty on life cycle impact assessment. Huijbregts[16] conducted early work on the topic of uncertainty in LCA and since then Lloyd and Ries[17] and Williams et al.[18] have published thorough summaries of previous work in the field and a recent contribution also provides a review of LCA uncertainty methods.[15] (We refer readers to the latter three references for a comprehensive literature review on uncertainty in LCA.) Major life cycle inventories including developers of ecoinvent[19] and the United States Life Cycle Inventory Database[20] have built upon and refined the frameworks outlined in the literature.

The literature and footprinting standards have coalesced around the terminology for types of uncertainty in LCA proposed by Hujbregts[16] and summarized in Lloyd and Ries[17] for both life cycle inventories (LCI) and life cycle impact assessment (LCIA) methods: parameter, scenario, and model uncertainty (parameter and scenario uncertainty were defined in the introduction; model uncertainty refers to uncertainty in the mathematical relationships used to develop LCIs and LCIAs).

Although the delineation of the three types of uncertainty appears straightforward, in practice differentiating the three types in an analysis can prove difficult because there is overlap among them. For example, parameters may be used in scenarios or choices may be made in models. de Koning et al.[21] have noted that these three types of uncertainty manifest themselves by contributing to the uncertainty of the final result of an aggregated cradle-to-gate LCA. They correctly point out that all forms of uncertainty are expressed as uncertainty in a parameter value, even though it is actually an aggregate of parameter, model, and scenario uncertainty. This overlap can make it challenging for practitioners to characterize uncertainty and select appropriate uncertainty analysis methods.

We attempt to clarify this matter by describing how literature in the field of risk and policy analysis has defined uncertainty for different types of quantities that are also used in LCAs. Morgan and Henrion[22] define eight types of quantities related to uncertainty and we will discuss the five quantities that are of most importance for uncertainty analysis in LCA. These five quantities are summarized in Table S1 of the SI and described here. Each analysis is framed by *decision variables* (subjectively selected by the analyst to frame the decision – a way to answer the question, "what is the best outcome?", or more specifically, "which product has the lowest environmental impact?") and *outcome criterion* (the metric from the life cycle impact assessment method used to measure the desirability of possible outcomes). *Empirical parameters* represent properties that are measurable, at least in principle, because they can be said to have a *true* value (such as electricity consumption by a laptop or particulate emissions from a diesel engine). By contrast, *model domain parameters* define the scope of the system being analyzed (e.g., temporal or geographic boundaries) and there is no true value. Rather, there is an *appropriate* value that is selected by the analyst (the interpretation of appropriateness may vary depending on the analyst). Similarly, *value parameters* represent aspects of the preferences of the analyst or decision-maker and an appropriate value is selected by the analyst. Examples include the discount rate applied in cost analyses (there is no true value), or the allocation method used for the life cycle burden of materials depending on end-of-life assumptions (such as 50/50 or cut-off methods).

All of the parameters used in the pavement LCA, their quantity type, and their associated uncertainty are included in Section S6 of the SI; a sampling is included in Table 1**Error! Reference source not found.**. It is worth noting that nearly all of the model inputs are empirical quantities, with the exception of five model domain parameters and two value parameters. Uncertainty characterization for the parameters will be discussed in the following section.

Table 1. A sample of the parameters used in pavement LCA model parametric analysis and their associated uncertainty values (see Section S6 of SI for a comprehensive list, including data sources for baseline and standard deviation values). M&R = maintenance and rehabilitation; SD = standard deviation. *Scope* refers to whether or not the phenomenon is included in the analysis.

Model input	Quantity Type	Mean	SD	Distribution
Scope: Albedo	Model domain	-	-	Binary
Scope: Deflection	Model domain	-	-	Binary
Scope: Roughness	Model domain	-	-	Binary
Analysis period	Model domain	-	-	uniform discrete
Design life	Model domain	-	-	uniform discrete
Salvage life allocation	Value	-	-	Binary
M&R strategy	Value	-	-	Binary
Roughness evolution	Empirical	-	-	uniform discrete
Traffic growth factor	Empirical	0.030	0.003	lognormal
Fuel efficiency-cars (mpg)	Empirical	23.70	2.152	lognormal
Fuel efficiency increase (%)	Empirical	0.005	0.0006	lognormal
Fuel loss prediction due to roughness, car (gal/in-mile)	Empirical	0.00017	0.00002	lognormal
Albedo: coefficient-Asphalt	Empirical	0.125	0.011	lognormal
Albedo: coefficient-Concrete	Empirical	0.325	0.030	lognormal
PCC thickness (in)	Empirical	8.000	0.154	lognormal
Cement content (lb/yd3)	Empirical	564.0	10.830	lognormal
AC thickness, layer 1 (in)	Empirical	2.000	0.038	lognormal
Binder percentage (%)	Empirical	0.087	0.002	lognormal
impact factor: cement impact	Empirical	1.00	0.230	lognormal
impact factor: kg of bitumen	Empirical	0.403	0.075	lognormal

UNCERTAINTY CHARACTERIZATION FOR PARAMETERS

Morgan and Henrion[22] argue that empirical quantities are the only types of quantities whose uncertainty may be represented by a weighted probability distribution because they have a true value. Thus, their implication may be evaluated using probabilistic methodologies, such as a Monte Carlo analysis. Conversely, Morgan and Henrion contend that model domain and value parameters should not be treated probabilistically because there are no true values and, hence, the frequency of values cannot be meaningfully defined within the context of the decision. Consequently, they argue it would be inappropriate to represent uncertainty for these parameters with a subjective weighting or probability, although it is technically feasible and certainly has been done.[21, 23] When the influence of these is convolved through weighting, important information about their impact is masked and lost.

We agree with this philosophy but depart from it in part of our approach simply to avoid unnecessary computation, but adhere to it otherwise. Specifically, we formulate model domain and value parameters probabilistically only to test for the extreme case of a wholly dominating alternative, and in the context of a sensitivity analysis to characterize their overall influence on model results. Furthermore, even in such a context they should be defined as a range of continuous or discrete values with equal likelihood (i.e., an unweighted or uniform distribution). This enables one to analyze a wide range of systematically or randomly-generated combinations of model domain and value parameters (each combination of these framing parameters is a scenario) without specifying that one scenario is more likely than another.

Empirical parameters are generally uncertain in nature. For those parameters for which there is no clear representative value and/or distribution, a rough distribution should be defined using any number of methods (e.g., the ecoinvent pedigree matrix[19] or underspecification[24]). In such cases, the analyst should err toward overestimating uncertainty and if these parameters are identified as influential, using a range of values. Value and model domain parameters should be characterized using a broad range of discrete or continuous values with equal likelihood (i.e., unweighted or uniform distribution). (A "broad" range clearly cannot be defined precisely, but in general one should err on the side of being conservative in this first step.)

A final complicating factor in characterizing uncertainty in parameters used in LCA, particularly empirical quantities with probabilistic distributions, is that multiple sources of uncertainty are addressed in different ways. Section S1 of the SI details our framework for types, sources, and methods for characterizing uncertainty in parameters, which builds upon the work of others. Section S2 provides details about how uncertainty characterizations for multiple uncertainty types can be combined into one probability distribution for a parameter, using the ecoinvent pedigree matrix methodology.

The uncertainty distributions and values for a selection of the parameters in the pavement LCA are included in Table 1 the complete list is in Section S6 of the SI. All empirical quantities have lognormal distributions, whereas model domain and value parameters have either binary or uniform discrete distributions, depending on the parameter type. Lognormal distributions were selected because a) all of the parameters were exclusively positive, b) it is a commonly used distribution throughout the LCA literature, and c) it is conveniently compatible with pedigree based approaches to estimate uncertainty. To maintain consistency, we use lognormal distributions even for values that are percentages because the mean and standard deviation values are significantly smaller than one, so the likelihood of sampling values close to one is essentially zero.

The approach outlined in Sections S1 and S2 of the SI was used to calculate standard deviations for the parameters in Table 1 (and Section S6 of the SI), including using the ecoinvent pedigree matrix to estimate quantities due to several types of uncertainty. Furthermore, all parameters are uncorrelated for calculations of one alternative, but common parameters in the comparative assessment of two alternatives are correlated across the two alternatives.

METHODOLOGY FOR EVALUATING UNCERTAINTY IN COMPARATIVE LIFE CYCLE ASSESSMENTS

Some studies exploring the incorporation of uncertainty in comparative life cycle assessments have focused on evaluating the impact of parameter uncertainty on outcomes.[25, 26] Methods typically involve evaluating the ratios of or differences between the impacts of products being compared. These metrics are usually referred to as comparison indicators and guidance to this effect is given in product carbon footprint standards.[4] In most LCAs, alternatives should be compared assuming some amount of correlation in input parameters across the alternatives. This means that meaningful tests of significance should accommodate that correlation. When Monte Carlo methods are used, statistical characteristics of a comparison indicator are usually the simplest option which meets this criterion.

While comparison indicator approaches and careful treatment of correlation are critical for the accurate evaluation of parameter uncertainty, they are only applicable for a given scenario. Comparative performance of alternatives should be evaluated through a probabilistic analysis which also attempts to explore the scenario space (i.e., all possible combinations of model domain and value parameters) comprehensively.

More expansive comparative LCAs that include both parameter and scenario uncertainty have been conducted by a few researchers, including Huijbregts et al.,[23] de Koning et al.,[21] Mattila et al.,[27] and Gregory et al.[28] Huijbregts et al. combined parameter, scenario, and model uncertainty in a single probabilistic assessment.[23] Notably, in doing so they characterized uncertainty in choices (i.e., model domain and value parameters) using weighted probability functions. Similarly, de Koning et al. explored parameter, scenario, and model uncertainty by using subjective probabilities for scenarios that reflect the preferences of a decision-maker.[21] Weighting of this form raises some abstract conceptual concerns, but more importantly also a real practical concern – convolving scenario outcomes through weighting potentially masks distinct outcomes among the different scenarios. For example, under scenario one, option A may be preferred; under scenario two, option B may be preferred. A weighted combination of the outcomes of one and two may suggest that either or no alternative is preferred. Whatever the specific outcome, details about the nature of comparison are lost.

Before describing our proposed methodology, some contextual comments must be made. As noted in the introduction, our objective is to be able to comment on the robustness of an assertion of difference among multiple products or processes. This objective recognizes that a) for any nominal comparison there are in fact numerous versions of that comparison each situated within distinct scenarios defined by specific combinations of model domain and value parameters; b) the significance of difference between alternatives can be evaluated within a given scenario, but that result may not hold (and may, in fact, be inverted) under other scenarios; and c) the goal of a comparative analysis is to identify the briefest description of the scenario space within which statistically significant results are observed and conversely where they are not. We believe that these points have not been specifically called out in previous work.

Although a scenario could technically be defined as a collection of parameters for a single analysis, this would include every simulation conducted in a probabilistic sampling method (such as a Monte Carlo analysis), which is not the way the term is typically used. Instead, we are defining a scenario to be a collection of framing assumptions; that is, the combined set of value and model domain parameters (represented by F). Any analyses which share a common set of F represent the same scenario. Scenario populations are a collection of scenarios with some common framing assumptions, (i.e., for two scenarios 1 and 2 to be in the same population then $F_1 \cap F_2 \neq \varnothing$). This terminology will be demonstrated in the case study in order to clarify its application.

Our proposed methodology for evaluating uncertainty in comparative life cycle assessments of alternatives (e.g., processes or products) is outlined in Figure 1. The process is for a single set of decision variables and outcome criteria (e.g., impact assessment methods) and therefore must be repeated for different sets of decisions or criteria. It may be necessary to iterate the process several times before drawing final conclusions.

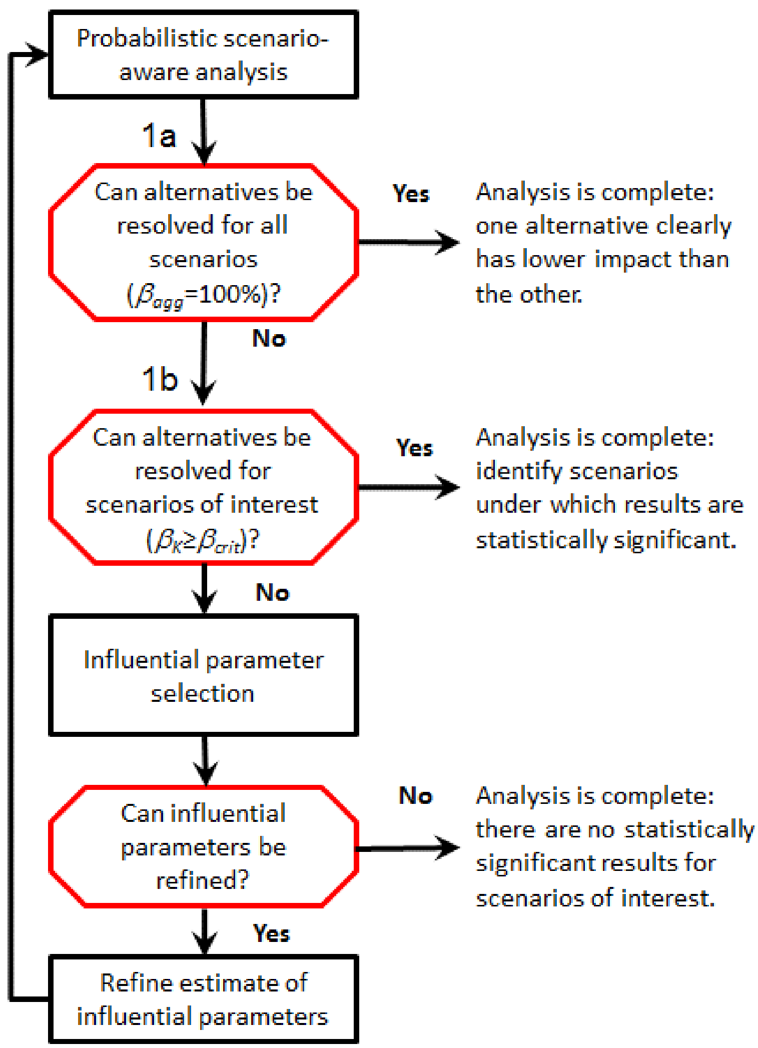

Figure 1. Methodology for evaluating uncertainty in comparative life cycle assessments. β is the frequency that one alternative has lower impact than the other across a set of simulations (β_{crit} is a minimum threshold for statistical significance, β_{agg} is the frequency for the aggregated analysis, or the combination of empirical, model domain, and value parameters in an analysis, and β_K is the frequency for each set of framing assumptions).

The methodology begins with an *aggregated probabilistic scenario-aware analysis* as shown at the top of Figure 1. This is a simultaneous analysis of uncertainty in empirical, model domain, and value parameters using a probabilistic analysis of the relative performance of the alternatives. (Using the conventional terminology found in the literature, this could be referred to as combined analysis of parameter, scenario, and model uncertainty across a wide scenario space.) The probabilistic analysis can be accomplished using any sampling-based method (such as a Monte Carlo or structured sampling) or in some cases analytical approaches.[25] Care must be taken in the analysis to correlate parameters that are common between the two alternatives.[21] (Indeed, one value parameter may involve the use of different correlation assumptions.) In subsequent mathematical expressions, we will assume that K samples of each set of value and model domain parameters (F) are generated and the index k represents the k^{th} instance of those samples. And for each of these K sets of value parameters, M samples of the empirical parameters are generated (indexed on m). In total, KM samples are generated.

The next step (Step 1a in Figure 1) is to calculate the probability that one alternative has a lower impact than another across all of the simulations. This is accomplished by calculating a comparison indicator for each simulation (k,m), $CI_{L,(k,m)}$,[23] which is defined as the ratio between the impacts of two alternatives as follows:

$$CI_{L,(k,m)} = \frac{Z_{L,B,(k,m)}}{Z_{L,A,(k,m)}} \qquad \text{Equation 1}$$

where $Z_{L,B,(k,m)}$ is the environmental impact for alternative B using the life cycle environmental impact assessment metric L for the specific realization of parameters k and m, and $Z_{L,A,(k,m)}$ is the environmental impact for alternative A using the same metric and same sampled sets of parameters. We define β as the frequency that alternative B has a lower impact than A across some set of scenarios. That is, as:

$$\beta = P(CI_L < 1) \qquad \text{Equation 2}$$

In practice, we estimate β through the use of Monte Carlo simulation trials. More specifically, we initially evaluate an aggregated measure β_{agg} which is the fraction of all results $\{CI_{L,(1,1)}, CI_{L,(1,2)}, \ldots CI_{L,(2,1)}, CI_{L,(2,2)}, \ldots CI_{L,(k,m)}\}$ that are less than one. Expressed symbolically, that is:

$$\beta_{agg} = \frac{\sum_{k=1}^{K}\sum_{m=1}^{M}\left[CI_{L,(k,m)} < 1\right]}{KM} \text{ where } [\xi] = \begin{cases} 1 & \text{if } \xi \text{ is true} \\ 0 & \text{otherwise} \end{cases} \qquad \text{Equation 3}$$

If β_{agg} (or (1- β_{agg})) = 100% (outcome 1a-yes in Figure 1), then one alternative clearly has lower impact than the other and the analysis is complete. However, this would be extremely unlikely for an aggregated analysis and thus, the next step (1b) would be to evaluate β_k for each scenario, where β_k is defined as:

$$\beta_k = \frac{\sum_{m=1}^{M}\left[CI_{L,(k,m)} < 1\right]}{M} \qquad \text{Equation 4}$$

The difference in impact of the two alternatives in a given scenario is considered to be statistically significant if β_k or (1- β_k) is greater than a threshold value, β_{crit}. In the interest of brevity, we will refer to such cases as resolvable (i.e., we can resolve the difference in the impact of A from the impact of B). This threshold, β_{crit}, is a decision parameter that controls the level of confidence in the decision and should be set by the analyst for a given context. As noted previously, it is unlikely that the two alternatives will be resolvable for all scenarios. By contrast, is likely that some scenarios are of more interest to a particular set of decision makers (e.g., because their convictions are more likely to be aligned to those scenarios or because they feel that particular set of framing conditions are likely to be considered valid). If the alternatives can be resolved for the scenarios of interest (outcome 1b-yes), then the analysis is complete and the scenarios under which one alternative has a lower impact than another can be identified as statistically significant.

In the case presented here, the β_k results were analyzed using a categorization and regression tree (CART) algorithm implemented in the software JMP. CART identifies a succinct description of the statistically differentiable subpopulations within the scenario populations by recursively partitioning the space of input data and fitting a simple regression model within each partition. Comprehensive structured sampling was performed for the value and model domain parameters to assess the combination of scenarios.

If the alternatives cannot be resolved for the scenarios of interest, then the *influential parameters* for all scenarios need to be identified in order to determine the parameters that are worthy of further refinement because of their influence on the result. Influence can be assessed using different methods of sensitivity analysis.[29] These methods include regression-based methods (such as Spearman rank correlation), variance-based methods (such as Sobol indices), and analytical approaches when uncertainty is propagated thusly.[30, 31]

Once influential parameters are identified, an assessment needs to be made as to whether resources are available to improve the fidelity of the analysis. This would manifest in the *refinement of uncertainty characterization* for influential parameters (e.g., more data collection). If the influential parameters cannot be refined then the analysis is complete and the outcome is that there are insufficient statistically significant results for the scenarios of interest. If they can be refined, then the entire process should be repeated using the refined uncertainty characterizations. An analogous, iterative approach to LCA parameter refinement was previously proposed by Huijbregts.[23]

PAVEMENT LCA RESULTS

For the pavement LCA seven value and model domain parameters were identified that define the scenario space and are members of the framing parameters vector (F). Five of these parameters are binary in nature; for the other two, two representative levels were selected to manage the computational expense of the analysis. The full factorial combination of these parameters represents 128 scenarios. For each k^{th} sample of F, 1,000 samples were taken of the empirical parameters comprising E (M=1,000). The number of samples has a significant influence on computational intensity because the samples must be run in each of the 128 scenarios. We conducted a convergence analysis and determined that 1,000 samples was sufficient to approximate the statistics of the scenarios. The probabilistic scenario-aware analysis results in an aggregate pool of results that can be disaggregated into 128 probability density functions (PDF) characterizing the comparison indicator for each scenario.

1. Probabilistic Scenario-Aware Analysis

The first results of this analysis are aggregate measures of the individual designs and their resolvability. Figure 2a plots the two aggregate probability density functions (PDF) of GWP for the two designs across the scenario populations. Figure 2b shows the corresponding PDF of CI_{GWP} and a graphical representation of the fraction of results that fall below one (shaded region). For these results, β_{agg} = 0.75 well below the 1.0 needed to draw a conclusion (c.f. Figure 1, outcome 1a-no). Based on the β_{agg} it would be tempting to conclude that this comparison is statistically irresolvable. However, that conclusion is misleading because the aggregate result does not differentiate the numerous underlying decision scenarios defined by combinations of model domain and value parameters (F).

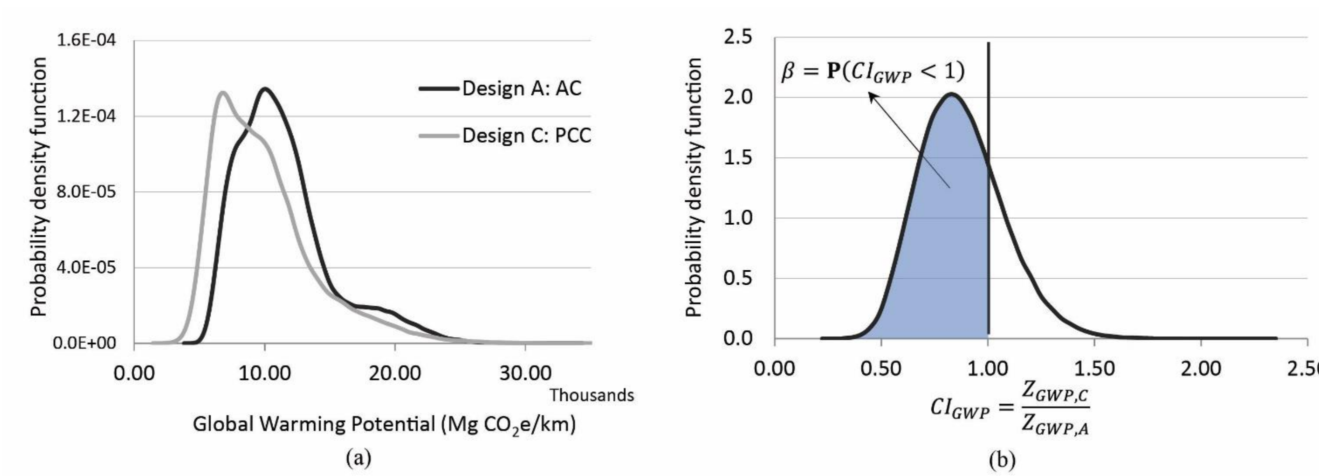

Figure 2. **The probabilistic description of aggregated results from combining 128 sets of Monte Carlo realizations. (a) the comparison of PDFs of GWP for design A (asphalt) and C (concrete). (b) the PDF of CI_{GWP}. The shaded region corresponds to the likelihood that the design A has lower impact than design C.**

We computed β_k (see Equation 4) for each of the underlying 128 scenarios as part of the next step in the methodology. For this case, 41 scenarios are statistically resolved for $\beta_{crit} = 0.9$ (highlighted in green in Figure 3). Using a CART algorithm it is possible to create a hierarchical categorization of the various scenarios in terms of their respective beta values to identify the characteristics of resolvable and irresolvable subpopulations. As such, we can say not only that scenario k produces a statistically significant result, but also what characteristics it shares with a larger subpopulation.

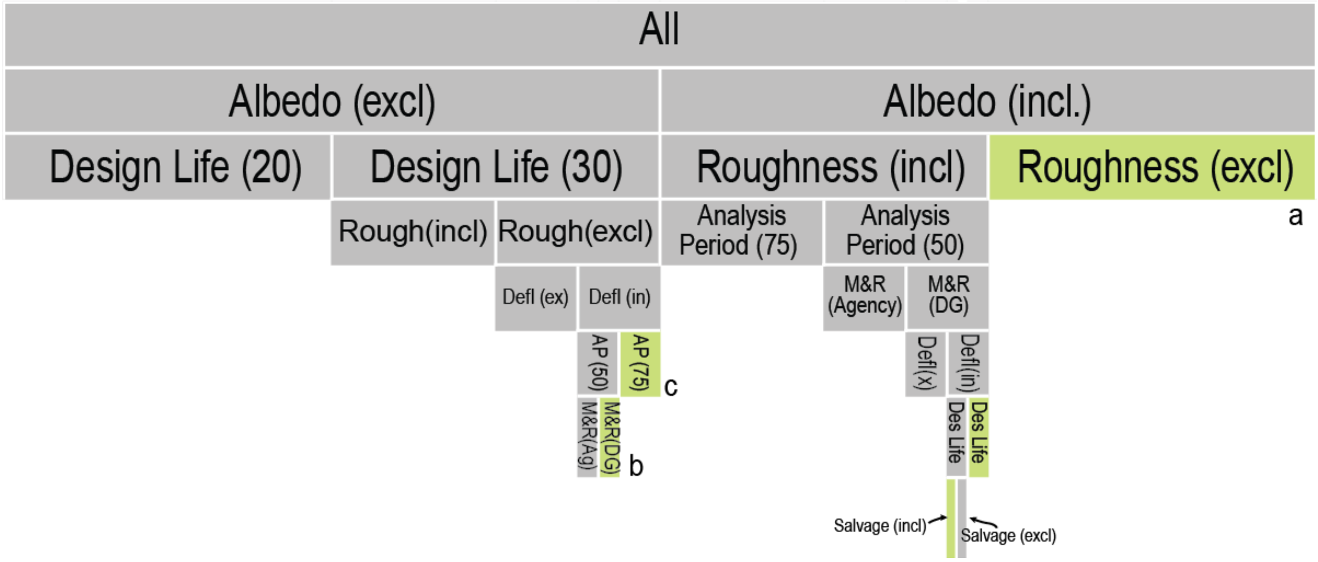

Figure 3. Categorization analysis of resolvable scenarios when all empirical quantities are at full range of values (iteration 1). Green bars differentiate scenarios that are statistically resolved for β_{crit} = 0.9 (design C has lower impact than design A). For binary model domain parameters (c.f. Figure 2) the scope is either included (incl) or excluded (excl). Parenthetical numbers indicate the value of the parameter. Letters a, b, and c denote scenarios discussed in the text. Rough = roughness; AP = Analysis period; Defl = deflection; M&R = maintenance and rehabilitation; Des Life = design life.

This partitioning analysis (shown in Figure 3) reveals that 32 of these resolved scenarios (labelled a in the figure) share the common features of including the impact of surface albedo (Albedo(incl.)) and excluding the impact of surface roughness (Rough(excl)). In fact, specifying only these two aspects of a scenario is sufficient to diagnose that these scenarios can be resolved (irrespective of the state of the other five scenario variables). The other 10 resolved scenarios are distributed among the states examined, but all share the common feature of including the impact of pavement deflection (Defl(Incl.)). The subpopulation of scenarios which exclude albedo effects (Albedo(Excl.) – the left half of tree), serves as an object lesson on the importance of considering and isolating individual scenarios and scenario populations. With a β_{agg} of 0.6, this subpopulation seems thoroughly irresolvable. Within this group, however, one can isolate six specific scenarios (labelled groups b and c in Figure 3) that are, in fact, resolvable.

For the purposes of exercising the method, we will presume that these initial results were deemed too ambiguous (i.e., there were too many unresolved scenario states which were deemed of interest). As such, it would be necessary to refine the influential data to improve the fidelity of the result and expand the scenarios under which alternatives are resolvable. To guide that refinement process, we first evaluate the influence of the various parameters.

2. Influential Parameter Selection

As noted earlier, there are several approaches to identify those parameters with the most influence on the results. Here we identify the influential parameters through the use of normalized squared Spearman rank correlation coefficients (SRCC) derived from the simulations run for step 1.[32]

Figure S3 in the SI shows the results of this global sensitivity analysis. The correlation coefficients are normalized and represented as a percentage characterizing the relative contribution to the variance of GWP for different input parameters. The results show that the model domain decision regarding including or excluding the impact of surface albedo in the scope of analysis has the largest effect (Scope: Albedo) on the result. Other model domain parameters such as the inclusion of roughness-derived impacts (Scope: Roughness), maintenance and rehabilitation schedule (M&R), and design life are also important. Among the empirical quantities, the rate of evolution of roughness (Roughness evolution) and the impact factor of bitumen (IF Bitumen) are among other top influential parameters.

3. Refine estimate of influential parameters

In this particular pavement analysis it was not possible to collect more refined data. In order to demonstrate the full, proposed methodology, we approximate that refinement by arbitrarily bounding the two most influential empirical parameters, the rate of roughness evolution and the impact factor for bitumen, to narrow ranges. Specifically, we will explore a case where the rate of roughness degradation is typical (around the median) and where the production of bitumen has high burden (the mean impact factor for bitumen is around 0.40 kg CO2-eq/kg). The artificial refinement is useful both to demonstrate the method and to explore the explanatory power of these quantities. If this analysis proves that resolution of these empirical quantities enables sufficient resolution among the alternatives, it should be easier to acquire the resources to collect more data and refine our uncertainty estimates.

The same analysis described in step 1 is repeated, but with the newly refined values for the two most influential empirical quantities. The β_{agg} for this analysis is improved (0.80), but is still far from 1.0 (outcome 1a-no). As such, we proceed to the disaggregated β_k analysis.

For this analysis, 83 of the 128 scenarios are significant using the criterion β_{crit} = 0.9. Figure 4 shows the CART analysis pruned to descriptions of resolvable or irresolvable subpopulations. For this round of analysis, all scenarios where the impact of albedo is included are resolvable irrespective of the state of any of the other model domain or value parameters (labeled a in Figure 4). Similarly, the subpopulation of scenarios labeled b (i.e. scenarios defined by excluding the impact of albedo, with long design lives (30) and analysis periods (75), and which exclude the impact of roughness (Roughness (ex)), produce significant results, irrespective of the state of the three remaining parameters: inclusion of deflection effect, maintenance strategy, and salvage allocation.

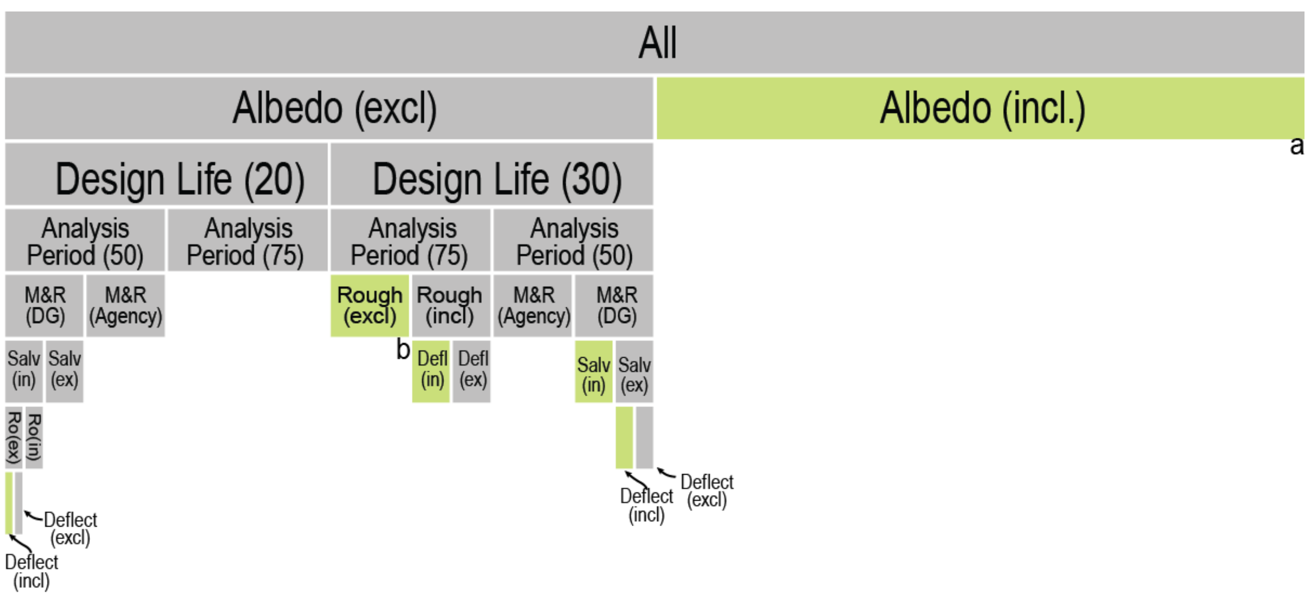

Figure 4. Categorization analysis for refined data analysis (iteration 2). Green bars differentiate scenarios that are statistically resolved for β_{crit} = 0.9. For binary model domain parameters (c.f. Figure 2) the scope is either included (incl) or excluded (excl). Parenthetical numbers indicate the value of the parameter. Letters a, and b denote scenarios discussed in the text. Salv = salvage allocation; Defl = deflection; M&R = maintenance and rehabilitation; Rough or Ro = roughness.

Although the data refinement step successfully produced significant resolution in about 65% (83 of 128) of scenarios, much of the scenario space remains unresolved. If those scenarios are possibly germane, then the analyst should iterate through the process again, identifying influential parameters and exploring whether resources are available to improve the fidelity of parameter estimates. Although an initial sensitivity, as presented in Figure S3, provides useful guidance for those iterations, that analysis should be repeated each time more refined information is introduced.

DISCUSSION

A promising result of this example is that resolution is most strongly driven by model domain parameters (the inclusion of albedo effects, the manner in which maintenance is modeled, and the design life – which together represent more than 90% of the variance of the β values), rather than value parameters such as the analysis period and allocation. Model domain parameters can be resolved through better information and science about a particular system and through consensus development processes within the decision-making community (e.g., product category rules). Many value parameters are inherent to the preferences of the stakeholder and often represent an irreducible form of uncertainty.

Uncertainty is a pervasive challenge in life cycle assessment. Conventional forms of uncertainty in empirical quantities are clearly important drivers of that uncertainty. It is critical to recognize, however, that uncertainty in framing (model domain parameters) and decision maker values (value parameters) can represent even larger sources of uncertainty in LCA results. As a consequence, it is equally critical for LCA studies to explore a broad range of the scenario space.

It is also important to recognize that these kinds of scenario parameters define specific decision contexts and as such are not appropriately described by frequency or probability distributions. More pointedly, any given combination of scenario parameters can represent the perspective of a specific decision-maker. Because of this, probabilistic comparative analyses should only be framed within the context of a given scenario.

Here we propose that the appropriate analysis around scenario uncertainty is to identify the classes of scenarios where statistically defensible decisions can be made (or cannot). The most effective descriptions are the most terse and, therefore, broad. This final goal has been facilitated through the use of decision-tree partitioning algorithms which appear to offer an efficient means to isolate meaningful scenario groups.

Finally, it is important to emphasize that this analysis was done for a single outcome criterion (global warming potential). A more complete LCA would include similar analyses for multiple outcome criteria (other LCIA metrics), which would add a multicriteria component to the decision. Results from all the comparative uncertainty assessments would need to be included in a multicriteria decision analysis, as is the case for deterministic LCAs. The result space in such a situation is even larger than that of a single outcome criterion situation. As such, methods like CART will be even more important to systematically evaluate the space. Future research will explore this topic.

ACKNOWLEDGMENTS

Early discussions on this topic with Gregory Norris, Trisha Montalbo, and Margaret Wildnauer are gratefully acknowledged.

This research has been partially supported by the Concrete Sustainability Hub at MIT, with sponsorship provided by the Portland Cement Association and the Ready Mixed Concrete Research & Education Foundation.

SUPPORTING INFORMATION AVAILABLE

Details on uncertainty characterization of parameters, the pavement LCA model and data, and sensitivity analysis results are in the SI. This information is available free of charge via the internet at http://pubs.acs.org/.

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