A method for Estimating the Degree of Uncertainty With Respect to Life Cycle Assessment During Design

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Life cycle assessment (LCA) is used to estimate a product's environmental impact. Using LCA during the earlier stages of design may produce erroneous results since information available on the product's lifecycle is typically incomplete at these stages. The resulting uncertainty must be accounted for in the decision-making process. This paper proposes a method for estimating the environmental impact of a product's life cycle and the associated degree of uncertainty of that impact using information generated during the design process. Total impact is estimated based on aggregation of individual product life cycle processes impacts. Uncertainty estimation is based on assessing the mismatch between the information required and the information available about the product life cycle in each uncertainty category, as well as their integration. The method is evaluated using pre-defined scenarios with varying uncertainty. [DOI: 10.1115/1.4002163]

Keywords: uncertainty, life cycle assessment, ecodesign, intervals, weighted objectives

1 Introduction

The ratio of product mass to waste mass produced as a result of the product during its life cycle is about one to twenty [1]. These wastes are produced in each phase of the product life cycle from raw material extraction to product retirement. Sustainable development is defined in Ref. [2] as "development which meets today's needs without placing the ability of future generations to meet their needs at risk." For such development, design can play a major role [3] where major requirements for the design including those for sustainable development must be identified and satisfied throughout the process [4] as decisions taken in design affect all stages of product development [5] and in turn all phases of the product's life cycle.

Life cycle assessment [6] is currently the most promising and scientifically defendable methodology for estimating environmental impacts of a product lifecycle [7]. Currently, detailed LCA [6] is critically dependent on high volumes of product-specific data, time consuming, often unaffordable, and reliably used only after detailed design. Abridged LCA [8,9] is either incomplete or inaccurate or requires prior knowledge of what data are important [10]. There is substantial uncertainty involved in the environmental impact calculations in LCA [11]. Literature [11] stresses that estimation of impact must be accompanied by estimation of its uncertainty or imprecision without which the decisions based on these results could be misleading.

If LCA is to be used throughout the design process, the degree of uncertainty involved in the estimations must be assessed and taken into account in the decision making processes during design without which the decisions might be unduly biased or incorrect. There is a need to understand the information required for using LCA in design and the information available at each design stage to ascertain the extent to which LCA could be used at each stage of design.

The objectives of this paper are as follows.

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- Understand uncertainty in the context of product lifecycle information in various stages of design. This is done using literature review and descriptive studies.
- Develop a method for estimating lifecycle environmental impacts of a product and the degree of uncertainty associated with this estimation. This is done by developing a method that integrates interval algebra [12] and weighted objectives [13] and evaluating this by using example scenarios of varying uncertainty.

2 Literature Review and Descriptive Studies

2.1 Literature Review. From a survey [14] of LCA studies, it is identified that LCA results are subject to various sources of uncertainty: uncertainties introduced by the data and the methodology such as the lack of site-specific data and the aggregation of data over different spatial and temporal scales. Studies [15,16] done on finding problems with LCA argue that LCA should include an explanation of the uncertainties that arise during LCA. Uncertainty assessment is necessary for better decision support, transparency and quality comparison. However, usually this is not carried out in LCA studies due to the additional effort needed and the lack of methods [7].

The methods, e.g., Refs. [17,18], have been developed for estimating impacts, taking into account uncertainties in lifecycle inventory data (LCI) in a specific domain. Their authors argue that fuzzy intervals and numbers are more informative and closer to human judgments and perceptions than crisp numbers, thus, improving the pertinence and the interpretation of the results. Some databases have statistical distributions of data [19], which can be used in LCA for impact calculations [20]. It is emphasized [20] that interpretation of uncertainty in data and results is an indispensable part of sound decision making and should be an integral part of the analysis itself. Tools like Simapro7 [21] and KCL-ECO [22] have some limited lifecycle inventory with data distributions, and a limited facility for uncertainty analysis based on the Monte Carlo method [23], which uses inventory values for which the distribution is available (like range, triangular, normal, or lognormal); the calculation is performed for a specified number of times, each time taking a random value within the distribution. The variation in results can be displayed in different distributions or as average or best estimate. However, this analysis is limited to estimating uncertainty in LCI data if the distributions for the data are available. It cannot deal with uncertainty arising from the design process such as those associated with the product structure or the lifecycle phases.

Normally, probability distributions [24] are used to represent random variability in input parameters, upper and lower bounds or fuzzy intervals are used to represent vagueness, and sensitivity analysis is used for methodological choices [25]. Some [26] suggest that for better decision making, all types of uncertainty must be propagated into a single result, using combined models for simulation and approximation.

Geographical, temporal or technological differences are typical sources for uncertainty associated with inventory data in LCA; for instance, geographical and technological differences in life cycle inventory data are shown to be major sources of uncertainty in LCA for processes in waste incinerators [27,28]. In Ref. [29], specific rules of thumb are suggested for the individual impact categories of global warming, acidification, eutrophication, and photo-oxidant creation; the rules quantify the difference in impact scores necessary for it to be significant in product comparison. The authors suggest that LCI data providers should supply quantitative uncertainty information, including correlation estimates for individual parameters. Some [30] emphasize the need for a framework for modeling data uncertainty in LCI. They [30] take uncertainty as data inaccuracy and lack of specific data, divide the latter into complete lack of data and lack of representative data, AQ: #1 and suggest as important the parameters that cause a larger spread in the model outcome.

In Ref. [26], a method is proposed for propagation of data uncertainty into the overall results of the LCA; it combines approximation formulae such as Gauss, Bader–Baccini, and Monte Carlo simulation to estimate the uncertainty. In Ref. [31], it is illustrated that in the initial stages of design, functional parameters, which are functional requirements and constraints for the design problem, should be made available for estimating environmental impacts of the design; use of statistical and sensitivity analysis are suggested for representing uncertainty.

According to literature [11,32], uncertainty exists in LCA because of data inaccuracy, data gaps, model uncertainties, choices, spatial and temporal variability, variability between sources, etc. In Ref. [11], it is argued that LCA results are usually presented as point estimates, which strongly overestimate the reliability; it is suggested that uncertainty arise due to lack of knowledge about the true value of a quantity. Also, stressed is the need for estimating and expressing the uncertainty. Even though there are various available methods for performing uncertainty estimations, such as classical statistical analysis, Bayesian statistical analysis (which needs expert judgments to ascertain the nature of distributions), interval algebra, vague error interval calculations, and probabilistic simulation (which involves the difficult task of finding all possible events), there is still need for a framework that explicate the important aspects of data quality and uncertainty in LCA to the practitioner [11].

2.2 Descriptive Studies. We have conducted a series of design exercises and analyzed their proceedings in order to understand the evolving levels of uncertainty in product lifecycle information during design. The goal was to identify the types of uncertainty that emerge when LCA is used in design; since this information was not available in existing literature, we carried out our own descriptive studies to identify these. The following is a summary of the descriptive studies, for details see Ref. [33]. Twenty-four design exercises were conducted involving 8 designers and 3 design problems; each problem was solved by each designer using one of the three interventions—use of general design literature, use of environmentally friendly design (EFD) literature, or use of detailed impact assessment software. The designers followed the ”think-aloud” protocol while designing; the whole process was videotaped and transcribed, which along with documentations were used for protocol analysis. Out of the 24 exercises, the 16 exercises that used EFD literature and detailed impact assessment software as intervention have been analyzed, and the summary of results are presented below.

- During design of product lifecycles in each of these exercises, it was observed that the structure of the product (assemblies, subassemblies, parts, interfaces, and features) evolved as design progressed.
- Various designers considered different lifecycle phases at different stages of their design process, each at different levels of completeness.
- Designers did not necessarily consider all lifecycle processes for each life cycle phase; in some cases these became more comprehensive as design progressed.
- In some of the design exercises, designers looked for specific data on environmental impacts, which were not available in the databases accessed.

2.3 Summary. As seen in Sec. 2.1, most of the literature in this area has been focused on identifying uncertainty associated with LCI data [13–19,22,23] with some focus on methodology [20,24]. However, the analysis of descriptive studies (Sec. 2.2) illustrate that information about the lifecycle of a product continues to evolve during its development: there is evolving uncertainty also in the product structure, in the completeness of the lifecycle phases, and in the lifecycle processes considered.

Traditionally, LCA is used after the detail design when detailed information about the product, its lifecycle phases, and associated data are available. In this case, the uncertainty will be confined to data and methodology, depending on the variations in these. However, if LCA is used during earlier stages of design where information about the product and its lifecycle phases are also uncertain, there is a greater degree of uncertainty. Hence, in these phases it is important to consider reducible uncertainties like those associated with product structure and lifecycle phase along with data and methodological uncertainty. For decision-making, the results should encompass both impact and associated uncertainty. While literature discusses uncertainty of impact data, there is no discussion on how to calculate and represent the overall uncertainty in the estimated potential impact of a product lifecycle proposal at any given stage in design with respect to LCA.

Therefore, a method for assessing environmental impacts for product life cycles should not only provide an estimate of the impact but also the associated degree of uncertainty that takes into account all these various sources of uncertainty.

The following section details the uncertainty categories identified in our work from literature and descriptive studies.

3 Uncertainty Categories

While existing literature discusses uncertainty in data and methodology; analyses of descriptive studies identified further uncertainty in product structure and life cycle phases. Impact estimation requires two things: the data and the methodology to process the data. The data pertain to processes related to the various elements of the product in its various lifecycle phases. Therefore, the overall uncertainty is affected by the uncertainty related to the product, its life cycle phases, and those related to the data pertaining to the processes and the methodology used to integrate this data. Therefore, in the context of LCA, these four are the only possible elements of uncertainty. We take uncertainty as the accuracy of the estimation rather than the probability of finding the correct estimate. The four uncertainty categories are further elaborated below.

3.1 Product Structure. Uncertainty about the structure of a product is related to its subsystems, parts and interfaces. LCA requires information about the materials and processes used in the life cycle of the product. A product’s structure fundamentally contains only parts and interfaces, each having various features.

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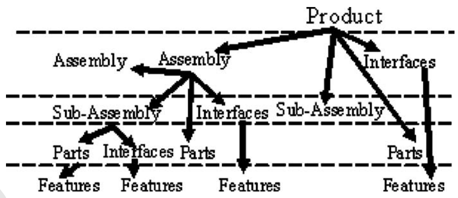

Fig. 1 A product and its subsystems

These parts and interfaces are hierarchically organized into groups called assemblies and subassemblies, where subassemblies contain only parts and interfaces while assemblies also contain subassemblies or other assemblies. The organization is important for capturing information about the various lifecycle processes, e.g., an assembly process that requires movement of the subassembly as a whole and not as its individual parts and features. The categories (Fig. 1) provide a complete set for describing a product's structure and are important for identification of the life cycle processes associated with the product. For instance, while material choice depends only on individual parts, manufacturing processes are dependent on part features, and assembly processes depend on the interfaces between features belonging to different parts, which may belong to different subassemblies or assemblies. Also, these categories are standard categories used in describing CAD models, such as in CATIA [34], and are important to be so, since a designer would typically use a CAD model for developing and describing a product's structure, which is required for defining the product's life cycle processes. Uncertainty in product structure definition is subdivided into the following (qualitative degrees of each uncertainty are proposed within brackets).

- Uncertainty in definition of assemblies, i.e., the collection of assemblies, subassemblies, parts, and interfaces between them in that particular assembly of the product (all, some, none).
- Uncertainty in definition of subassemblies, i.e., the collection of parts and interfaces in the subassemblies of the product (all, some, none).
- Uncertainty in definition of interfaces, i.e., the connection between one or more features of one part and one or more features of another part in the product (all, some, none).
- Uncertainty in definition of parts, i.e., the smallest physical element in the product, not in size but in that it cannot be divided further into parts and interfaces (all, some, none).
- Uncertainty in definition of features, i.e., the geometrical forms in a part (all, some, none).

3.2 Lifecycle Phases. This uncertainty is related to the material, production, distribution, usage, and after-use phases of the product life cycle. There are also subphases within each of these: extraction, manufacturing, and transportation in the material phase (all, some, none); manufacturing and assembly in the production phase (all, some, none); packaging and transportation in the distribution phase (all, some, none); use, maintenance, and repair in the usage phase (all, some, none); and reuse, recycle, and disposal in the after-use phase (all, some, none). For example, at a particular stage of design, a designer may have information only about the material of a component, and not about its other phases. The uncertainty in the lifecycle-phases category is accounts for whether or not a designer considers individual phases (i.e., material, production, distribution, usage, or after-usage). Table 1 shows some instances of designer utterances, from an exercise from the descriptive studies, that involves the lifecycle phases of the product. Note that many of these deliberations involve classes (noncrisp) of lifecycle processes—such as plastics rather than a specific plastic, transportation rather than transportation by a specific means, etc. These would affect the specificity of values and associated uncertainty.

3.3 Data Quality. This uncertainty is related to the relevance of data in terms of its temporal relevance, spatial relevance, and sample size, see details below. The uncertainty in the data quality category can be in terms of the data being old (temporal), nonlocal (spatial) and the number of sources on which the data are based (sample size). Uncertainty in data quality is subdivided into the following.

- Uncertainty in temporal relevance of the data (current, old, very old): how close in time the data collected is to when the process it describes is to be used.
- Uncertainty in spatial relevance of the data (national, continental, world): geographically how close the area from which the data collected is to where the process it describes is to be used.
- Uncertainty in sample size on which the data is based (multiple samples, single sample): in terms of the number of samples used for creating the data.

3.4 Methodological Choices. This uncertainty comes from the temporal relevance, spatial relevance and the comprehensiveness of the methodology. The uncertainty in methodological choices can be in terms of being old, being from a different region than where applied, and in terms of only some of the potential impacts being considered. Uncertainty in methodological choices is subdivided into the following.

- Uncertainty in temporal relevance of the choices: how recent (current, old, very old).
- Uncertainty in spatial relevance of the choices: how close geographically (national, continental, world).

Table 1 Lifecycle processes and protocol instances from a design exercise

Lifecycle process	Protocol instance
Material	Balloons in terms of rubber, plastic, flexible material probably cloth I can use those (*designer trying to evaluate and select material*)
Production	Will be injection molded; Mainly stitching and aluminum frame bolted (*designer trying to select the production (manufacturing and assembly) processes required for the solution*)
Distribution	It should be easy to pack, no damage in transportation (*designer is generating the requirements for product's distribution phase*)
Usage	It should not have any maintenance (*designer generating requirement for usage phase*)
After-usage	Easy to disassemble; should be recyclable (*designer generating the requirement of after-usage phase for the solution*)

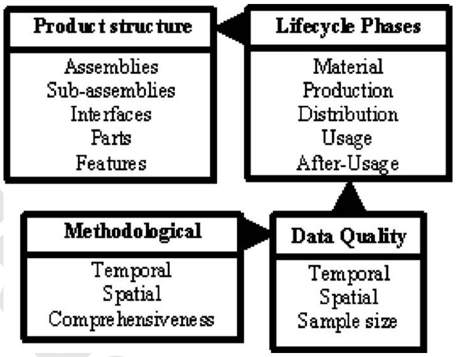

Fig. 2 Uncertainty propagation

- Uncertainty in comprehensiveness of the choices: how comprehensive the categories of impact considered by the methodology are (all, some, none).

3.5 Uncertainty Propagation. Figure 2 shows the uncertainties in different categories and their propagation to the overall uncertainty.

There can be uncertainty in the product structure—i.e., the definition of the product is uncertain. For instance, take a product that has two parts, Part1, Part2, and one interface Int1 between these parts such as a cutting edge connected to a handle for a vegetable cutting knife. If information about the interface is not available, e.g., how the handle is connected to the cutting edge is yet to be defined, there would be uncertainty in the product structure definition. Even if the product structure definition is complete, there can still be uncertainty in terms of the definition of the product lifecycle. For instance, the after-usage details of Part1 and Part2 may not be specified yet, giving uncertainty in the lifecycle definition. Even if the definition of the lifecycle is complete, there can still be uncertainty in terms of data quality; for instance the data about Part1 and Part2 in the material and distribution phases may be uncertain, resulting in data quality uncertainty. Even if the data quality is certain, there may still be uncertainty in methodological choices. For example, the method used for impact assessment may have been developed for a different region, is old or does not consider all the impact categories.

At any design stage, uncertainty in information available is a combination of these individual uncertainties. We need to identify what information is required in all these categories so as to accurately estimate the environmental impact of the product lifecycle at that stage and what information is available in all these categories at that stage; based on these, the uncertainty in impact estimation is assessed.

4 Method Development

A method is developed using interval algebra and weighted objectives, which takes uncertainties about the product structure definition, lifecycle definition and data quality into account while assuming that the uncertainty related to methodological choices remains unchanged. This is because estimation of impact is always based on a particular methodology, and the uncertainty related to methodology will be the same for all proposals compared using that methodology.

During design, information about life cycle processes range from no selection (i.e., complete lack of data) to class selection (i.e., noncrisp data) to point selection (i.e., complete data). If we use probability theory [35], we need to have probability densities from previous data which is not available in LCI databases. Even if this data were available, this could be used only for crisp values, and not for noncrisp data such as classes as prevalent in the situations considered in this work. Dempster–Shafer theory [36] can be used for sets (i.e., classes) but will require computation of belief and mass functions for each such class based on previous data, which is not available in LCI databases.

As a result, noncrisp data such as those corresponding to classes are represented in our method as intervals, which provide the range within which the value for the class should lie. Aggregation of such data from the life cycle processes, each with different impacts representing their relative importance, as required for LCA during earlier stages of design, require a method that integrates these data taking into account the relative importance. Development of a method that blends interval algebra and weighted objectives is a reasonable choice, therefore, for impact and uncertainty estimation in these situations. The proposed method offers an estimate of the environmental impact of a product lifecycle proposal as it evolves during various design stages while also providing an estimate of the uncertainty associated with the estimated impact in terms of a confidence (discussed below) on the impact estimated.

The proposed method has two major parts: impact estimation and uncertainty estimation. Impact estimation makes straightforward use of interval algebra—an established mathematical tool to deal with noncrisp values. Uncertainty estimation is harder. The challenge is to aggregate uncertainties associated with a list of processes, which fall into the following three categories of processes:

- having given impacts and uncertainty, both as intervals
- those that show no impacts as they have not been chosen by the designer but are known to exist
- those that have no impacts because they are not harmful to the environment

For aggregation, weighted objectives method is a commonly used Ref. [13] when criteria have different weights. In our case, the challenges of using weighted objectives are as follows.

- Impacts can be crisp or noncrisp values, and weights are proportional to the size of impact.
- Some processes cannot have weights since their impact values are zero by choice or by virtue of them being environmentally benign.

Our method uses a weighted sum on interval values by integrating weighted objectives method with interval algebra. Since both these are standard mathematical tools for decision making and are integrated in a manner ensuring that each applies to its designed domain of application, the method has a clear mathematical foundation. The processes that have zero values are counted in a nonweighted manner since weighting does not apply in these cases.

The method can be used to estimate, as an interval of values, the environmental impact of each chosen class or instance of a lifecycle process, for a given product as a collection of individual assemblies, subassemblies, parts, and interfaces. The method can then be used to aggregate these process-specific impacts into an overall impact measure for the product for its whole life cycle. Finally the method can be used to estimate the confidence on the impact of each individual process, and aggregate these to estimate the confidence on the overall impact of the product lifecycle.

The measure developed enables the impact value for a given class of lifecycle processes with given environmental impacts to be taken as an interval between two impact values—the maximum and the minimum possible in that class. The confidence level of an estimate is described using a number between 0 and 1, where 0 specifies no confidence on the estimation while 1 specifies 100% confidence. If for an entity (i.e., a part or an interface) neither a class nor a specific value is chosen for a given lifecycle phase (e.g., material phase), its impact is taken to be 0 with confidence equivalent to zero. If, on the other hand, any choice is made, confidence on the value of chosen is taken to be 1, which needs to

Table 2 Temporal, spatial relevance, and sample size

Years	Factor	Location	Factor	Sample size	Factor
<5	1	Country	1	Multiple	1
>5&<10	0.94	Continent	0.98	Single	0.9
>10	0.88	Other continent	0.82		

be multiplied by the temporal factor, spatial factor, and sample size factor (from Table 2) to account for the associated data uncertainty.

Estimation of impact and confidence of a life cycle process is performed as follows, for the four choices possible (the first two referred henceforth as "zero-impact values," while the remaining two as "nonzero-impact values").

1. No lifecycle processes are selected

$$\text{Impact value}_i = 0 \tag{1}$$

$$\text{Confidence}_i = 0 \tag{2}$$

2. A lifecycle process is selected with impact being zero

$$\text{Impact value}_i = 0 \tag{3}$$

$$\text{Confidence}_i = 1 \tag{4}$$

3. A lifecycle process class is chosen

$$\text{Impact}_i = [V_{\min}V_{\max}]_i * \prod_{j=1}^{n} \text{LCPP}_j * \prod_{k=1}^{m} \text{PSEP}_k \tag{5}$$

$$\text{Confidence}_i = [(tf * sf * ssf)_{\min}(tf * sf * ssf)_{\max}]_i \tag{6}$$

Here, n is the number of LCPP, m is the number of PSEP, $[V_{\min}V_{\max}]$ is the impact values in range for a specific unit of lifecycle process range, tf is temporal factor, sf is spatial, sf is sample size factor, LCPP (*life cycle process parameters*): depend on the lifecycle process (for example for transportation, distance in km), PSEP: These are *product structure element parameters* and depend on the elements of the product structure (e.g., part mass in kg). So for transporting a product of x kg over y km, x and y need to be multiplied. The final value is x∗y kgkm, which is multiplied by the unit impact value (specified in number of impact units per kgkm) to estimate the impact of transportation of this product.

4. A specific lifecycle process is chosen

$$\text{Impact value}_i = V_i * \prod_{j=1}^{n} \text{LCPP}_j * \prod_{k=1}^{m} \text{PSEP}_k \tag{7}$$

$$\text{Confidence}_i = tf_i * sf_i * ssf_i \tag{8}$$

Here, V_i is the impact value for a specific unit of lifecycle process. Note that the specific values of these factors can sometimes be derived from the analysis of life cycle inventory data, such as those in Simapro databases [21]. The database contains sets of data for each process; each data differs in terms of the time, space and the number of samples from which it was created.

Depending on which data are picked for impact estimation and which data best represent the time or space of the life cycle of a product, an error will occur in the estimation that will vary from 0 to some absolute maximum value, depending on the choice of data. The absolute mean percent error $\%e_m$ for a given data set representing a given process should be calculated as the average, across all data-points in the set (extended from mean deviation in statistics [37]), of the percent difference between the value of each data point and the mean value of the data set; (1-$\%e_m$) is used as the spatial or temporal factor depending on the nature of the data set.

$$\%e_m = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{|v_k - v_m|}{v_m}\right]_i \tag{9}$$

Here, n is the number of data points, V_k is the value of kth data point, and V_m is the mean value of the data set

For temporal relevance, the data sets available in the databases consulted [17] are either within a 5 years span, or within a 10 years span. Figure 3 shows the absolute mean percent error ($\%e_m^t$) for different processes, for 5 years and 10 years span. The average $\%e_m^t$ across all processes analyzed for a 5 year span is 6.13; for 10 year span it is 12.07; this implies that if older data is used, the error increases. In these cases, the average temporal factors are 0.94 and 0.88, respectively.

For spatial relevance, typical data sets available in the databases are either within a continent, or across continents. Figure 4 shows the absolute mean percent error ($\%e_m^s$) in impact values for various processes, plotted for data from the same continent and from different continents. The average $\%e_m^s$ across different processes within a continent is 2; across continents it is 18 (nine times); $\%e_m^s$ is thus smaller within a continent than across continents. In these cases, the average spatial factors are 0.98 and 0.82, respectively.

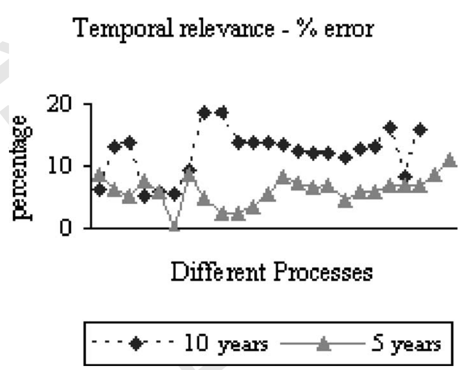

Fig. 3 Temporal relevance

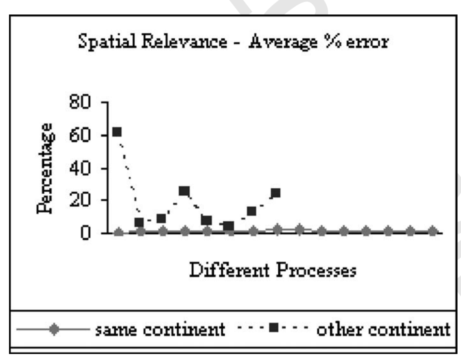

Fig. 4 Spatial relevance

Generally, data accuracy would be more if multiple samples are used to create the data. For estimating the sample size factors, we need the original samples from which each data-point in the databases, typically the average of the sample values, have been created. The percent error $\%e_s$ due to sample size variation is calculated using Eq. (10) [37]. However, current databases do not provide these individual samples. As placeholders, we currently take 1 for multiple data and 0.9 for single data; in reality the database provider can be asked to provide the original samples so that the sample size error can be accurately estimated using Eq. (10).

$$\%e_s = \left[\frac{t * s}{\sqrt{n}}\right] \tag{10}$$

Here, n is the number of samples, which is 1, s is the standard deviation, and t is the factor based on n should be taken from t-table.

Based on the above discussion, indicative average temporal factor, spatial factor and sample size factors are provided in Table 2. For instance, for data less than 5 years old, the temporal factor could be taken as 1, i.e., 100% accurate; for data older than 5 years and less than 10 years, the factor could be taken as 0.94, and so on. For the Spatial values, if the data is from the same country, the factor could be taken as 1; if it is not from the same country but from the same continent, the factor could be taken as 0.98, and so on. According to the sample size values in the Table 2, if the data are from multiple samples, the factor is taken as 1, if it is from a single source, the factor is taken as 0.9. With greater data availability, these values could be made more specific to the process, space, time and sample size used. In the example case discussed in scenario 1 (Sec. 6), let the minimum value of a process class in the material phase be temporally within 5 years and spatially across continent from the usage scenario, and based on multiple samples; the maximum value for this process class be temporally over 5 years, spatially within continent, and is also based on multiple samples; then the confidence interval of the process class, estimated using Eq. (6), is $(1\times 0.82\times 1.94\times 0.98\times 1) \sim (0.8 \quad 0.9)$.

4.1 Lifecyclewise Impact and Confidence Estimation. The impact of a product in the material phase is an aggregation of the individual material impacts of its assemblies, subassemblies and parts. Equation (11) is used to estimate the impact of a product in the material phase.

- The impact of an assembly in the material phase is an aggregation of the individual material impacts of the assemblies, subassemblies and parts in that assembly.
- The impact of a subassembly in the material phase is an aggregation of the material impacts of the parts in that subassembly; interfaces have no material impact.
- The impact of a part in the material phase is an aggregation of the impacts of the individual material processes in that part.

Equation (12) is used to estimate the confidence on the impact of a product at the material phase. The aggregated confidence on the impact value is dependent on the impact values (as weights) and the associated confidences for nonzero impact values, and only on the confidences for zero impact values (since zero-impact values have no impact). This is to take into account the fact that our confidence of a sum of values is affected proportionately by the values as well as confidence on them: a given confidence on a larger value influences more the confidence on the sum than does the same confidence on a smaller value.

Similar logic is used for finding the impacts and associated confidences for other subsystems and other lifecycle phases.

The assumptions behind Eqs. (11) and (12) are the following.

- Impact in a given life cycle phase can be estimated by aggregating the impacts of all processes in that phase.
- For a life cycle process, the impact will be zero (if it is environmentally benign) or nonzero (if not). In each case, there will be some confidence on this impact.
- The confidence on the aggregate value (for a given phase) will be shared proportionately by the aggregate confidence on the zero-impact value processes and the nonzero-impact value processes.
- The aggregate confidence of the nonzero-impact value processes is proportional to the number of these processes as well as the value and confidence of the processes.
- The aggregate confidence of the zero-impact value processes is proportional to the number of these processes as well as the confidence on each such process (since the impact value is zero in these cases).
- For normalization purposes, the equation should reflect that the scale of aggregate confidence on the impact value within a phase should be between 0 and 1.

$$PI_iM = \sum_{j=1}^{\text{No. of } A} AI_{ij}M + \sum_{l=1}^{\text{No. of } SA} SAI_{il}M + \sum_{n=1}^{\text{No. of } Pa} PaI_{in}M \tag{11}$$

$$PC_iM = \frac{NZ_i}{NZ_i + Z_i}\left[\frac{\sum_{j=1}^{NZ_{iA}} AI_{ij}M * AC_{ij}M + \sum_{l=1}^{NZ_{iSA}} SAI_{il}M * SAC_{il}M + \sum_{n=1}^{NZ_{iPa}} PaI_{in}M * PaC_{in}M}{\sum_{j=1}^{NZ_{iA}} AI_{ij}M + \sum_{l=1}^{NZ_{iSA}} SAI_{il}M + \sum_{n=1}^{NZ_{iPa}} PaI_{in}M}\right] + \frac{Z_i}{NZ_i + Z_i}\left[\frac{\sum_{a=1}^{Z_{iA}} AC_{ia}M + \sum_{b=1}^{Z_{iSA}} SAC_{ib}M + \sum_{c=1}^{Z_{iPa}} PaC_{ic}M}{\sum_{a=1}^{Z_{iA}} AC_{ia_{\max}}M + \sum_{b=1}^{Z_{iSA}} SAC_{ib_{\max}}M + \sum_{c=1}^{Z_{iPa}} PaC_{ic_{\max}}M}\right]$$

$$NZ_i = NZ_{iA} + NZ_{iSA} + NZ_{iPa} Z_i = Z_{iA} + Z_{iSA} + Z_{iPa} \tag{12}$$

Table 3 Impact and confidence of life cycle processes of product elements in different scenarios

		Material phase		Production phase		Distribution phase		Usage phase		After-usage phase	
		I_m	C_m	I_p	C_p	I_d	C_d	I_u	C_u	I_a	C_a
S1	Part1	[2,4]	[0.8 0.9]	[2,3]	[0.9 1]	[1,2]	[0.3 0.4]	0	1	–	0
	Int1			–	0						
	Part2	[1,2]	[0.5 0.6]	2	1	[1,3]	[0.4 0.4]	0	1	–	0
S2	Part1	[2,4]	1	[2,3]	1	[1,2]	1	0	1	–	0
	Int1			–	0						
	Part2	[1,2]	1	2	1	[1,3]	1	0	1	–	0
S3	Part1	[2,4]	1	[2,3]	1	[1,2]	1	0	1	[2,3]	1
	Int1			–	0						
	Part2	[1,2]	1	2	1	[1,3]	1	0	1	1	1
S4	Part1	4	1	3	1	2	1	0	1	3	1
	Int1			2	1						
	Part2	2	1	2	1	3	1	0	1	1	1

Here, $PI\ M$ is the product environmental impact in material phase, $AI\ M$ is the assembly environmental impact in material phase, $SAI\ M$ is the subassembly environmental impact in material phase, $PaI\ M$ is the part environmental impact in material phase, M is the material, A is the assemblies, SA is the subassemblies, i is the identifier for product, j is the identifier for assembly, l is the identifier for subassembly, n is the identifier for part, $PC\ M$ is the product confidence in material phase, $AC\ M$ is the assembly confidence in material phase, $SAC\ M$ is the subassembly confidence in material phase, $PaC\ M$ is the part confidence in material phase, NZ_i is the total number of nonzero valued items in material phase in product i, NZ_A is the number of nonzero valued assemblies, NZ_{SA} is the number of nonzero valued subassemblies, NZ_{Pa} is the number of nonzero valued parts, Z_i is the total number of zero valued items in material phase in product i, $AC_{\max}\ M$ is the maximum possible Assembly confidence in material phase, $SAC_{\max}\ M$ is the maximum possible subassembly confidence in material phase, $PaC_{\max}\ M$ is the maximum possible part confidence in material phase, Z_A is the number of zero valued assemblies, Z_{SA} is the number of zero valued subassemblies, and Z_{Pa} is the number of zero valued parts.

4.2 Overall Impact and Overall Confidence. The method for estimating the overall impact value and the overall confidence on this impact for a product lifecycle is based on Eqs. (13) and (14), with similar assumptions as in Eqs. (11) and (12) but now applied to zero-impact-value and nonzero-impact-value life cycle phases (rather than processes).

The estimates on impact and associated confidence of product structure elements, life cycle phases, etc. will be aggregated together to form the impact of the overall product. There are two possible levels of addition: addition of impacts of all the child elements (e.g., extraction, production, and distribution) in a parent element for a given life cycle phase (e.g., material), and addition of impacts from all life cycle phases. The addition of impacts is carried out using interval algebra while estimation of confidence is made using a weighted sum of the individual confidence of impacts, where the impact values are used as the weights.

The overall environmental impact of the product lifecycle proposal is estimated by adding all nonzero individual lifecycle impacts, using Eq. (13). The overall confidence is estimated by taking both nonzero-impact lifecycle phases and zero-impact lifecycle phases, using Eq. (14).

$$PI_i\ \text{total} = \sum_{l=1}^{\substack{\text{No. of LCP} \\ \text{in } i\text{th product}}} PI_{il}\text{LCP} \tag{13}$$

$$PC_i\ \text{total} = \frac{NZ_L}{NZ_L + Z_L}\left[\frac{\sum_{j=1}^{NZ_L} V_{ij} * C_{ij}}{\sum_{j=1}^{NZ_L} V_{ij}}\right] + \frac{Z_L}{NZ_L + Z_L}\left[\frac{\sum_{k=1}^{Z_L} C_{ik}}{\sum_{k=1}^{Z_L} C_{ik_{\max}}}\right] \tag{14}$$

Here PI total is the overall product environmental impact (in all lifecycle phases), PI LCP is the product environmental impact (lifecycle wise), PC total is the overall product confidence (in all lifecycle phases), NZ_L is the number of nonzero valued lifecycle phases in ith product, Z_L is the number of zero valued lifecycle phases in ith product, V_{ij} is the environmental impact values of jth lifecycle phase of ith product, C_{ij} is the confidence of jth lifecycle phase of ith product, C_{ik} is the confidence of kth lifecycle phase of ith product, and $C_{ij\ \max}$ is the maximum confidence of kth lifecycle phase of ith product. For a range of values of V_i, we get confidence in range

5 Calculation Example

The proposed method for assessing environmental impact and associated confidence is evaluated using a set of example scenarios with varying levels of uncertainty. The hypothesis is that, those scenarios that have more elements in the various categories of uncertainty that are not considered, known, known precisely, or known with what relevance, are likely to have less environmental impact estimates with less confidence values. As the number of such elements is reduced, the impact values should increase with an associated increase in their confidence.

Let us take the example from Sec. 4.1 in which a product proposal has two individual parts Part1 and Part2 with one interface Int1; the impact values (in intervals) and confidence on these values (also in intervals) for the parts and the interface, in various life cycle phases, are specified in Table 3. Here, I is used to denote impact value and C to denote confidence. Five lifecycle phases are considered: material, production, distribution, usage and after-usage.

Four scenarios are taken to check the consistency of calculation using the above equations.

- Scenario1 (S1): Uncertainty exists in all three categories (product-structure, lifecycle, and data quality). Data on Int1 is not available (reflected in no values in impact or uncertainty for Int1 in the table), which accounts for uncertainty in product structure, the after-usage details of the parts are not specified, which gives uncertainty in lifecycle, and the

Table 4 LCP wise overall impact values and associated confidence in the four scenarios

	Material phase		Production phase		Distribution phase		Usage phase		After-usage phase		Over all	
	I_m	C_m	I_p	C_p	I_d	C_d	I_u	C_u	I_a	C_a	I	C
S1	[3,6]	[0.3 1]	[4,5]	[0.5 0.6]	[2,5]	[0.2 1]	0	1	0	0	[9,16]	[0.3 0.8]
S2	[3,6]	[1]	[4,5]	[0.5 0.6]	[2,5]	[1]	0	1	0	0	[9,16]	[0.4 0.8]
S3	[3,6]	[1]	[4,5]	[0.5 0.6]	[2,5]	[1]	0	1	[3,4]	[1]	[12,20]	[0.6 1]
S4	6	1	7	1	5	1	0	1	4	1	22	1

initial confidence values of the parts in material and distribution phases are uncertain, resulting in data quality uncertainty.

- Scenario2 (S2): Uncertainty exists in two categories (product structure and lifecycle). Here also, the product structure and lifecycle uncertainty are the same as in S1 but data quality uncertainty is removed by selecting relevant data, as seen in the new confidence value of 1.
- Scenario3 (S3): Uncertainty exists in only one category (product structure). Here, the product structure uncertainty remains as before while the lifecycle uncertainty is removed by specifying the necessary values for Part1 and Part2 in the after-usage phase.
- Scenario4 (S4): There is no uncertainty: all the required data is available. Here, necessary values for Int1 are provided, so that the product structure uncertainty is removed and thus the overall confidence should be 1.

The four scenarios in the example are designed such that the amount of information about the product lifecycle proposal is increased steadily from scenario 1 to scenario 4. If the proposed method for assessing impact and associated uncertainty is reasonable, it should predict a steady increase in the impact value and a steady reduction in uncertainty reflected in a steady increase in confidence. For it to be acceptable, the method embodied in the equations should be able to provide estimates on the confidence in the calculated impact value as would be intuitively expected in the scenarios, which are varied depending on the lack of detailed information about the product lifecycle proposal. Table 4 shows the summary of impact values and the estimates of confidence on them, as estimated using the proposed method. As can be seen from this table, as the uncertainty is reduced across the scenarios, the impact values and confidences on them are increased as expected. In S1, the overall impact ranges from 9 to 16; the confidence on this impact ranges from 0.33 to 0.8. The difference between S1 and S2 is only in data uncertainty; so the overall impact value remains the same (9 16) but the lower value of the confidence range increases (0.46 0.8).

From S2 to S3, further information about the after-usage phase is added, resulting in an increase in both impact value (12 20) and confidence (0.6 1). In S4, information about product structure element is also added, resulting in an increase in both impact value (22) and confidence (1). Note that during design, multiple life cycle alternatives may have to be compared, taking into account both impact and associated confidence. For example, if an alternative has a greater impact with greater confidence than another, choice using traditional methods will favor the latter for its lower impact. This might be an error in judgment since the impact estimated for the latter is less complete, as shown in its lower confidence, and hence likely to increase more as more information becomes available; the decision might have to be deferred. For these situations, new decision methods are necessary. One such method is discussed in Ref. [38].

6 Summary and Conclusions

Various categories of uncertainty associated with using LCA for a product lifecycle proposal in various stages of design are identified. Based on this, a method for estimating lifecycle environmental impact and associated confidence of a product is developed. This method is evaluated using example scenarios with varying uncertainty.

As the method is capable of taking into account all three categories of uncertainty, it is likely to be better suited to support decision-making throughout the design process where information continues to develop and uncertainties progressively get reduced. The scope for this paper is using LCA in design for estimating impacts and associated uncertainties. Within this, methodological uncertainty is currently not addressed. Also, for a different methodology such as MET matrix, the nature of uncertainties might be different. These need further investigation.

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#1 Au: References 26 and 31 are the same. Please check our renumbering of Refs. 31–38.

#2 Au: Please provide the definition of CAD, CATIA, LCP, and MET if possible.

#3 Au: Please check change from Sec. 4.5 to Sec. 4.1 as there is no Sec. 4.5 in this paper.