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Actionable insights with less data: guiding early building design decisions with streamlined probabilistic life cycle assessment

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Abstract

Purpose: Two obstacles that impede wider use of life cycle assessment (LCA) are its time- and data-intensiveness and the credibility surrounding its results – challenges that grow with the complexity of the product being analyzed. To guide the critical early design stages of a complicated product like a building, it is important to be able to rapidly estimate environmental impacts with limited information, quantify the resulting uncertainty, and identify critical parameters where more detail is needed.

Methods: The authors have developed the Building Attribute to Impact Algorithm (BAIA) to demonstrate the use of streamlined (not scope-limiting), probabilistic LCA for guiding the design of a building from early stages of the design process when many aspects of the design are unknown or undecided. Early-design uncertainty is accommodated through *under-specification* – characterizing the design using the available level of detail – and capturing the resulting variability in predicted impacts through Monte Carlo simulations. Probabilistic triage with sensitivity analyses identifies which uncertain attributes should be specified further to increase the precision of the results. The speed of the analyses allows for sequentially refining key attributes and re-running the analyses until the predicted impacts are precise enough to inform decision making, such as choosing a preferable design alternative.

Results and discussion: Twelve design variants for a hypothetical single-family residential building are analyzed. As information is sequentially added to each variant, the significance of the difference in performance between each variant pair is calculated to determine when enough information has been added to resolve the designs (identify which design is preferable) with high confidence. At the sixth step in the analysis, all variant pairs whose mean impacts differ by at least 4% are resolvable with 90% confidence, even though only 6 attributes are specified and dozens of attributes remain under-specified. Furthermore, the comparative results for each variant pair is validated against a set of conventional LCA results, showing that BAIA identifies the correct preferable design among each resolvable pair at this step.

Conclusions: Iterative specification guided by probabilistic triage can help identify promising early design alternatives even when details are only provided for key attributes. The analysis of hypothetical design variants demonstrates that BAIA is both efficient (arrives at statistically defensible conclusions from design variant comparisons based on few pieces of information) and effective (identifies the same preferable design variants as conventional LCAs).

Keywords Buildings • Early design guidance • Life cycle assessment • Sensitivity analyses • Streamlined • Uncertainty

Abbreviations

AAM – Attribute-to-Activity Model

BAIA – Building Attribute to Impact Algorithm

BEopt – Building Energy Optimization, NREL software

BIM – Building information modeling

BOA – Bill of activities

CI – Comparison indicator

CV – Coefficient of variation

FS – Fully specified

GWP – Global warming potential

HVAC – Heating, ventilation, and air conditioning

IE – Athena Impact Estimator

JMP – Statistical software from SAS

LCA – Life cycle assessment

MC – Monte Carlo

NREL – National Renewable Energy Laboratory

ESM – Electronic Supplementary Material

1 Introduction

Though life cycle assessment (LCA) is a valuable method for determining the environmental impacts of a product or service, LCA has not reached its potential to impact design because of its resource intensive nature and because of concerns surrounding credibility of the results (Olinzock et al. 2015; Saunders et al. 2013). These difficulties are even more pronounced for complex products like buildings and electronics. This paper describes a novel approach to significantly reduce the time and resources required to conduct a complex-product LCA while still providing estimates of impact uncertainty. This is carried out in the context of a case involving the design of residential buildings.

There is wide consensus on the significance of the environmental impacts from the built environment and the importance of early design decisions in determining those impacts (Al Gharably et al. 2016; Basbagill et al. 2013; Basbagill et al. 2014; Granadeiro et al. 2013; Hygh et al. 2012; Konis et al. 2016; Kuo et al. 2016; Marsh 2016; Mueller et al. 2004; Nielsen 2005; Østergård et al. 2016). As the plan for a proposed building becomes more developed during the design process, it becomes more difficult and expensive to make significant changes and improve environmental performance. Therefore, making informed early-design decisions can lead to buildings with significantly lower environmental impacts. However, whole-building LCAs are often only carried out in the later stages of development when the details of the design are known but also are largely fixed. LCAs would be more impactful if they could be done rapidly during the planning, conceptual, and schematic phases of the design process and in a way that helps the analyst identify the most influential inputs (and, thereby, avoid collecting unnecessary data.)

A prominent challenge to realizing this vision is that at the earliest stages of the design process, the majority of details are specified with widely varying degrees of precision. Furthermore, design parameters of interest may vary from project to project. As such, to be applicable at this stage, an LCA method must be able to accommodate information of arbitrary specificity for all design attributes. To be credible, the method must also quantify the uncertainty in the resulting LCA. At the same time, since the early design process is about choosing among high-level variations, the usefulness of an early-design LCA method depends on being able to differentiate (with sufficient statistical confidence) the performance of design alternatives that may have overlapping distributions of environmental impacts. To be accepted and applied, an LCA method should be *efficient* (require the least amount of data necessary to differentiate between said alternatives with sufficient statistical confidence) and *effective* (correctly identify preferable design alternatives). This paper presents a flexible modeling approach that addresses these criteria. Compared to recent papers that address early-design building guidance (Basbagill et al. 2013; Basbagill et al. 2014; Gervásio et al. 2014; Hollberg and Ruth 2016; Østergård et al. 2017; Samuelson et al. 2016), one of the primary contributions of this work is the hierarchical definition of building attributes (using under-specification) to accommodate various levels of uncertainty in any subset of those attributes and facilitate the incremental and iterative refinement of influential parameters that are triaged using sensitivity analyses as the design develops. This framework is applied to the sequential design of a hypothetical single-family residential building to demonstrate the value of targeting key parameters while allowing others to remain under-specified, resulting in the most precise

LCA predictions possible with the least amount of data. An analysis of 12 hypothetical design variants is used to demonstrate the effectiveness and efficiency of this method in identifying preferable alternatives with limited design details.

2 Streamlined life cycle assessment

Since its inception as a method, a number of approaches have been used to reduce the data and time required to conduct LCAs. One way to avoid extensive data collection is to do a qualitative assessment with matrix scoring methods based on experts' knowledge about the various stages of the product's lifecycle (Graedel 1998; Graedel et al. 1995). Another straightforward method is to limit the assessment scope to the most significant product components based on cost, mass, or some other metric, or to focus on a specific portion of the life cycle (i.e., cradle-to-gate rather than cradle-to-grave assessments) (Graedel 1998; Hunt et al. 1998; Kellenberger and Althaus 2009; Malmqvist et al. 2011; Soust-Verdaguer et al. 2016). (This was found in Soust-Verdaguer et al. (2016) to be a predominant method of simplification in LCAs of single-family houses.) For LCAs of any scope, proxy data is often used when data about a particular component or material is unavailable (Graedel 1998; Hunt et al. 1998). An issue with these streamlining methods is that they introduce an unknown amount of uncertainty, which may lead to inappropriately high confidence in the predicted impacts or misinterpretation of comparisons between alternatives.

More recently, to reduce the burden of LCA for buildings, a range of studies have proposed the development of parameterized models to estimate the bill of activities (BOA) or life cycle inventories, which include the bill of materials (BOM) and associated processes for manufacturing, transportation, etc. The analyst then only needs to collect data on the inputs to the parametrized model. An example is Heeren et al. (2015), in which a parametric LCA model is used to compare wooden and thermally massive residential and office buildings. In the building sector, several parametric models to estimate the BOA have been described that leverage the outputs of using building information modeling (BIM) tools. This method has been applied to a single-family house (Gervásio et al. 2014), a single story office building (Wang et al. 2005), a multi-building complex (Basbagill et al. 2013; Basbagill et al. 2014), a 21-story office building (Oh and Na 2017), the refurbishment of a multi-story office building (Seo et al. 2007), and an apartment building and single-family house (Hollberg and Ruth 2016). A review of BIM-based LCA methods is given in Soust-Verdaguer et al. (2017). Finally, a separate body of literature also discusses using regression models (a form of parametric model) to enable rapid estimates of use-phase energy consumption without detailed energy modeling simulations (Al Gharably et al. 2016; Asadi et al. 2014; Hester et al. 2017; Hygh et al. 2012; Romani et al. 2015; Srivastav et al. 2013).

By themselves, parametric models do not provide feedback to the designer on which inputs require more precision and which do not. However, the computational efficiency of parametric models makes them well-suited for sensitivity analysis. For example, Heeren et al. (2015) use Monte Carlo analyses with a parametric building LCA model to perform sensitivity analyses and identify the input parameters that correlate with energy use, material use, and life cycle impacts. Though not an LCA study, Østergård et al. (2017) run Monte Carlo simulations with models of building energy use, occupant comfort, and daylighting, and they use Morris sensitivity analyses and parallel coordinate plots to identify and visualize the effects of influential parameters on these three building performance metrics. One of the main aspects that differentiates the approach presented here from these previous papers is the use of information gained from sensitivity analysis to iteratively refine the building design and explicitly quantify the reduction in variability of the predicted impacts as design decisions are made, illustrating the benefits of an informed design process. The only other study the authors are aware of that includes a similar analysis is the work of Basbagill et al. (2013), in which a set of LCA results representing the design space of interest is iteratively filtered according to a series of design decisions in order to analyze the reduced uncertainty in predicted impacts. The authors of the present paper use a different approach to a similar goal. Specifically, continuous models are developed to estimate the BOA for a building, overcoming a limitation of the iterative filter method by not limiting the design variants to a pre-defined set.

The LCA modeling method described in this paper, referred to as the Building Attribute to Impact Algorithm (BAIA), attempts to address these various limitations. Unknown or undecided building, assembly, and material attributes are *under-specified* within BAIA by representing them with ranges or groups of related options. This allows the model to be used with an arbitrary amount of information about the design. Under-specification also addresses the concerns of unquantified uncertainty being introduced by proxy data, as raised by Hunt et al. (1998), since the unknown entity is represented by a group rather than a single value. Under-specification was previously used by Olivetti et al. (2013) to analyze embodied energy for consumer products while only requiring specific data for a targeted portion of the bill of materials (BOM) and yielding results similar to those from a fully detailed BOM. More recently, Tecchio et al. proposed a data structure to enable under-specified cradle-to-gate analyses of building materials and assemblies Tecchio et al. (a). The efficiency of this data structure was tested against predefined BOMs of wall systems (Tecchio et al. a) and predefined BOMs for single-family and multi-family structures (Tecchio et al. b). BAIA uses a novel combination of a regression model of energy use within a parameterized LCA model in a Monte Carlo (MC) framework to quantify the variability in predicted environmental impacts associated with an uncertain (conceptual) building design. Compared to work by Olivetti et al. (2013) that first suggested the use of under-specification with pre-established BOMs, this work extends the concept to a parametric model that estimates the materials and associated activities and considers the full life cycle (with some exceptions listed in Section 3.1, though the method's efficiency does not depend on these exclusions). In addition, this paper extends work previously done by exploring how these methods can be used to guide sequential design decisions, as well as validating the preferable design variants identified by BAIA at multiple steps of the sequential design process against results from a conventional LCA method.

BAIA uses MC results to conduct probabilistic triage with variance-based sensitivity analyses to provide feedback on which attributes contribute the most to the variability in environmental impacts. The variability in predicted life cycle impacts will decrease most noticeably with the specification of the most influential attributes, allowing the less influential attributes to remain under-specified. This is an important contribution because it not only reduces the data, expertise, and time required to conduct an LCA but also provides a more statistically rigorous way of representing uncertain aspects of the building design than using single default or proxy values. Under-specification allows an analysis to be conducted with an arbitrary amount of information about any subset of inputs, and targeted specification guided by probabilistic triage is what enables BAIA to be more efficient than conventional LCAs while still effectively identifying preferable design alternatives. The demonstration of BAIA's agreement with conventional LCA results is also novel, as the authors are not aware of parametric models described in the literature that have been compared to conventional LCA approaches to confirm their effectiveness.

3 Methods

3.1 Residential building LCA goal and scope

The goal of this streamlined LCA method is to inform decisions at earlier stages of the design process. Its intended use is to rapidly compare the probabilistic impacts of early-design alternatives in order to identify influential attributes and guide the selection of lower-impact options when the design is most flexible. It applies to single-family residential houses that are 1-3 stories tall with 900-8100 sq. ft. of conditioned area.

The analysis scope is cradle-to-grave (material extraction through end-of-life), with some limited exceptions. Though the method presented here does not rely on scope limitations to increase the speed and efficiency of the assessments, the unavailability of certain data has precluded the consideration of some life cycle stages: installed use (B1 in standard EN 15978, which includes impacts that do not relate to energy or water usage, such as material off-gassing), maintenance (B2), repair (B3), refurbishment (B5), operational water use (B7), and benefits and loads beyond the system boundary (D). Data capturing these impacts should be incorporated in the future as such data becomes more available. Transportation impacts are based on calculations for one representative US city in the Impact Estimator for Buildings from the Athena Sustainability Materials Institute. More precise transportation impact estimates are another area for improvement in the future. The embodied impacts of appliances and the HVAC, plumbing, and electrical systems are also excluded. Finally, energy use from plug-in appliances is included in the total rather than reported separately as called for in the standard.

3.2 Overview of building attribute to impact algorithm

The Building Attribute to Impact Algorithm (BAIA) comprises a data structure and set of attribute-to-activity models (AAMs) that transform information on the building design into a bill of activities (BOA), from which BAIA estimates the corresponding life cycle environmental impacts. BAIA is implemented in a macro-enabled Microsoft Excel 2013 spreadsheet with the Oracle Crystal Ball plug-in to enable MC simulations. Figure 1 is a high-level schematic of the tool and how it can be used to guide the design process, outlined below:

1. The building is described with a set of under-specified building, assembly, and material attributes, which capture early-design flexibility and/or uncertainty (see Section 3.4).
2. AAMs estimate the bills of activities from under-specified attributes (see Section 3.3).
3. The impacts associated with material and energy use are calculated based on the AAM outputs (see Section 3.5).
4. MC simulations capture the variability in life-cycle impacts due to design attribute variability, life cycle inventory data, and uncertain model parameters (such as impact factors for electricity and gas).
5. The analyst decides whether the impact prediction is sufficiently precise, for example, to determine that the design has met a certain performance target or that the current design has higher or lower predicted

impacts compared to an alternate design based on statistical methods such as the comparison significance presented in section 3.7.1.

   a. If the results are not precise enough, probabilistic triage is used to rank the attributes based on their contribution to the variability in the predicted impacts (see Section 3.6) and the process continues at Step 6.
   b. Otherwise, the iterative process ends, resulting in a targeted design where details have been added to influential attributes and less influential attributes can be left under-specified.

6. Additional details are added to one or more influential attributes identified by the probabilistic triage. Specifying higher-ranked attributes will increase the prediction precision more efficiently.

The analyst is guided through iterations of model runs to prioritize decisions that most reduce the variability in predicted impacts. With this approach, results of the simulations can help inform design decisions earlier on in the design process when fewer design details are available. The various components of the tool are described in more detail below.

3.3 Attribute-to-activity models

Attribute-to-activity models (AAM) for materials (AAM-M) and use phase energy use (AAM-E) estimate the bill of activities associated with a particular building from the attributes of that building. These attributes include the geometry, key HVAC parameters, and general material choices for major building components. Such attributes can be more easily characterized at early design stages compared to lists of construction materials (referred to as takeoffs) and construction activities that would be required for a conventional LCA.

The attributes used to characterize the building are grouped into building, assembly, and material attributes, with approximately 180 attributes in total. The building attributes describe the building geometry, building systems, and scenario (climate and analysis period). Assembly inputs further define the foundation, exterior walls, floors, ceilings, interior partition walls, windows, and roof. The assembly attributes in turn define the set of sub-assemblies or element groups, and each element group option includes a set of elements. Each element has one material and a range of possible thicknesses or area densities, and the material selection is under-specified by default as described in Section 3.4.

3.3.1 Attribute-to-activity model for materials

The AAM-M estimates the required material masses over the analysis period. Each assembly option in the assembly hierarchy defines a group of elements that are in turn defined by an under-specified material and range of possible quantities (thickness or mass per unit of area, depending on the element), both of which can be specified further if desired. In each MC trial, a specific assembly is chosen for each under-specified assembly. Then, within each assembly, a particular material and quantity is chosen for each element based on the material option and range of quantities currently specified for that element. Assembly areas are determined from the randomly sampled building attributes in each MC trial, and these formulas are given in Section 5 of the Electronic Supplementary Material

(ESM). As shown in Eq. (1), each element mass m_e is calculated from the associated assembly area A_a and either the area density (mass per area, D_A) or thickness h and density D of the element, depending on which information is available. Replacement is considered through a multiplier ϕ derived from the analysis period and element lifetime (set to 1 if the element lifetime is longer than the analysis period). Element service lives were chosen based on data from three studies (International Association of Certified Home Inspectors 2016; National Association of Home Builders and Bank of America Home Equity 2007; Royal Institution of Chartered Surveyors 2006) and are summarized in Section 6 of the ESM.

$$m_e = \phi_e \times A_a \times \begin{cases} D_{A,e} \\ h_e \times D_e \end{cases} \tag{1}$$

The aggregated masses in each MC trial comprises the total building material inventory for that trial. The mass of each element is later multiplied by environmental impact factors for each life cycle stage (see Section 3.5).

3.3.2 Attribute-to-activity model for energy

The AAM-E is a set of regression models that estimate the annual use-phase energy consumption from relevant building, assembly, and material attributes, allowing the rapid estimation of energy use from the randomly sampled attributes in each MC trial. Energy consumption is broken down into five usage types (t), with distinct regression models:

1. Electricity for heating
2. Electricity for cooling
3. Electricity for other purposes (such as lighting and appliances)
4. Natural gas for heating
5. Natural gas for other purposes (predominantly domestic hot water)

Data for these models was generated with over 10,000 simulations of randomly-generated building designs in each of 15 climates using EnergyPlus, a widely-used energy modeling tool. The regression models (similar to the model in Hester et al. (2017)) were developed using the stepwise regression platform in JMP, data analysis software from SAS. The form of this equation is the following, where E is the resulting predicted energy consumption, C is the intercept term or regression coefficient for the variables indicated, x_i is one of the model inputs, and τ_i is a constant scaling term for variable x_i representing the mean of that parameter:

$$E = C + C_a x_a + C_b x_b \ldots + C_{ab}(x_a - \tau_a)(x_b - \tau_b) + C_{ad}(x_a - \tau_a)(x_d - \tau_d) + \cdots \tag{2}$$

The interaction of inputs x_a and x_b is omitted in the equation above to illustrate that some but not all interaction terms are included. After finalizing the model, a test set was used to assess the model performance by calculating the R^2 value with this "new" data. The overall test-set R^2 value was above 0.9 for each usage type. However, when analyzing the model performance separately in each climate, this metric was markedly lower for some climates where that usage type is small compared to in other climates (i.e., heating electricity in El Paso, Texas, which is a hot climate). These cases do not significantly affect the overall performance of the model since they occur in usage types that are a small percentage of the total energy consumption in those locations (for example, heating electricity is 3 % of the total energy use in El Paso). More details on the construction and R^2 values of these models are provided in Sections 7 and 8 of the ESM.

3.4 Under-specification structure

Sets of building (B), assembly (A), and material (M) attributes are categorized hierarchically in under-specified levels based on the principles of structured under-specification (Olivetti et al.), allowing data to be input only where necessary and at a level of precision appropriate for a given stage of design. The levels progress from L1 (most under-specified) to increasing levels of specification as illustrated in Fig. 2. Though not every attribute has the same number of levels, the highest-numbered level for a given attribute always corresponds to specific, fixed options or values, and the lower-numbered levels are increasingly broad groupings of these most specific optionsNote that although the material example in this figure only shows three levels, there is one more level in this hierarchy representing specific materials. Detailed hierarchies can be found in Section 10 of the ESM.

When an attribute is under-specified, any of the most specific options connected to that point in the hierarchy can be sampled in the MC simulation. Referring to the example in Fig. 2, if a material is specified at L1 with *Any non-rigid insulation*, then any of the most-specific non-rigid insulations can be selected in any given MC trial. If, however, the material is specified at L2 with *Glass wool*, then only *Batt* or *Glass wool mat* options will be selected. The analyst can also select a specific material. In this hierarchical framework, numerical building attributes are treated as categorical options and the most specific options correspond to discrete values. The one type of input that does not use hierarchical options is the thickness or area density of each element. These are under-specified as uniform random variables within preset ranges with the option of setting them to constant values.

Each option in the hierarchy can have a different number of options attached to it (associated with the subsequent level of specification). For example, again referring to the example in Fig. 2, the L2 options *Fiberglass* and *Rock wool* have three options and one L3 option, respectively. To ensure that this does not cause fiberglass options to be chosen more frequently than the rock wool option (thus over-representing fiberglass in the MC samples), the chain rule of conditional probability is used to determine the probability that each of the most specific are selected, thus guaranteeing that less represented categories are sampled with equal probability as more represented categories. Effectively, this represents selecting one of the options in each subsequent level with equal probability until one of the most specific options has been chosen. Therefore, if *Any non-rigid insulation* is selected at the L1 level, any one of the L2 options can be selected with equal probability. Then, any of the L3 options connected to that L2 option is selected with equal probability, and so on, until a specific material is chosen. Additional information about random selection within the under-specification hierarchies and details of the hierarchies themselves are provided in Sections 9 and 10 of the Electronic Supplementary Material.

3.5 Impact calculations

The environmental impacts (I) for all life cycle stages (s) except for B6 (operational energy use) are calculated by multiplying the element material masses m_e from the AAM-M by the impact factors i for that life cycle stage and element material and summing over all elements as shown in (Eq. (3)).

$$I_{s \neq B6} = \sum_e m_e \times i_{s,e} \quad (3)$$

There is significant variation between the environmental impact factors of similar material datasets compiled by different organizations (Reis 2013). BAIA incorporates environmental impact factors from the United States Life Cycle Inventory (NREL 2013), Ecoinvent 2.2 (Ecoinvent Centre - Swiss Centre for Life Cycle Inventories 2007), GaBi (Thinkstep 2013), and Athena Impact Estimator version 4.5 (IE) (Athena Sustainable Materials Institute 2015) and groups similar materials from different data sources together in the under-specification scheme (see Section 3.4) to capture this uncertainty. IE is also the only data source used that estimates impacts for A4 (transport), A5 (construction-installation process), B4 (replacement), and C1-4 (end of life). When a material from one of the other sources is chosen by BAIA, data from one of the most similar Athena materials in BAIA's material hierarchy is randomly selected to fill in the data for these life cycle phases.

Operational energy impacts (I_{B6}) are calculated by multiplying each energy usage E_t output from the AAM-E with impact factors for either electricity or natural gas as appropriate and summing these values over each usage type t (Eq. (4)). For electricity use, data from the Emissions & Generation Resource Integrated Database (U.S. Environmental Protection Agency 2010) are used to capture the location-specific transmission loss factors ρ_{loc} and impact factors i_{loc} from different grid mixes. The impact factor for natural gas i_{rand} is not location-specific but is randomly sampled from a set of natural gas impact factors from Ecoinvent.

$$I_{B6} = \sum_t E_t \times \begin{cases} \rho_{loc} \times i_{loc}, & Electricity \\ i_{rand}, & Natural\ gas \end{cases} \quad (4)$$

3.6 Probabilistic triage

Squared Spearman rank correlation coefficients (ρ^2) are used to provide feedback on which under-specified attributes should be prioritized for further specification in order to most efficiently reduce the variability in predicted life cycle impacts. When squared, ρ provides an approximation of the contribution to variance, as discussed in Ikonen and Tulkki (2014) and implemented in Oracle Crystal Ball. This method was chosen over other approaches such as the Sobol method due to its computational efficiency. At the end of each set of MC trials, these coefficients are computed to provide an attribute ranking, which can then be used to guide additional refinements to the design (via the specification of attributes that are still under-specified). This method of iterative specification focuses design development and allows less influential attributes to be left with a higher degree of under-specification, reducing the burdens of data collection.

One ρ^2 value is calculated per element based on the correlation of that element's impacts to the overall building impacts. If all material attributes of a given assembly are under-specified, the mean of the ρ^2 values for those elements is used as an aggregated value for the assembly. Once the material or quantity of any element within the assembly has been defined, each element is then treated separately in the ranking. This allows for a more high-level comparison of under-specified assemblies (i.e., which is more important, the floors or the foundation?) with the flexibility of analyzing the details of those assemblies after information has been added to them.

3.7 Evaluating model performance

The probabilistic results from BAIA enable the use of statistical analyses to measure the significance of the difference between two designs, or their *resolvability*. Early in the design process, it is important to be able to quickly analyze the comparative performance of design alternatives and understand whether or not there is a statistical basis for choosing one design over another. As such, to be useful, an LCA modeling approach should be able to statistically differentiate (or resolve) designs whose environmental impacts differ by some reasonable amount. Furthermore, a streamlined method should be *efficient* by generating statistically differentiable estimates using significantly less data than conventional methods. Finally, a streamlined method should be *effective* by generating estimates that are consistent with those from a conventional LCA.

Here, the resolvability of two designs is measured by their *comparison significance* (Section 3.7.1), and the difference between their predicted impacts is measured by their *mean normalized difference* (Section 3.7.2). As details are sequentially added to a set of designs in the case studies below, these metrics are calculated to support the evaluation of BAIA's efficiency (the number of details required to resolve two designs) and effectiveness (the percentage of resolvable pairs for which BAIA identifies the same preferable design as a conventional LCA model).

3.7.1 Comparison significance

The purpose of the comparison significance is to evaluate whether or not there is a statistically significant difference between the predicted environmental performance of two designs, even when many attributes are under-specified. This metric is based on a comparison indicator (*CI*) for pairs of variants. Following Huijbregts et al. (2003), Gregory et al. (2016), and Tecchio et al. (a), here *CI* is defined as the distribution of the ratio of the impacts of two alternatives (*A* and *B*). *CI* is evaluated using paired impact values for a given trial i (denoted $I_{A,i}$ for alternative *A* and $I_{B,i}$ for alternative *B*) where appropriate energy-related inputs are correlated and other attributes are uncorrelated.

$$CI = \frac{I_{B,i}}{I_{A,i}} \qquad (5)$$

The *comparison significance* (β) over n trials is then defined as

$$\beta = \frac{1}{n}\sum_{i=1}^{n} \begin{cases} 1, CI < 1 \\ 0, CI \geq 1 \end{cases} \qquad (6)$$

When β is greater than an established critical value, β_{crit}, design B performs significantly better than design A, and the reverse is true when $\beta \leq (1-\beta_{crit})$. For example, when $\beta \geq 0.9$, there is at least 90% confidence that design B is better than design A, but when $\beta \leq 0.1$, there is at least 90% confidence that design A is better than design B. This is referred to as discernibility analysis by Heijungs and Kleijn (2001) and is comparable to the probability of relative difference (PRD) presented in (Rezaee et al. 2015).

3.7.2 Mean normalized difference

Two designs that have similar predicted performance would not be expected to be readily resolvable. Therefore, an additional metric, the *mean normalized difference* (δ, Eq. (7)) was calculated to capture the similarity in performance of two designs. It is the average difference in impacts I between pairs of n MC trial results for design A and B, normalized by the average MC trial results of both designs.

$$\delta = \frac{\frac{1}{n}\sum_{i=1}^{n}(I_{A,i} - I_{B,i})}{\frac{1}{2n}\sum_{i=1}^{n}(I_{A,i} + I_{B,i})} \qquad (7)$$

4 Results: comparison of early design alternatives

The following analyses explore BAIA's effectiveness and efficiency through the use of a case study involving a set of twelve hypothetical design variants being considered at early stages of the design process.

4.1 Design variants for case analysis

A set of twelve hypothetical design variants was established for a 2,400 square-foot house in Minneapolis, Minnesota. An analysis period of 60 years is assumed, based on the 2009 mean residential building lifetime from the distribution given in (Aktas and Bilec 2012), which was calculated from American Housing Survey microdata. The American Institute of Architects lists building form, window-to-wall ratios, window types, shading, and R-values of opaque walls as factors that are often experimented with in design performance modeling at early stages of the design process (The American Institute of Architects 2012). This example focuses on two of these: window types and envelope insulation – attributes which were also explored by Ramesh et al. (2012). Four levels of insulation were chosen to cover a range of R-values in both the exterior walls and the roof, and three window types were selected with contrasting U-values and solar heat gain coefficients (a measure of solar radiation that is transmitted through the window). The wall and roof insulation were varied in parallel for the purposes of this evaluation, though they are independent attributes in BAIA. The insulation and wall options for each of the design variants are provided in Section 11 of the ESM.

4.2 Sequential design specification of a single variant

The sequential, guided specification of a single design illustrated in Fig. 1 of Section 3.2 is the most basic use of BAIA to reduce the data requirements for an LCA by leveraging under-specification and focusing on influential attributes. This method was used to guide the specification of the first building variant, illustrating how BAIA could be used in practice to guide the early design process. Only the location, area, insulation, and window parameters were initially specified, and the rest of the attributes were fully under-specified, meaning that each attribute was sampled from among the largest available group of related options. At each step of the analysis, the model was executed with 5,000 MC trials and the results of the probabilistic triage were used to identify the most influential attribute to specify in the following step. This sequential process was repeated for 20 steps (beyond the point at which designs can be differentiated, which will be seen in the following sections). The resulting sequence of design decisions can be found in Section 12 of the ESM. A fully specified design was also modeled in which detailed options were selected for all 180 building, assembly, and material attributes. As the design developed, the option chosen for each attribute was meant to represent an arbitrary but reasonable selection; in practice, these decisions could be informed either by a quick exploration of the alternatives within BAIA or made based on other project constraints, such as cost.

Figure 3summarizes the embodied, use-phase, and total global warming potential (GWP) as well as the coefficient of variation ($CV = standard\ deviation/mean$) in total impacts at each step. All life cycle stages not related to operational energy use (B6) are grouped together as embodied impacts in this figure. An example of a more detailed breakdown of the embodied impacts is available in Section 13 of the ESM. Though GWP was used for this example, other impact types can also be calculated. The steep, early reduction in the CV demonstrates the benefit of probabilistic triage: Specifying the most influential variables first leads to the biggest decrease in variability of predicted impacts while allowing more variables to be left under-specified. The CV decreases from 0.172 to 0.049 from the first to the tenth step (a reduction of 70 %), then begins to plateau by the tenth step. Beyond this point, additional details will not significantly increase the precision of the estimate, and thus may not help in making early-design decisions. From step 19 to the fully specified design (labeled FS in Fig. 3), the CV only decreases from 0.037 to 0.033 – a reduction of only 11 % – even though over 150 additional attributes have been specified. This comparatively small reduction in CV indicates that there is little advantage, in terms of increasing the precision of the predicted impacts, in specifying the remaining attributes once this plateau has been reached. Furthermore, it underscores the importance of identifying and focusing on influential attributes at early stages of the design process. The analyses that follow will demonstrate that it is possible to identify preferable alternatives even before this plateau occurs.

4.3 Efficiency: resolution of design variants

The attribute specification sequence from Section 4.2 (presented in Section 12 of the ESM) was used for all 12 building variants (starting with different insulation and window options in the first step) so that the differences in impacts between variants at any step would only reflect the design attributes of interest. Figure 4 summarizes the percentage of all 66 pairwise comparisons of the 12 building variants that are statistically resolved (i.e. $\beta. \geq \beta_{crit}$ or $\beta \leq (1 - \beta_{crit})$, see Section 3.7.1), unresolved but close ($\delta \leq \delta_{crit}$, see Section 3.7.2), and neither resolved nor close at each step of the sequential design, using two different values for β_{crit} (0.90 in Fig. 4A and 0.75 in Fig. 4B). By the 6th step of the design process, all comparisons are either resolved with 90 % confidence, or the mean impacts for the two designs are within 4 % of each other. If a confidence level of 75 % is used, then all variant pairs are resolved or have mean impacts within 2 % of each other by the 6th step. This means that it is possible to differentiate the performance of highly under-specified designs (and thus make more informed design decisions) even when those designs are similar and only a handful of the hundreds of attributes have been specified for each design. As would be expected, using a higher confidence level for such designs requires there to be a larger difference between the average impacts of the two designs in order to differentiate them.

Uncertainty is present even in a conventional LCA result. As such, even conventional LCAs will have some finite limit to their ability to statistically resolve two alternatives. To calculate this limit, a fully specified set of building variants was modeled where the only source of uncertainty was the impact factors for the bill of activities, representing the uncertainty for a conventional LCA where the bill of activities is fixed and known. The limit to resolvability, δ^*_{crit}, was calculated by the minimum δ at which each pair of conventional LCA results was no longer resolvable (i.e. $\beta \leq \beta_{crit}$). The average δ^*_{crit} was 2 % across all of the pairs of alternatives for β_{crit}=0.9, and 1 % for β_{crit}=0.75. This value is used to establish a reference for the definition of pairs that are close and would not be expected to be statistically resolvable even using conventional LCA methods. Based on the results in Fig. 4, BAIA can resolve all variant pairs that are at least 4 % apart for $\beta_{crit} = 0.9$ (and at least 2 % apart for $\beta_{crit} = 0.75$) by step 6. These values for δ_{crit} are only slightly higher than δ^*_{crit} for each β_{crit}.

By iteratively identifying and specifying the most influential attributes, BAIA is much more efficient than a conventional LCA in that for most of the evaluated pairs it only requires a handful of details to identify which design is preferable. Furthermore, even with limited inputs, the BAIA results provide an ability to statistically differentiate that it is close to that of a conventional LCA with a fixed BOA.

4.4 Effectiveness: validation of variant comparisons

The purpose of conceptual design comparisons is to identify environmentally preferable alternatives at early stages of the design process. This information can then be used in conjunction with other project constraints (such as cost) to identify which alternatives are most appropriate. To determine how effectively BAIA identifies the preferred alternative, BAIA results for the variant comparisons were compared to those of a conventional LCA using Impact Estimator, the early-design LCA software from the Athena Sustainable Materials Institute, with use-phase energy consumption calculated by BEopt, the energy modeling and cost optimization tool from NREL. Specifically, the lower-impact variant (i.e., the preferred combination of window and insulation options) of each resolvable pair was identified using the BAIA results and this identification was compared against the results from BEopt and Impact Estimator. In Table 1, the letters in each cell indicate whether the variant in the row (R) or column (C) have lower impacts. The first letter is based on the conventional LCA analysis. The second letter is based on the BAIA results and is a dash if the comparison is irresolvable at this step. Shaded cells indicate agreement between the two methods. The BAIA results that identified the same preferred alternative as the conventional models for a given case were considered effective. For the BAIA model results, it is not possible to identify a preferred alternative for irresolvable pairs ($\beta < \beta_{crit}$). As such, effectiveness can only be evaluated for resolvable pairs. This analysis was performed for each step of the sequential design process.

Table 1 is best interpreted one row or column at a time. Based on the first row, BAIA and the conventional LCAs agree that any variant is preferable to the design using insulation 1 and window 1. In the second row, there is agreement for every resolvable pair (8 of the 10 pairs), but the first two pairs are irresolvable ($\beta < 0.9$). As shown in Section 4.2, all irresolvable pairs using this β_{crit} threshold at step 6 have means within 4 % of each other, which indicates that these variants (the second, third, and fourth) are alternate strategies for achieving similar performance. Though it may be a goal of the conceptual design process to identify the highest-performing alternatives, identifying alternate paths to buildings with similar impacts can create flexibility to respond to other design constraints, such as cost. In every resolvable variant comparison at each step of the analysis, even with a low level of detail, the BAIA result identified the same preferred alternative as the conventional LCA. A table summarizing these findings is provided in Section 17 of the ESM.

5 Conclusions

The main advantage of the approach presented here is that it provides the ability to conduct an LCA (including impacts from use-phase energy consumption) that accommodates early-design uncertainty in building, assembly, and material attributes. The hierarchical definition of these attributes allows for information to be progressively added to any arbitrary set of parameters, rather than requiring a high level of detail for all aspects of the design. Targeted design development based on the results of probabilistic triage facilitates emphasis on the key attributes of the product (in this case, a building, though the approach can be extended to other products and technologies), leaving the less influential attributes under-specified. Probabilistic triage also saves time that would normally be spent in data collection because the majority of materials can be represented by under-specified data without significantly reducing the precision of predicted impacts (demonstrated in Fig. 3 since most materials are under-specified in steps 1-20 and all materials are fully specified in the step labeled “FS”). This refined focus further facilitates the use of LCAs at earlier stages of the design process, which is when key decisions are made that affect the performance of the building. In addition, the predicted impacts of under-specified early designs can be compared using efficient and effective statistical methods such as the comparison significance to help steer the design process to lower-impact alternatives and ultimately assist in reducing the environmental burdens of the building sector.

Though this approach can save time in conducting LCAs, its main limitation is the time and effort to set up the under-specification hierarchies and attribute-to-activity models. In order to extend BAIA to other building types and to other product classes, new attribute-to-activity models would have to be created to estimate materials and processes (especially energy use) based on relevant attributes. Similarly, additional under-specified data structures would need to be developed to extend this method to a broader array of products. The ideal use of this approach is for an industry or group that would like to explore a broad design space and can accurately parameterize the bill of activities over the range of designs being considered. Since many design decisions are made on cost, an additional limitation to this method is that this important metric is not captured. Future models employing this method should also include financial estimates to better facilitate the understanding of economic and environmental tradeoffs.

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Electronic Supplementary Material

BAIA paper SI.docx: Formulas for assembly area calculations, details on construction and performance of regression model for energy consumption, details on under-specification method and hierarchies, design variants used in case study, sequence of design decisions made in case study, sample breakdown of embodied impacts, and summary of agreement between BAIA and conventional LCA at each step of sequential design.

AAM-E regression coefficients.xlsx: Coefficients for stepwise regression models used in estimating building energy consumption.

References

Aktas CB, Bilec MM (2012) Impact of lifetime on US residential building LCA results. Int J Life Cycle Assess 17:337-349

Al Gharably M, DeCarolis JF, Ranjithan SR (2016) An enhanced linear regression-based building energy model (LRBEM plus) for early design. J Build Perform Simu 9:115-133 doi:10.1080/19401493.2015.1004108

Asadi S, Amiri SS, Mottahedi M (2014) On the development of multi-linear regression analysis to assess energy consumption in the early stages of building design. Energ Buildings doi:http://dx.doi.org/10.1016/j.enbuild.2014.07.096

Athena Sustainable Materials Institute (2015) Impact Estimator for Buildings v5.1.0102

Basbagill J, Flager F, Lepech M, Fischer M (2013) Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts. Build Environ 60:81-92

Basbagill JP, Flager FL, Lepech M (2014) A multi-objective feedback approach for evaluating sequential conceptual building design decisions. Automat Constr 45:136-150

Ecoinvent Centre - Swiss Centre for Life Cycle Inventories (2007) Ecoinvent database. Duebendorf

EN 15978:2011 Sustainability of construction works. Assessment of environmental performance of buildings. Calculation method.

Gervásio H, Santos P, Martins R, Simões da Silva L (2014) A macro-component approach for the assessment of building sustainability in early stages of design. Build Environ 73:256-270

Graedel TE (1998) Streamlined life-cycle assessment. Prentice Hall, Upper Saddle River, NJ

Graedel TE, Allenby BR, Comrie PR (1995) Matrix Approaches to Abridged Life Cycle Assessment. Environ Sci Technol 29:134A

Granadeiro V, Duarte JP, Correia JR, Leal VMS (2013) Building envelope shape design in early stages of the design process: Integrating architectural design systems and energy simulation. Automat Constr 32:196-209

Gregory JR, Noshadravan A, Olivetti EA, Kirchain RE (2016) A Methodology for Robust Comparative Life Cycle Assessments Incorporating Uncertainty. Environ Sci Technol 50:6397-6405

Heeren N, Mutel CL, Steubing B, Ostermeyer Y, Wallbaum H, Hellweg S (2015) Environmental impact of buildings – what matters? Environ Sci Technol 49(16):9832-9841

Heijungs R, Kleijn R (2001) Numerical approaches towards life cycle interpretation five examples. Int J Life Cycle Assess 6:141-148

Hester J, Gregory J, Kirchain R (2017) Sequential early-design guidance for residential single-family buildings using a probabilistic metamodel of energy consumption. Energ Build 134:202-211

Hollberg A, Ruth J (2016) LCA in architectural design - a parametric approach. Int J Life Cycle Assess 21:943-960

Huijbregts MA, Gilijamse W, Ragas AM, Reijnders L (2003) Evaluating uncertainty in environmental life-cycle assessment. A case study comparing two insulation options for a Dutch one-family dwelling. Environ Sci Technol 37:2600-2608

Hunt RG, Boguski TK, Weitz K, Sharma A (1998) Case studies examining LCA streamlining techniques. Int J Life Cycle Assess 3:36-42

Hygh JS, DeCarolis JF, Hill DB, Ranjithan SR (2012) Multivariate regression as an energy assessment tool in early building design. Build Environ 57:165-175

Ikonen T, Tulkki V (2014) The importance of input interactions in the uncertainty and sensitivity analysis of nuclear fuel behavior. Nucl Eng Des 275:229-241

International Association of Certified Home Inspectors (2016) Standard Estimated Life Expectancy Chart for Homes. https://www.nachi.org/life-expectancy.htm. 2016

Kellenberger D, Althaus H-J (2009) Relevance of simplifications in LCA of building components. Build Environ 44:818-825

Konis K, Gamas A, Kensek K (2016) Passive performance and building form: An optimization framework for early-stage design support. Sol Energy 125:161-179

Kuo T-C, Smith S, Smith GC, Huang SH (2016) A predictive product attribute driven eco-design process using depth-first search. J Clean Prod 112, Part 4:3201-3210

Malmqvist T, Glaumann M, Scarpellini S, Zabalza I, Aranda A, Llera E, Díaz S (2011) Life cycle assessment in buildings: The ENSLIC simplified method and guidelines. Energy 36:1900-1907

Marsh R (2016) LCA profiles for building components: strategies for the early design process. Build Res Inf 44:358-375

Mueller KG, Lampérth MU, Kimura F (2004) Parameterised inventories for life cycle assessment. Int J Life Cycle Assess 9:227-235

National Association of Home Builders, Bank of America Home Equity (2007) Study of Life Expectancy of Home Components

National Renewable Energy Laboratory (2016) BEopt 2.6. https://beopt.nrel.gov/home.

Nielsen TR (2005) Simple tool to evaluate energy demand and indoor environment in the early stages of building design. Sol Energy 78:73-83

NREL (2013) U.S. Life Cycle Inventory Database. http://www.nrel.gov/lci/

Olinzock MA, Landis AE, Saunders CL, Collinge WO, Jones AK, Schaefer LA, Bilec MM (2015) Life cycle assessment use in the North American building community: summary of findings from a 2011/2012 survey. Int J Life Cycle Assess 20:318-331

Olivetti E, Patanavanich S, Kirchain R (2013) Exploring the Viability of Probabilistic Under-Specification To Streamline Life Cycle Assessment. Environ Sci Technol 47:5208-5216

Oracle (2014) Crystal Ball Release 11.1.2.4.000 (32-bit). http://www.oracle.com/us/products/applications/crystalball/overview/index.html.

Østergård T, Jensen RL, Maagaard SE (2016) Building simulations supporting decision making in early design – A review. Renew Sust Energ Rev 61:187-201

Østergård T, Jensen RL, Maagaard SE (2017) Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis. ENB Energy & Buildings 142:8-22

Ramesh T, Prakash R, Shukla KK (2012) Life cycle approach in evaluating energy performance of residential buildings in Indian context. Energ Building 54:259-265

Reis L (2013) An exploration of materials taxonomies to support streamlined life cycle assessment. Massachusetts Institute of Technology. http://worldcat.org. http://hdl.handle.net/1721.1/85797.

Rezaee R, Brown J, Augenbroe G, Kim J (2015) Assessment of uncertainty and confidence in building design exploration. Artificial Intelligence for Engineering Design, Analysis and Manufacturing 29:429-441 doi:10.1017/S0890060415000426

Romani Z, Draoui A, Allard F (2015) Metamodeling the heating and cooling energy needs and simultaneous building envelope optimization for low energy building design in Morocco. Energ Building 102:139-148

Royal Institution of Chartered Surveyors (2006) Life expectancy of building components : surveyors' experiences of buildings in use : a practical guide. Building Cost Information Service Ltd., London

Samuelson H, Claussnitzer S, Goyal A, Chen Y, Romo-Castillo A (2016) Parametric energy simulation in early design: High-rise residential buildings in urban contexts. Build Environ 101:19-31

SAS Institute Inc. (2013) JMP Pro 11.2.0

Saunders CL, Landis AE, Mecca LP, Jones AK, Schaefer LA, Bilec MM (2013) Analyzing the practice of life cycle assessment: Focus on the building sector J Ind Ecol 17:777-788

Seo S, Tucker S, Newton P (2007) Automated Material Selection and Environmental Assessment in the Context of 3D Building Modelling. J Green Build 2:51-61

Soust-Verdaguer B, Llatas C, Garcia-Martinez A (2017) Critical review of bim-based LCA method to buildings. Energy and Buildings 136:110-120

Soust-Verdaguer B, Llatas C, García-Martínez A (2016) Simplification in life cycle assessment of single-family houses: A review of recent developments. Build Environ 103:215-227

Srivastav A, Tewari A, Dong B (2013) Baseline building energy modeling and localized uncertainty quantification using Gaussian mixture models. Energy and Buildings 65:438-447

Tecchio P, Gregory J, Ghattas R, Kirchain R Structured under-specification of life cycle impact assessment data for building assemblies. Accepted for publication in J Ind Ecol

Tecchio P, Gregory J, Olivetti E, Ghattas R, Kirchain R Streamlining the life cycle assessment of buildings by structured under-specification and probabilistic triage. Accepted for publication in J Ind Ecol

The American Institute of Architects (2012) An Architect's Guide to Integrating Energy Modeling in the Design Process. doi:http://www.aia.org/practicing/AIAB097932

Thinkstep (2013) GaBi Software Professional Database. http://www.gabi-software.com/databases/professional/.

U.S. Department of Energy (2014) EnergyPlus 8.1.0. http://apps1.eere.energy.gov/buildings/energyplus/

U.S. Environmental Protection Agency (2010) Emissions & Generation Resource Integrated Database (eGRID)

Wang W, Zmeureanu R, Rivard H (2005) Applying multi-objective genetic algorithms in green building design optimization. Build Environ 40:1512-1525

Figure captions

Fig. 1 High-level schematic illustrating how BAIA can interface with and guide the design process

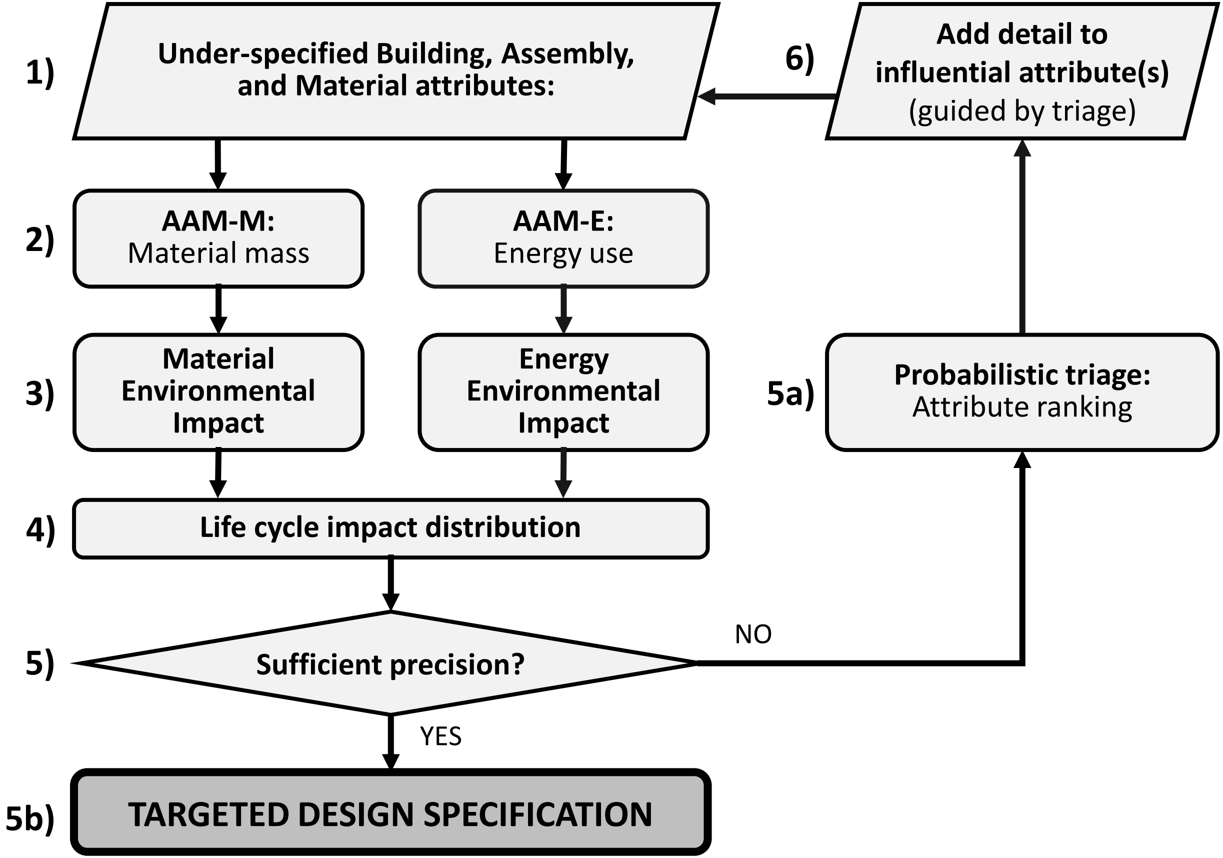
Fig. 2 Attribute under-specification hierarchy for an example of a building, assembly, and material attribute with increasing levels of specificity from L1 through L3. Single-option categories are indicated with a bar connecting it to the previous level

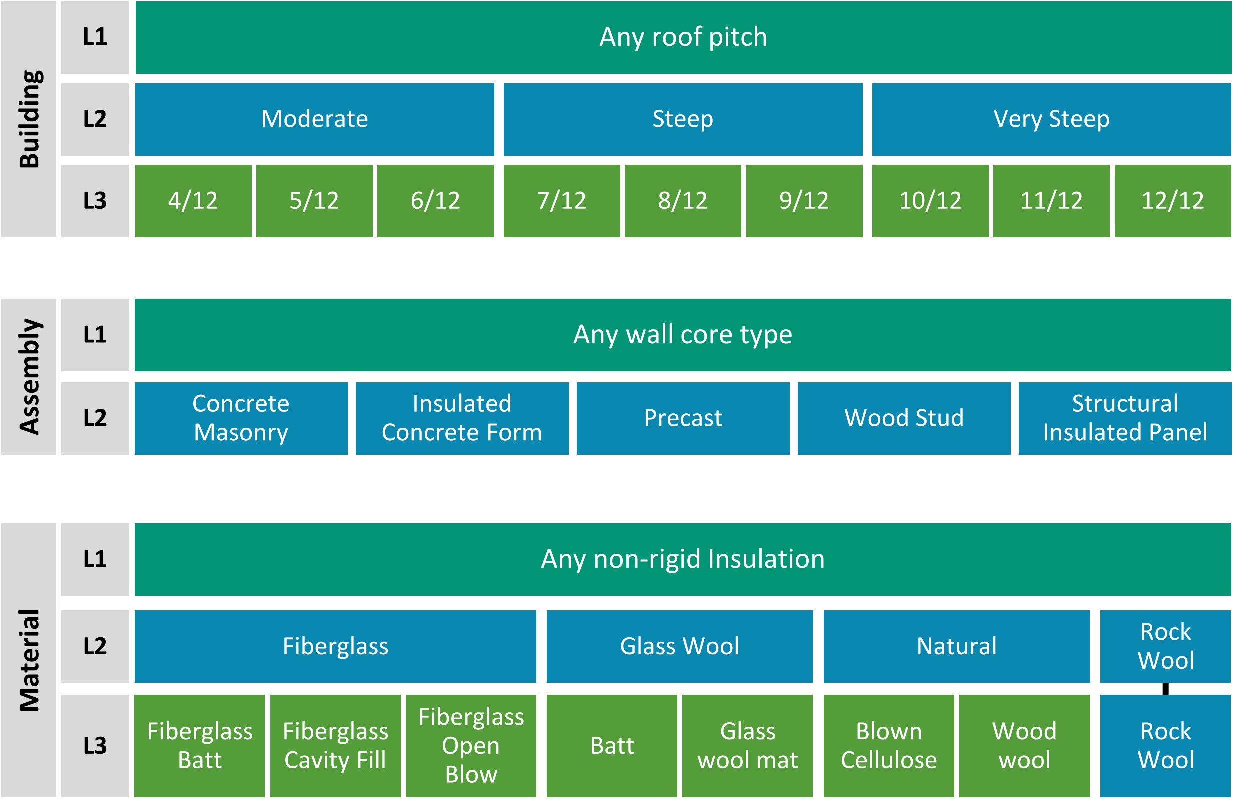
Fig. 3 Steep, early reduction in variability of results for first design variant through targeted specification of most influential attributes. The figure shows the distribution of predicted global warming potential (box plots referencing the left axis) and coefficient of variation (solid line referencing the right axis) of the total impacts. The box plots show the 5th, 25th, 50th, 75th, and 95th percentiles. The CV for the fully specified (FS) design is shown with an X and a dashed line

Fig. 4 Percentage of comparisons that are resolved, unresolved but close, or neither resolved nor close at each step of the analysis for A) $\beta\_crit = 0.9$ and $\delta\_crit = 0.04$ and B) $\beta\_crit = 0.75$ and $\delta\_crit = 0.02$

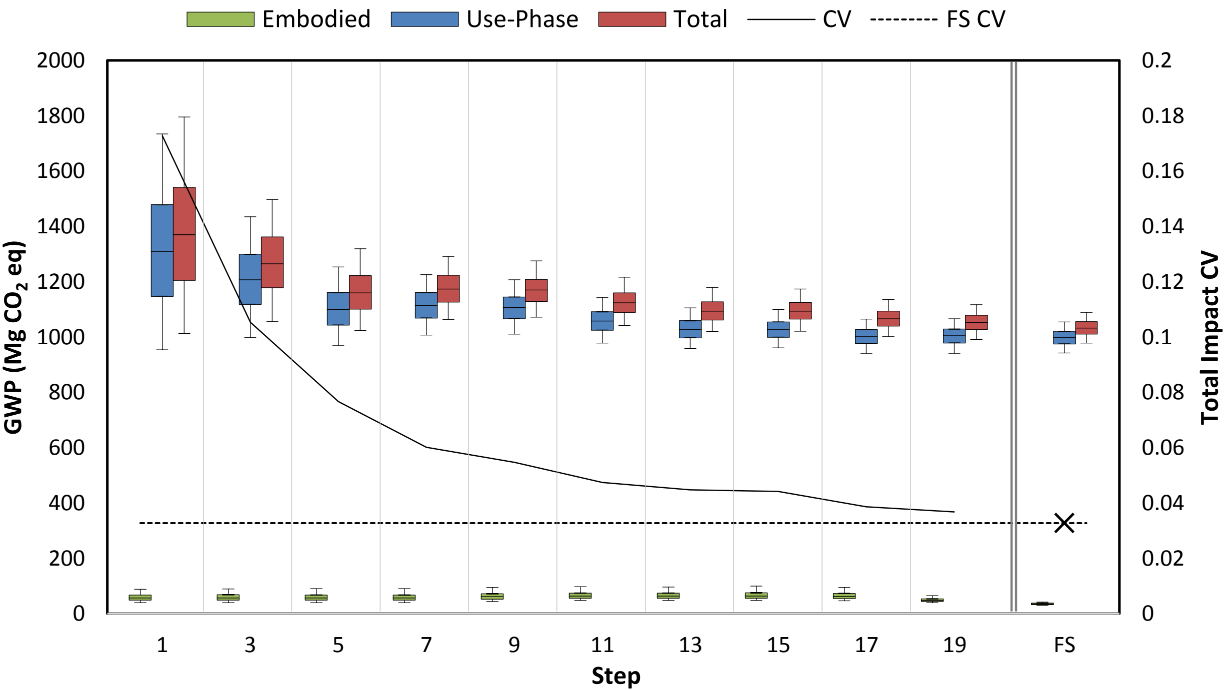
Table 1 Validation of each pairwise comparison of different combinations of window and insulation options at step 6 with β_{crit} = 0.9

		Ins1			Ins2			Ins3			Ins4		
		Win1	Win2	Win3	Win1	Win2	Win3	Win1	Win2	Win3	Win1	Win2	Win3
Ins1	Win1		CC	CC	CC	CC	CC	CC	CC	CC	CC	CC	CC
	Win2			C-	C-	CC	CC	CC	CC	CC	CC	CC	CC
	Win3				C-	C-	CC	C-	CC	CC	CC	CC	CC
Ins2	Win1					CC	CC	CC	CC	CC	CC	CC	CC
	Win2						C-	C-	CC	CC	C-	CC	CC
	Win3							R-	C-	CC	C-	CC	CC
Ins3	Win1								CC	CC	C-	CC	CC
	Win2									C-	R-	C-	C-
	Win3										RR	R-	C-
Ins4	Win1											CC	CC
	Win2												C-
	Win3												

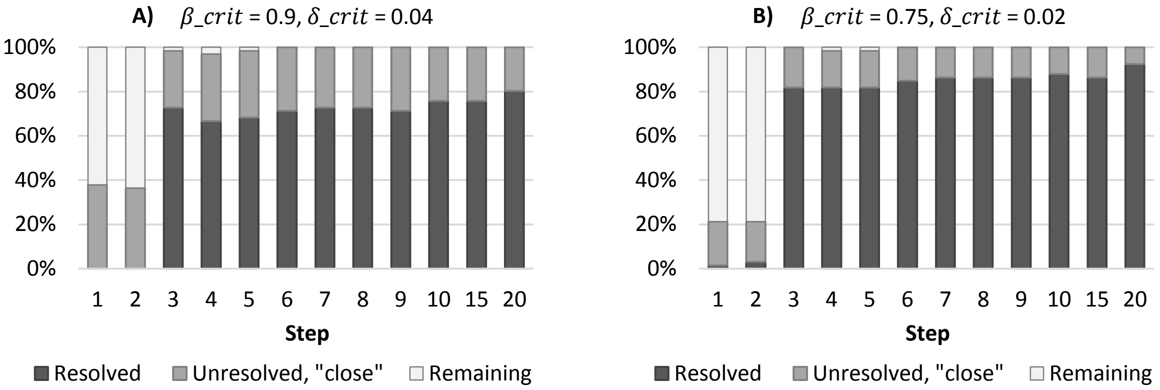

1)
Under-specified Building, Assembly, and Material attributes:
6)
Add detail to influential attribute(s)
(guided by triage)
2)
AAM-M:
Material mass
AAM-E:
Energy use
3)
Material Environmental Impact
Energy Environmental Impact
5a)
Probabilistic triage:
Attribute ranking
4)
Life cycle impact distribution
NO
5)
Sufficient precision?
YES
5b)
TARGETED DESIGN SPECIFICATION



Building
L1
Any roof pitch
L2
Moderate
Steep
Very Steep
L3
4/12
5/12
6/12
7/12
8/12
9/12
10/12
11/12
12/12
Assembly
L1
Any wall core type
L2
Concrete Masonry
Insulated Concrete Form
Precast
Wood Stud
Structural Insulated Panel
Material
L1
Any non-rigid Insulation
L2
Fiberglass
Glass Wool
Natural
Rock Wool
L3
Fiberglass Batt
Fiberglass Cavity Fill
Fiberglass Open Blow
Batt
Glass wool mat
Blown Cellulose
Wood wool
Rock Wool



Embodied
Use-Phase
Total
CV
FS CV
GWP (Mg CO2 eq)
Total Impact CV
2000
1800
1600
1400
1200
1000
800
600
400
200
0
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1
3
5
7
9
11
13
15
17
19
FS
Step



A) β_crit = 0.9, δ_crit = 0.04
B) β_crit = 0.75, δ_crit = 0.02
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
8
9
10
15
20
Step
Resolved
Unresolved, "close"
Remaining