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Classifying design-related uncertainties in LCA-based building optimization : A systematic review

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Abstract. Handling design-related uncertainties (DRUs) is critical for improving the reliability of life cycle assessment (LCA)-based building optimization, especially in the preliminary stages of the design process. Existing studies either focus on single aspects of DRUs' influence or oversimplify their handling in optimization. Building on a broader research effort aimed at addressing uncertainties in LCA, this paper proposes a dual-dimension classification approach for DRUs, based on their impact on both building environmental performance and subsequent design decisions, and provides a practical guidance for their handling in LCA-based building optimization. Through a systematic literature review (SLR), 16 DRUs were identified from 58 papers, and their decision-making stages in optimization processes were documented. Two semi-quantitative evaluation metrics, optimization interest (OI) and decision-making priority (DP), were introduced to evaluate the characteristics of DRUs in optimization. Based on evaluation results, a classification into four categories for the DRUs is proposed with targeted uncertainty-handling strategies: Monte Carlo simulation for High OI-High DP DRUs; scenario analysis for Low OI-High DP DRUs; simplified assumptions for High OI-Low DP DRUs; and default values for Low OI-Low DP DRUs. This study aims to simplify LCA methods and tools in building design practice, while establishing a foundation for developing robust optimization frameworks in the future.

Abbreviations

DRU	Design-related uncertainty	S_FLOOR	Floor specification
DP	Decision-making priority	S_HVAC	Heating, ventilation and air conditioning system specification
G_OPN	Opening area		
G_ORI	Building orientation	S_IW	Interior wall specification
G_PLN	Plan configuration	S_LIGHT	Lighting system specification
G_SCA	Building scale	S_REN	Renewable energy system specification

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G_VRT	Vertical configuration	S_ROOF	Roof specification
LCA	Life cycle assessment	S_STR	Structure specification
MCS	Monte Carlo simulation	S_WIN	Window specification
OI	Optimization interest	SA	Sensitivity analysis
S_CLG	Ceiling specification	SLR	Systematic literature review
S_DHW	Domestic hot water system specification	UA	Uncertainty analysis
S_EW	Exterior wall specification		

1. Introduction

The building sector is a major target for environmental improvement [1]. Life cycle assessment (LCA) has been increasingly integrated into the design process to quantify the environmental impacts of buildings [2] and combined with automated optimization algorithms to identify optimal design solutions [3]. However, design-related uncertainties (DRUs) caused by unspecified design parameters would compromise the reliability of LCA results [4], thus undermining the robustness of optimization.

Currently, most studies handling DRUs focus on manual design decision-making rather than automated optimization. LCA tools based on hierarchically structured databases [5,6] and DRU refinement approaches guided by uncertainty analysis (UA) [7,8] have been developed, both enabling more informed design decisions under uncertainty. Nevertheless, manual methods remain less efficient compared to automated optimization and fail to illustrate the performance gap between selected solutions and the optimal ones [9].

In contrast, existing automated optimization studies tend to handle DRUs by simply assigning default values or excluding them from LCA calculations [10,11]. While such simplifications streamline the optimization process [12], the impact of critical DRUs on optimization results is overlooked. This underscores the need for a structured classification of DRUs to enable targeted strategies for handling uncertainties.

Some studies have classified DRUs from various perspectives. Wang et al. [13] identified influential DRUs by analyzing how frequently they appeared as variables across published papers. Zhou et al. [14] conducted sensitivity analysis (SA) to distinguish DRUs with significant contributions to buildings' environmental impacts. Li et al. [4] ranked DRUs based on uncertainty analysis (UA) results compiled from existing literature. While these studies provide valuable insights into DRU classification, they focus exclusively on single aspects of DRUs' influence rather than offering an integrated analysis.

This study proposes a dual-dimension classification approach for DRUs in LCA-based building optimization, integrating their potential impacts on both environmental performance and subsequent design decisions. Based on this classification, targeted uncertainty-handling strategies are provided to enhance the robustness of simplified LCA methods and LCA-based optimization.

2. Methods

This study followed a four-step methodology (Figure 1). First, a systematic literature review (SLR) was conducted on LCA-based building optimization. Second, DRUs have been identified from the selected literature and documented their decision-making stages in all optimization processes. Then, these DRUs were semi-quantitatively evaluated across optimization interest (OI) and decision-making priority (DP). Finally, they were classified based on the dual-dimension evaluation results to provide targeted recommendations for handling uncertainty.

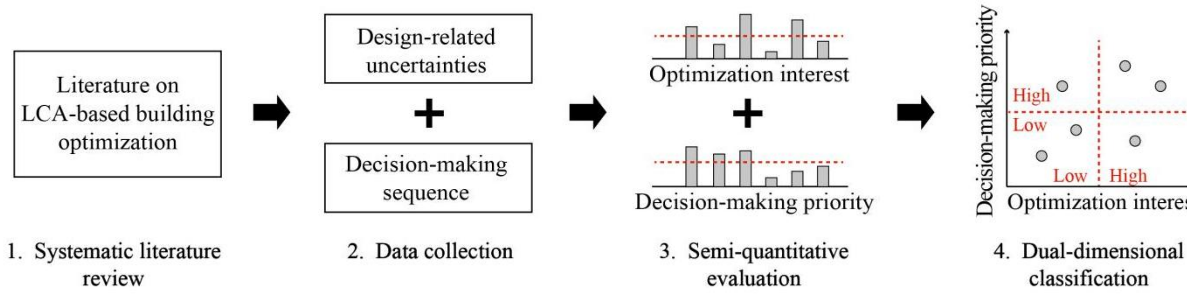

Figure 1. Workflow of this study

2.1. Literature search and selection

The literature search and selection process is illustrated in Figure 2. Literature search was conducted using Web of Science and Scopus, two widely recognized authoritative databases [15]. A combination of four keyword sets was employed for the topic search (including title, abstract, and keywords of publications): (building* OR residence* OR office*), design, (lca OR "life cycle" OR "whole life" OR "environmental impact*" OR "embodied carbon"), and (optimiz* OR optimis*). To enhance literature relevance and readability, the search was restricted to English-language journals and conference papers in the architecture and engineering fields. After removing duplicates, a total of 3,749 papers were retrieved. Following the SLR protocol [16], literature was screened by examining titles, abstracts, and full texts in sequence. This study included only literature addressing automated optimization of environmental impacts for new building design. After three rounds of screening, 56 papers remained, with 2 more added via snowballing [17].

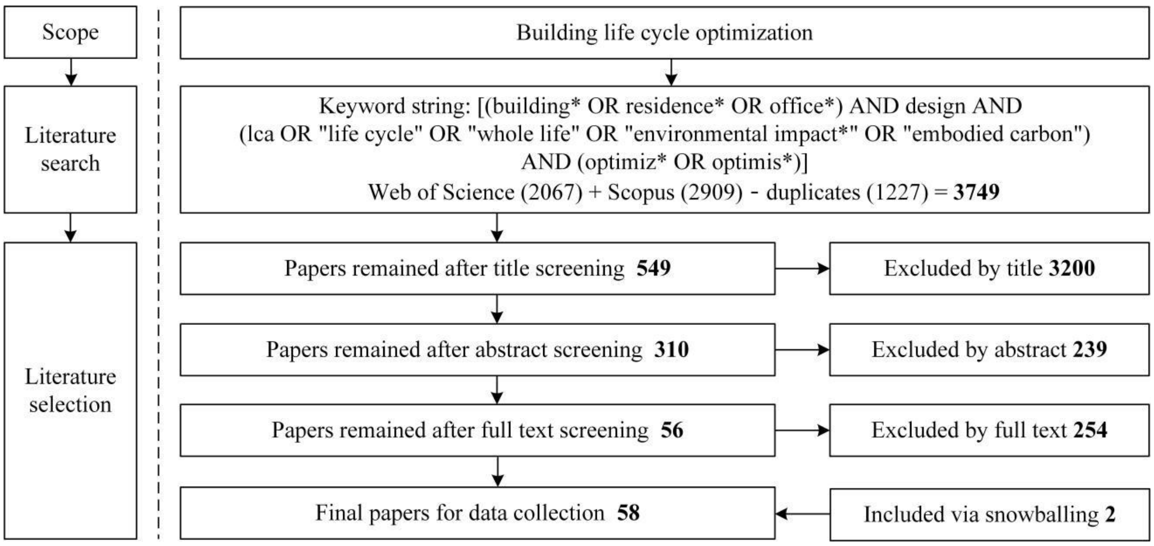

Figure 2. Literature search and selection process

Our research did not specifically prioritize any design stages or optimization objectives, only requiring that LCA in the selected papers include the embodied stage. Nearly 40% of the selected papers explicitly focused on early design stages. About a quarter of the papers examined the trade-off between operational and embodied environmental impacts, while the majority treated environmental impacts as a whole.

2.2. Data collection

The literature obtained via SLR included 63 optimization processes in total. From these, the following data were extracted:

(1) DRUs in LCA-based building optimization

Terminology for DRUs varied among studies. For statistical analysis, we standardized these terms based on our previous work [4]. Table 1 presents 16 DRUs identified in LCA-based building optimization: 5 derived from building geometry, 7 from construction specification, and 4 from equipment specification. Notably, uncertainties not fully caused by unspecified design decisions (e.g., heating setpoint temperature) were excluded.

Table 1. Design-related uncertainties in LCA-based building optimization

Source	Design-related uncertainties
Building geometry	Building scale (G_SCA), Building orientation (G_ORI), Plan configuration (G_PLN), Vertical configuration (G_VRT), Opening area (G_OPN)
Construction specification	Structure (S_STR), Exterior wall (S_EW), Roof (S_ROOF), Floor (S_FLOOR), Window (S_WIN), Interior wall (S_IW), Ceiling (S_CLG)
Equipment specification	Heating, ventilation and air conditioning system (S_HVAC), Lighting system (S_LIGHT), Domestic hot water system (S_DHW), Renewable energy system (S_REN)

(2) Decision-making stages of DRUs in optimization processes

The decision-making stages of DRUs in each optimization process were documented, regardless of whether they served as optimization variables. Three decision-making stages were defined: pre-optimization, first-round optimization, and subsequent optimization. DRUs decided in the pre-optimization stage comprised those explicitly assigned values through architects' decisions, inherited values from case buildings, or set as optimization scenarios. DRUs without explicit values, and those assigned provisional settings (e.g., researcher assumptions, reference values from standards, or software templates), were considered undecided.

2.3. Semi-quantitative evaluation

This study proposed two evaluation metrics focusing on key concerns in handling DRUs in optimization processes:

(1) Optimization interest

OI evaluates researchers' preference to handle DRUs through optimization, reflecting their potential influence on buildings' environmental performance [13,18]. OI was calculated as the proportion of optimization processes in which the DRU was included as an optimization variable.

(2) Decision-making priority

DP evaluates the timing of handling DRUs in optimization processes, indicating their potential impact on other design decisions [19,36]. DP was assessed through a weighted scoring system:

- Pre-optimization: 3.00

- First-round optimization: 2.00
- Subsequent optimization: 1.00
- Undecided: 0.00

This weighting allocation follows the principle of diminishing design influence [2]. DRUs decided at earlier stages globally influence the subsequent design process, constraining design space and shaping key boundary conditions, thus receiving the highest weight. As design progresses, later-decided DRUs have a narrow influence scope, warranting lower weights. This approach quantifies both temporal characteristics and potential impact of DRUs on other design decisions. For each DRU, scores were assigned across all optimization processes and then averaged to calculate its overall DP.

2.4. Dual-dimensional classification

Based on the evaluation results, a dual-dimensional classification approach was developed. Thresholds of metrics were selected based on their mean values to maintain statistical relevance and interpretability:

- Optimization interest: 0.30
- Decision-making priority: 1.50

For OI, the mean value (0.32) supported a threshold of 0.3. Nearly 70% of the optimization processes included no more than 5 DRUs, resulting in generally low OI scores. In this context, the 0.50 threshold suggested by Wang et al [13], which would lead to an unbalanced classification excluding certain categories. Therefore, 0.30 is a more appropriate threshold.

For DP, the mean value (1.32) was rounded to 1.50, ensuring a clear and practical distinction between high- and low-priority DRUs.

3. Results and discussion

3.1. Optimization interest analysis

OI scores of DRUs are presented in Figure 3. Higher scores indicate a greater preference for including these DRUs as optimization variables, implying their significant influence on buildings' environmental performance [13,18].

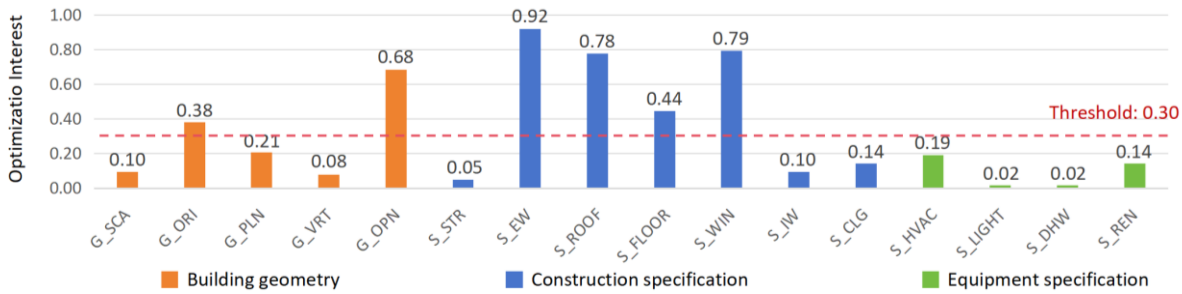

Figure 3. Optimization interest scores of DRUs

In terms of building geometry DRUs, only opening area (0.68) and building orientation (0.38) have OI scores above the threshold (0.30). Opening area ranked highest among all DRUs in Jung et al.'s [20] SA of passive energy-saving strategies across multiple environmental impact indicators. Building orientation directly influences the indoor thermal environment and energy consumption [21], and is often optimized in conjunction with opening area to enhance passive design benefits [22]. Despite the considerable impact of building scale (0.10), plan configuration (0.21), and vertical configuration (0.08) on shape factor and material quantities [23], these DRUs are less frequently chosen as optimization variables, since decisions regarding them are subject to other crucial considerations such as functional requirements [24].

Among construction specifications, exterior wall (0.92), window (0.79), roof (0.78), and floor (0.44) specifications have higher OI scores, as there is a consensus on their crucial role in balancing operational and embodied environmental performance [25-27]. Building structure (0.05) information is typically not available in the early design stages when most optimization processes occur [10]. Additionally, structure has minimal impact on the operational phase, primarily affecting embodied impacts, and is therefore often excluded from studies focusing on operational-embodied performance trade-offs [28]. Interior wall (0.10) and ceiling (0.14) specifications are seldom chosen as optimization variables, which corresponds to their minor impact on building LCA [20].

DRUs related to equipment specifications exhibit OI scores below the threshold. HVAC (0.19) is generally considered the responsibility of mechanical engineers [19]. Lighting and DHW systems have the lowest OI scores (both 0.02) , with only one study incorporating each into optimization models [9,29]. While renewable energy systems (0.14) are gradually gaining attention in sustainable building design [30,31], they remain underrepresented in LCA-based optimization studies.

3.2. Decision-making priority analysis

DP scores of DRUs are presented in Figure 4. Higher scores indicate that these DRUs are decided earlier in the optimization process, suggesting that they may have critical influence on other design decisions [19,36].

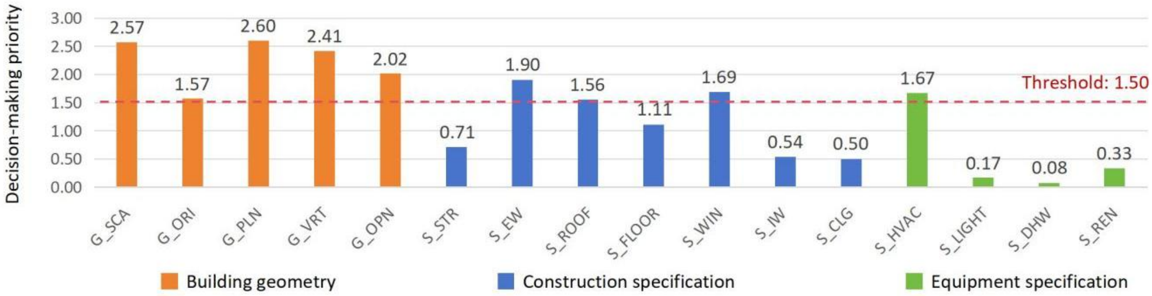

Figure 4. Decision-making priority scores of DRUs

All DRUs derived from building geometry have DP scores above the threshold (1.50). Building scale (2.57) is typically decided directly by developers, establishing a foundational premise for other design decisions. The DP scores of plan configuration (2.60) and vertical configuration (2.41) align with the common practice that they are typically decided before the optimization begins [32], having a significant impact on subsequent decisions by constraining design flexibility. Shadram et al. [28] found through comparative studies that optimizing construction specifications under fixed building shape achieves only one-fifth of the environmental performance improvement potential compared to simultaneous optimization. Building orientation (1.57) and opening area (2.02) have lower DP scores, as they are more often decided in the first-round optimization.

Within construction specifications, the DP scores of exterior wall (1.90), window (1.60) and roof (1.56) specifications exceed the threshold. Yu et al. [10] found that assuming different values for these DRUs when they are undecided significantly affects optimization results. Floor specification (1.11) shows the lowest DP score among building envelope components, consistent with previous findings that its variations have limited impact on building LCA [4], possibly because floors don't directly expose to the outdoor environment [33]. Building structure (0.71), interior wall (0.54), and ceiling (0.59) specifications tend to remain undecided and be excluded from LCA calculation in optimization process [10,34,35].

Regarding equipment specifications, only HVAC (1.67) has a DP score above the threshold, with nearly 40% of optimization processes having it decided in the pre-optimization stage. Although active technologies are typically decided after passive technologies in practice [36,37], the choice of HVAC has substantial impact on other design decisions. Kiss et al. [3] found that optimal building solutions obtained under different HVAC scenarios can differ in environmental performance by more than 15%. Lighting (0.17) and DHW (0.08) system loads are typically set to default values [38,39], while renewable energy system (0.33) is often not explicitly mentioned in many studies.

3.3. Classification results and recommendations

By integrating the evaluation results from optimization interest and decision-making priority, DRUs are classified into four categories (Figure 5), and uncertainty handling recommendations are proposed based on their characteristics.

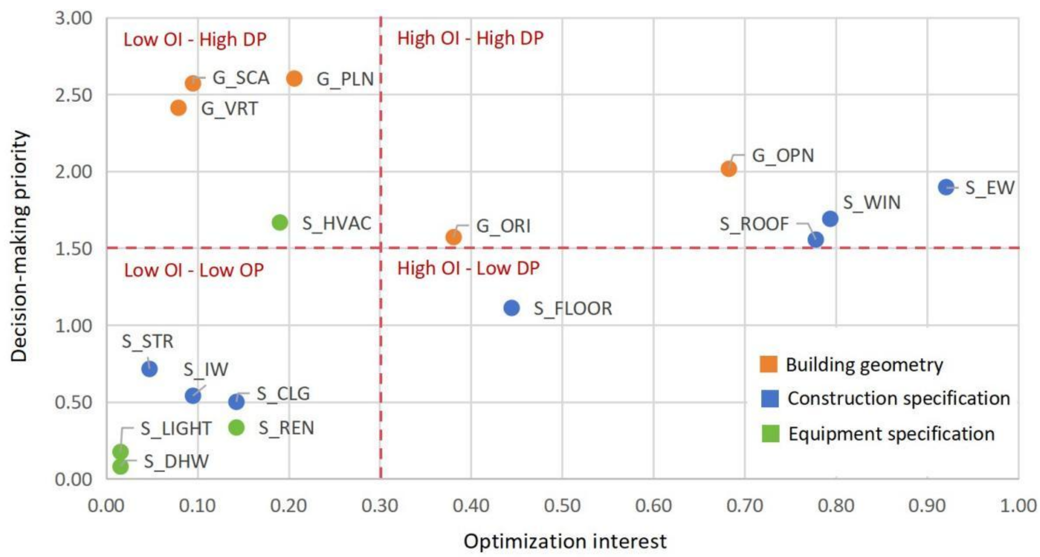

Figure 5. Dual-dimension classification of DRUs

The High OI - High DP category comprises 5 DRUs: building orientation, opening area, exterior wall, roof, and window specification. These DRUs are typically decided through optimization in early design stages, demonstrating substantial influence on both buildings' environmental performance and interdependent design decisions. When these DRUs remain undecided during optimization, Monte Carlo simulation (MCS) is recommended to efficiently explore combined impacts of their uncertainties simultaneously [40], capturing interaction effects that scenario analysis might overlook. In this case, MCS can help identify design solutions that are more likely to maintain good environmental performance regardless of what values these critical DRUs eventually take.

The Low OI - High DP category comprises 4 DRUs: building scale, plan configuration, vertical configuration, HVAC specification. These DRUs are typically decided early in the design process without optimization, yet they establish key constraints for subsequent decisions. Although these DRUs may not be decided solely based on their environmental impacts, they should ideally be optimized together with the High OI - High DP parameters when possible. If comprehensive optimization is not feasible, scenario analysis [41] could be conducted to illustrate how optimization results vary when different values of these DRUs are set as optimization scenarios, enabling designers to make more informed decisions.

The High OI - Low DP category comprises 1 DRU: floor specification. Despite its relatively high contribution to buildings' environmental impacts, this DRU is typically decided later in optimization process, thus having minor influence on other decisions. In such cases, using simplified assumptions before making a decision on its value would not significantly compromise the robustness of optimization results.

The Low OI - Low DP category comprises 6 DRUs: structure, interior wall, ceiling , lighting system, DHW, and renewable energy system specification. These DRUs are typically not included in optimization, and are often decided after most crucial decisions have been made. Given these characteristics, setting them as standard values or default settings is acceptable.

3.4. Limitations and future work

There are three main limitations in this study. First, the 16 standardized DRUs could be further subdivided based on variable definitions in optimization (e.g., plan configuration could be split into shape, layout, and dimensions). Such refinement would improve characteristic analysis and support more practical uncertainty handling strategies. Second, the current classification of DRUs relies solely on semi-quantitative scoring of data from building optimization studies. Validation and complementary perspectives through architect surveys, or sensitivity and uncertainty analyses on typical buildings are needed. Third, while recommendations are provided for each category, an integrated framework for systematically managing uncertainties throughout the LCA-based optimization process remains to be developed.

4. Conclusion

Handling uncertainties caused by unspecified design parameters is crucial for improving the reliability of LCA-based building optimization results. To address this issue, we identified 16 design-related uncertainties from 58 papers, and proposed a dual-dimension classification approach based on their impact on building environmental performance and influence on other design decisions, providing targeted uncertainty handling recommendations for each category.

For High OI - High DP DRUs, MCS is recommended to propagate their uncertainties to identify robust optimization solutions; for Low OI - High DP DRUs, scenario analysis is suitable to compare optimization results under different pre-decided values; for High OI - Low DP DRUs, simplified assumptions can be adopted without significantly compromising optimization robustness; and for Low OI - Low DP DRUs, standard values or default settings can be used to streamline the optimization computation.

This study provides practical guidance for efficiently handling design-related uncertainties in simplified LCA methods and tools for building optimization, and lays a foundation for developing a robust optimization framework addressing design-related uncertainties in the future.

5. Acknowledgements

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