Uncertainties in Whole-building Life Cycle Assessment: A Systematic Review

Haibo Feng[1]; Jianfeng Zhao[2, *]; Haonan Zhang[3]; Shiyao Zhu[4]; Dezhi Li[5]; Niraj Thurairajah[6]

[1] Department of Mechanical and Construction Engineering, Northumbria University, Newcastle upon Tyne, UK. haibo.feng@northumbria.ac.uk.
[2] Department of Architecture and Built Environment, Northumbria University, Newcastle upon Tyne, UK. jianfeng.zhao@northumbria.ac.uk. * Corresponding author
[3] School of Engineering, University of British Columbia (Okanagan Campus), 1137 Alumni Avenue, Kelowna, BC, V1V 1V7, Canada. haonan.zhang@ubc.ca.
[4] School of Transportation and Civil Engineering, Nantong University, Nantong, Jiangsu, China. crystal_zsy@126.com.
[5] School of Civil Engineering, Southeast University, Nanjing, Jiangsu, China. njldz@seu.edu.cn.
[6] Department of Architecture and Built Environment, Northumbria University, Newcastle upon Tyne, UK. niraj.thurairajah@northumbria.ac.uk.

Abstract

Environmental impacts (EIs) of building stocks have been receiving significant attention in recent decades as they consume more than 40% of the world’s energy, release one third of total greenhouse gas emissions, and account for 30% of global landfill waste. Prior efforts have focused on mitigating EIs during the operation stage of buildings, while the environmental performance of other stages is relatively overlooked. Addressing this, whole-building life cycle assessment (WBLCA) has gained prominence from a life-cycle perspective to ensure the best environmental performance. However, there is an array of factors that can affect WBLCA results, and such uncertainties render decisions made for sustainable development untenable. Aiming to understand the comprehensive uncertain sources of WBLCA (*what*) and their corresponding solutions (*how*), this paper systematically reviews existing publications on WBLCA, presents its status and challenges, and analyses the taxonomy of uncertainties and eight uncertainty methods and variants thereof. Accordingly, a framework is developed that enables LCA practitioners to readily understand the correlation between WBLCA uncertainties and solutions, and conveniently locate and appraise them throughout the WBLCA process. Upon answering the *known-what* and *known-how* questions, this study contributes to the body of knowledge of LCA by providing a comprehensive and systematic methodology to evaluate the EIs of buildings.

Keywords: Whole-building life cycle assessment, Uncertainty, Environmental impact, Solution, Building performance

1 Introduction

Confronted with the pressing challenge on climate change, governments around the globe are prioritising environmental consideration on their agenda. For example, the United Kingdom (UK) became the first major economy to commit to achieving net zero greenhouse gas (GHG) emissions by 2050 [1]. Among the various GHG emitters, the building sector instigates a massive impact on the environment due to its intensive resource depletion and energy consumption [2,3]. However, such a striking phenomenon will not disappear imminently due to the population growth, longer time spent inside buildings (e.g., over 20 hours due to Covid-19 restriction rules), and demands for better building services and comfort (e.g., 300,000 new homes per year by the mid-2020s in England) [4]. Therefore, concepts such as green buildings, sustainable buildings and net-zero energy buildings [5], and different types of building rating systems, including Building Research Establishment Environmental Assessment Method (BREEAM), Leadership in Energy and Environmental Design (LEED), and Deutsche Gesellschaft für Nachhaltiges Bauen (DGNB) [6] have been developed and adopted by countries to optimise building design and reduce energy consumption and emissions. To name a few, a net-zero building requires that the energy use of a building equals to its energy generation [7], and the LEED rating system requires a building to earn credits in six categories, covering location and site selection, water and energy efficiency, materials, and resources [8]. Nevertheless, endeavours of this kind only consider one or a few aspects of building performance, failing to capture buildings' full inventory and variations over time. Given that the ultimate goal is to deliver overall sustainable buildings throughout their life cycle [9,10], there is a need to develop a more comprehensive method to evaluate the 'cradle to grave' EIs of a building.

To do so, whole-building life cycle assessment (WBLCA) has pervaded the analysis of the overall building performance [11,12] by monitoring and assessing buildings' life-cycle EIs (e.g., production, construction, operation and maintenance, and decommission phases) [13]. According to [14], WBLCA can avoid passing the environmental load from one life cycle phase to another in the decision making process. However, it should be noted that buildings' lifecycle is relatively long (e.g., 50 to 70 years), contains complex structures, and necessitates a great number of materials [13]. This may explain the copious LCA studies that have focused on materials. For example, Lan *et al*. [15] emphasied the integration of system-level management (e.g., forest management) into harnessing the benefits of cross-laminated timber in GHG emission. Hollberg *et al*. [16] argued that the building information modelling (BIM)-LCA appraoch (using BIM to automatocally take bill of quantities of materials) could be misleading due to the use of placeholder materials. However, a BIM-based life cycle sustainability assessment (covering wider aspects than LCA) helped Patel and Ruparathna [17] confirm geomembrane can be a sustainable material of roads. As an important material in construction, Zhang *et al*. [18]investigated how LCA should be properly applied to evaluate the application of recycled aggregate concrete. Despite these promising efforts, their findings have not been widely adopted in the building sector, and more importanly, Nwodo and Anumba [10] contend that the lack of uncertainty analysis strikes as a major challenge in building LCA. Failure to do so, as argued by Igos *et al.* [19], would decrease the reliability and credibility of LCA results.

Faced with the uncertainties casued by these ‘dynamics’ and the subsequent inconsistent and perhaps unreliable final WBLCA results [20,21], several uncertainty analyses have been conducted to improve the WBLCA results and facilitate decision making. For example, Robati *et al.* [22] applied Monte Carlo simulation (MCS) to examine the uncertainty in materials. Harter *et al.* [23] proposed the variance-based method to understand uncertainties in design parameters at different building development levels. For uncertainty emanated from the LCA method itself, Buyle *et al.* [24] promoted consequential LCA to identify marginal suppliers, market boundaries and market volume trends as the attributional LCA has only a single set of model assumptions. Nevertheless, these studies have a tendency to: (1) select specific methods (e.g., MCS) or a mixture of them (e.g., MCS and sensitivity analysis) to address specific uncertainties (e.g., materials and parameters) (i.e., they appear in a sporadic manner); and (2) use uncertainty analysis as a ‘procedure’ in the paper without providing how it was conducted and associated implications [25,26]. In other words, a thorough investigation of the complete uncertainty sources, solutions and practical guidance is currently not available in the literature. Without such a line of inquiry, the capability to further minimise the uncertainties of WBLCA results is hindered. More importantly, identifying the roots that cause the uncertainties of WBLCA results and illuminating the possible solutions are of the uttmost concern of decision makers to realise sustainable building developments. Therefore, this present study aims to critically review the current status of WBLCA, the uncertainties of WBLCA results, and the latent methods to reduce the uncertainties, as well as propose a conceptual framework to assist LCA practitioners in understanding and curbing the uncertainties of WBLCA.

Unlike previous examples, this study provides an aggregated view of the uncertainties of WBLCA, their solutions and a practical pathway. Acknowledging the proliferating signifance of WBLCA in improving building performance, this timely inquiry also paves an avenue for future headways to be made.

The remainder of this paper is structured as follows: Section 2 explains the systematic method followed throughout. Section 3 and Section 4 critically review the state-of-the-art WBLCA and the factors/ sources that lead to its uncertainties, respectively. Section 5 details the existing methods to quantify uncertainties of WBLCA. Building on the uncertainties and their solutions, Section 6 proposes a conceptual framework to facilitate LCA practitioners' decision making. This paper finishes by summarising its conclusions and channelling future work.

2 Methodology

To fulfill the research aim identified above, a systematic literature review was conducted to identify, evaluate and interpret the current status of WBLCA, the uncertainties of WBLCA results, their solutions, and the prospect of a framework in mitigating the uncertainties of WBLCA results. Literature review, as a research methodology, is robust in synthesising research findings and facilitating new knowledge production [27]. On the other hand, an unthorough, unsystematic and selective literature review will result in flaws in the target research [27]. Hence, a step-by-step (i.e., systematic) searching and sifting process similar to Feng *et al*. [14] was implemented to eschew authors' bias in selection (i.e., thorough and impartial). Figure 1 outlines the research flow of this study, comprising: (1) database and sequential search; (2) screening and sifting; and (3) evaluation and interpretation.

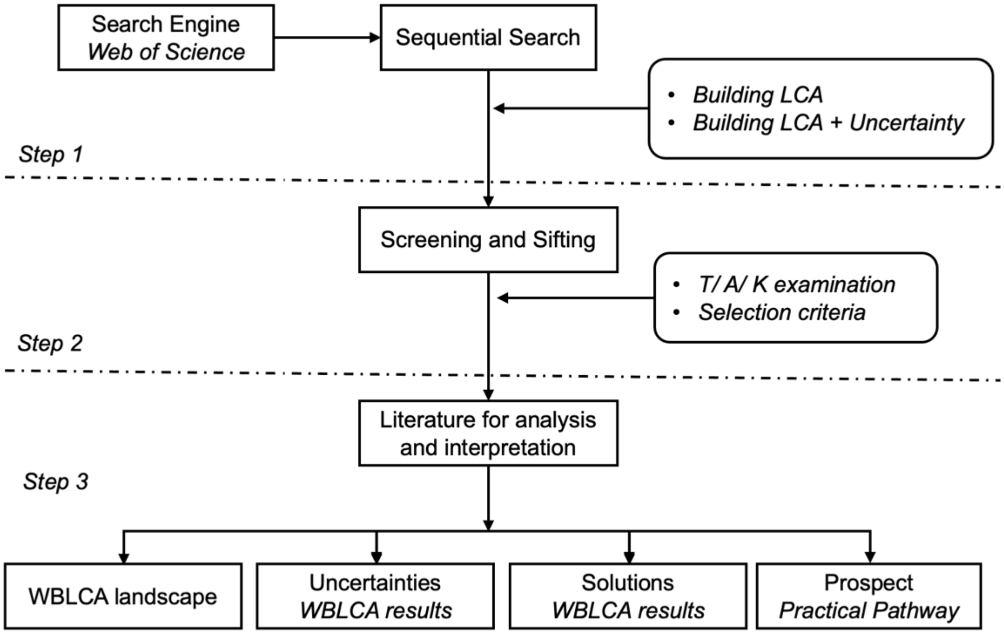


Figure 1. Research flow

2.1 Database and Sequential Search

To serve our research aim, the search engine Web of Science (WoS) was selected to conduct the literature search. WoS is a well-recognized database for academic articles and publications, which allows users to retrieve pertinent research with the function of advanced search [28]. In order to focus on the most valuable studies in the database and minimise authors' bias in selecting publications [27], titles, abstracts and keywords (T/A/K) were manually examined at each sequence. Moreover, four criteria were established and maintained to mitigate subjectivity throughout the screening and sifting process: (1) Year: 2000 to 2020 (both sides inclusive); (2) Type: peer-reviewed journals; (3) Language: English; and (4) Relevance: T/A/K related to search strings. In other words, only journal articles which are from 2000 to 2020, written in English, and focussed on building LCA were initially included. For instance, although Dai *et al*. [29] proposed a multilevel modelling approach to quantify uncertainties in terms of missing data, and temporal and geographical characteristics in the life cycle inventory (LCI) databases, this article was excluded as it applies to the agriculture sector (i.e., nitrogen fertilizer application for corn production).

The keyword "building LCA" was first used to identify the related literature. Consequently, a total of 5890 results were generated to analyse the status of WBLCA. Then, the keyword "uncertainty" was added to the previous search output, providing 426 results to have an in-depth view of the uncertainty related to building LCA. Furthermore, among the 426 articles, those that not only mention 'uncertainty' but also present a 'solution' were shortlisted (i.e., 43 publications) to examine the existing solutions to WBLCA. This sequential literature identification process provides a staged and comprehensive view of each aspect (Table 1) studied in this research. It also shows the priorities and negligences of existing studies, for example, only 43 out of 426 articles have performed an uncertainty analysis. A similar procedure has been followed in Feng *et al*. [14] and Muazu *et al*. [30].

Table 1. Number of papers used for each stage of the review

Review objective	Number of papers for review
Status of WBLCA (Section 3)	5890
Uncertainties of WBLCA (Section 4)	426
Solutions to WBLCA uncertainties (Section 5)	43

2.2 Evaluation and Interpretation

Bibliometric analysis and content analysis were applied to evaluate and interpret the selected literature (Table 1) [31,32]. Specifically, VOSViewer was adopted to facilitate the bibliometric analysis to provide a visualised view of the *status quo* of WBLCA in the existing literature, viz. development trend (i.e., publication yearly distribution), publication sources (i.e., density visualisation), and research hotspots (i.e., keywords occurrence). VOSViewer is a computer program that is capable of creating maps of scientific journals, researchers, keywords, etc. based on co-occurrence, bibliographic coupling or co-citation networks extracted from literature database [33]. Content analysis, on the other hand, was performed to deepen our understanding of the uncertainties associated with the WBLCA and the current methods proposed to increase the accuracy of WBLCA results. By synthesising the findings from the review, new knowledge on how practitioners can better conduct a full WBLCA, treat WBLCA uncertainties, and make informed building performance decisions were acquired.

3 Status of Whole-building LCA

Figure 2 displays the distribution of the 5890 papers over the period under investigation, which is consistent with the statement that the topic of building LCA is becoming increasingly popular.

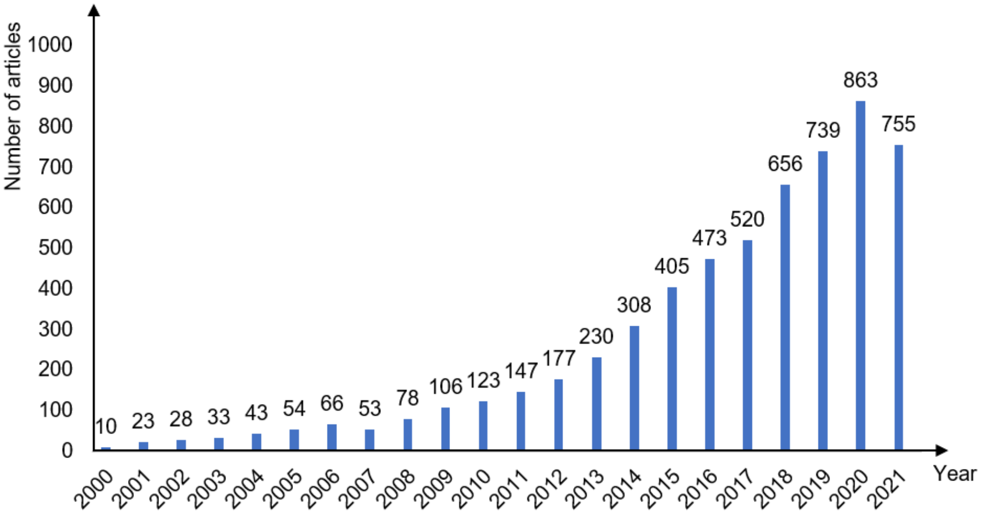


Figure 2. Distribution of source documents by publication year (search conducted in August 2021)

Among the 5890 papers published, *Journal of Cleaner Production* and *International Journal of Life Cycle Assessment* were found two be the top two journals that have the most journal papers published in this topic, which accounted for 26% in total. *Energy and Building* and *Building and*

Environment are the second top group that contributed a total of 13%. *Sustainability*, *Journal of Industrial Ecology* and *Renewable & Sustainable Energy Reviews* are the third top group that shared 10% of the selected journals. Among the bulky portions of journals that sometimes overwhelm academics and practitioners [34], the resultant publication names can be readily used by them to search and publish studies relating to building LCA. We now commence with the analysis of the status of WBLCA.

Using the function of keywords occurrence VOSViewer, ‘LCA’ and ‘building’ were shown to be the most occurred keywords, and “LCA” has different kinds of notation styles. ‘Energy’, ‘embodied energy’, ‘impact(s)’, and ‘environmental impact(s)’ were the second most occurred keywords. Based on the keywords occurrence density, current studies on building LCAs mainly focused on energy or environmental performance. While the embodied energy/carbon were highlighted as the most occurred keywords, the operational energy/carbon emission haven’t been paid enough attention. However, studies show that the operational energy/carbon emission is as important as the embodied energy/carbon emission [35,36]. Furthermore, these two aspects are intertwined and need to be considered together. Table 2 lists the relationships between the operational and embodied carbon emissions compiled by different researchers for different buildings. It shows that a comprehensive analysis of building emissions requires the consideration of embodied emissions in material production stage and the emissions in the operation stage, since the emission percentage from other building life-cycle stages would increase when operational energy consumption reduces. Based on the keyword occurrence density, it is suggested that more studies should be conducted to analyse the operational energy/carbon emissions.

Table 2. Percentage of embodied and operational carbon emissions in different buildings

Building type	Building location	Building lifespan (years)	Embodied carbon emission (%)	Operational carbon emission (%)	References
Four student apartments	Israel	50	60	40	[36]
Low energy house	Sweden	50	40-60	40-60	[37]
New-built house	UK	25	20	80	[38]
20 apartments	Sweden	50	40	60	[39]
Energy efficient homes	Dutch	50	36-46	54-64	[40]
97 apartment buildings	Portugal	50	20.2	79.8	[41]
4-bedroom house	UK	60	20-26	74-80	[42]
95 residential buildings	worldwide	50	9-80	20-91	[43]
17-story resident building	China	50	17	83	[44]
Low energy buildings	worldwide	50	26-57	43-74	[45]
Low energy buildings	worldwide	50	9-46	54-91	[46]
Residential and office buildings	worldwide	50	10-20	80-90	[47]

‘Design’ and ‘construction’ were the other highlighted keywords in building LCA; however, there are other life cycle stages (e.g., the maintenance and repair stage and disposal stage) that have not been highlighted. However, [48,49] have shown that the percentage of emissions from maintenance and repair stages increases with a corresponding significant reduction in operational emissions. By only focusing on the design and construction stages, it is unlikely that designers can garner a complete understanding of the building energy/environmental performance. In turn, according to [22,50], this creates difficulties for designers to make the best decisions on the overall building environmental performance. Therefore, the next step is to focus on the building over its whole life cycle from the building material manufacturing stage, construction stage, to operation and maintenance stage, and disposal stage. By following the EN15978 standard, WBLCA is a comprehensive method that measures the building performance at all the life cycle stages, which allows the designers to work out the optimal solution to improve building performance [51,52].

‘Residential buildings’ is another keyword that occurs frrequently in the building LCA keyword search output, which demonstrates a number of research have been conducted on residential buildings. For example, Kylili *et al*. [51] conducted a WBLCA for a passive house located in Cyprus to assess the environmental performance. In Norway, Kristjansdottir *et al*. [53] performed a LCA for eight different single-family houses, and the results illustrated the relationships between the operational and the embodied environmental impacts. Atmaca and Atmaca [54] analysed the life cycle carbon and energy emissions of two residential buildings from the construction phase to the demolition phase. Evangelista [55] presented a “cradle to grave” LCA analysis for four typical Brazilian residential buildings under eight impact categories. However, WBLCA has not been widely used in other building types, such as commercial and industrial buildings. One of the reasons could be the relatively simple structures of residential building, which makes it possible to conduct the comprehensive WBLCA. Therefore, more attention should be paid to apply WBLCA to other building types besides residential buildings.

WBLCAs are becoming increasingly popular in building construction-related decision making due to the comprehensive and systematic approach of LCA to environmental evaluation [56,57]. Green building rating systems worldwide also start to assign credits to WBLCA. Table 3 outlines a few popular building rating schemes around the world that adopt WBLCA into the assessment criteria. Most of these rating schemes analyse all the materials that form the building structure and enclosure, and a whole-building life cycle is included from material production, building construction, to building operation and demolition. Since no keywords related to building rating systems were highlighted, future research could focus on analysing the impacts after applying WBLCA into the green building rating systems.

Table 3. WBLCA methods applied in green building certification schemes.

Certification	Boundary	Details
BREEAM	Cradle to grave	All building materials used in construction included in the LCA, BREEAM LCA tools and benchmark established for credit calculation, and EcoPoints indicator introduced.
DGNB	Cradle to grave	Building elements clearly described with exclusions, environmental values of the reference building established for credit calculation, and five impact factors included.
LEED v4	Cradle to grave	Materials of building's structure and enclosure included in LCA, design building should achieve min. 10% reduction from reference building, and six impact factors included.
Green Globes	Cradle to grave	Building elements clearly described with exclusions, building final design achieves 10-20% reductions for different indicators in comparison with the reference buildings, and six impact indicators included.
CASBEE	Cradle to grave	Building elements defined, building final design reaches different level based on the reference building which is developed from historical data, life cycle CO_2 calculated.
Green Star	Cradle to grave	Building elements clearly defined, building final design achieves points by comparing with reference building (two options), and seven impact indicators included.

WBLCA is a valuable tool to help the public understand the life cycle impacts of buildings on energy/carbon emissions. It also helps the government to fulfil the legislative requirement and achieve the environmental targets. However, due to the uncertainties related to modelling, material choices, data variability, and source parameters throughout the LCA process, ensuring the reliability of WBCLA results is always a challenge [58,59]. Therefore, it is significant to elucidate all the factors that might create uncertainties on WBLCA results and summarise all the possible methods in the literature that could help reduce the uncertainties of WBLCA.

4 Sources of Uncertainties on WBLCA Results

The uncertainties of WBLCA results are mainly because of the complication of LCA development processes and the complexity of building structures [60,61]. For example, due to the data availability in LCA, the system boundary might not be complete which leads to uncertainty in results. Citherlet and Defaux (2007) [62] conducted a WBLCA for three home designs in Switzerland. However, the system boundary of this study was not complete and additional material losses were considered in the LCA. Due to the variety of LCA methods and databases, the LCA results could also be significantly different with uncertainties. One study indicates that the embodied CO_2e results could be over 50% different between Ecoinvent database and ICE database for different building designs [63].

On the other hand, the variances in building materials and cut-off rules could lead to LCA result uncertainty, and the reference service life of the building could also result in a variation of WBLCA results. For example, studies have indicated that the annual energy demand could decrease approximately 14% when the building service life changes from 50 years to 75 years [43,64]. Silvestre *et al*. [65] further argue that the prediction of construction materials' service life is subjected to methodological uncertainty (i.e., the deterministic approach and the stochastic approach) that can impact LCA decisions at the design stage. Moreover, Su *et al*. [66] reveal that the parameter identification of building insulation materials, and in particular, physical parameters (e.g., thermal conductivity) of glass wool are a significant source of the uncertainty of its life cycle energy consumption.

Furthermore, the variances on construction practices and design parameter selection could also lead to LCA results uncertainties. For example, Hong *et al*. [67] stated that the inherent uncertainty during building construction phase could result in a coefficient of variation of 18% in uncertainty analysis. The major uncertainty sources during building construction, such as transport measurement method and geographic representativeness, were identified in this study. Escamilla and Habert [68] also indicated that the use of proper construction practices could build high technical performance building with low LCA impacts using geographic information system (GIS). In terms of design, Vuarnoz *et al*. [69] stated that the adoption of reality-based input parameters at the building design stage, such as occupancy rate, appliance usage, and energy conversation factor, would substantially impact LCA results. Therefore, the selection of construction practice and design parameters are also sources of uncertainties on WBLCA results.

Huijbregts [70] listed the types of uncertainty that are related to LCA development phases, which could be at the goal and scope definition phase, inventory analysis phase, as well as life cycle impact assessment phase including life cycle inventory analysis (LCIA) method and database (choice of impact categories, classification, characterisation and weighting methods). The source of uncertainty could be parameter uncertainty, model uncertainty, and uncertainty due to choices [59][70]. Elsewhere in the existing literature, Hong *et al*. [71] summarised those uncertain sources could result from data availability and quality [72], technical performance, emission factors and the functional unit [73] and cut-off, aggregation, temporal and geographic considerations [74]. To encapsulate the sources, Huijbregts *et al*. and Lloyd and Ries concluded that they can be categorised as parameter uncertainty, scenario uncertainty, and model uncertainty [75,76]. Favi *et al*. [95] further cited Der Kiureghian and Ditlevsen [77] and classified them into epistemic uncertainty, which can be mitigated by collecting more data and/ or optimising models, and uncertainty in aleatory, which exists in the natural randomness in a process and thus is unavoidable.

Here, Table 4 identifies the most notable factors from the 426 papers that create uncertainties on WBLCA results, namely system boundary (including service life), different building components/ elements, LCI, databases and methods used. In addition, Table 4 summarises the most relevant WBLCA development details to facilitate a better understanding of the uncertain sources of WBLCA results. The results show that the current WBLCA development methods are inconsistent in different LCA phases, and the WBLCA results are presented with uncertainties, which point out the necessity of proposing solutions to address them.

Table 4. The inconsistency of WBLCA methods in different case studies

Reference	**Type**	**Goal and scope**			**LCI**	**LCIA**
		Boundary	**Building elements**	**Life (yr.)**	**Scenario development**	**Database/Method**
[51]	Passive house	Cradle to site	Ground and first floor bill of quantity	50	External drainage, sewage, excavation not included	EcoHestia/ CML2001
[78]	Net-zero energy building	Product stage	Major components from structure to interior as well as ductwork, PV panel	50	Landscaping, interior finishes not included	Franklin USA98/ CED
[54]	Resident building	Cradle to gate	Major building structures, material replacement factors considered	50	Energy consumption and CO_2 emission in different stages accumulated	ICE database
[79]	Resident houses	Cradle to grave	BoQ from construction guides and material specifications	50	Energy and water in usage stage assumed	Econinvent/Gabi V4.3
[80]	Three types of buildings	Cradle to grave	Envelope and equipment system classified based on UNI 8290	50	Transport distance assumed, MC4 software for usage stage	Ecoindicator 99, IPCC 2007, CED
[81]	Passive house	Cradle to grave	Ground and first floor, entrance ramp and two exterior stairs, detailed end-of-life recycling stage	70	Life cycle improvement stage included, construction waste considered	Ecoinvent/ EPD 2007 Ecoindicator 99
[82]	Three hypothetical buildings	Cradle to gate	Building components built in Revit, VIP insulation material studied	50	Material transport not included	International, German and Norwegian EPD system
[83]	Three residential buildings	End-of-life stage not included	Seven building elements info obtained from original drawings.	75	Retrofit phase included, Only energy and GHG impact considered	ICE 2.0
[84]	10 case studies	Product stage	Material quantities from standard BoQ in public works department	n/a	Only embodied energy and carbon calculated	ICE 2.0/I-O LCA
[85]	26 buildings	Cradle to grave	BoQ not clearly presented, building floor area included	50	Life cycle CO_2 calculated only, retrofit phase not included	BELES database
[86]	Heritage theatre	Cradle to grave	Five main materials analysed	n/a	Usage stage excluded, only GWP and CED calculated	Ecoinvent 2.0
[87]	Industrial building	Cradle to grave	Equipment not analysed, electrical & mechanical components included	20	Designer builder applied in usage stage, Retrofit not studied	Ecoinvent 3.0 & ESUCO
[88]	Apartment building	Cradle to grave	Major renovation materials exterior walls, doors, windows, balcony	30	Retrofit not considered	Ecoinvent 3.1/ReCiPe
[55]	Four Brazilian dwellings	Cradle to grave	BoQ of main construction materials listed	50	water, energy use, waste during construction considered	Ecoinvent 3.01/CED 1.08 & ILCD 2011

5 Solutions to Reduce the Uncertainties

Through the literature review, it is revealed that while most of the studies (i.e., 426 publications) acknowledge the existence of uncertainties of WBLCA results, less than 1/4 of them (i.e., 43 publications) attempt to resolve the problem. This finding concurs with Blengini and Carlo (2010) and Rodrigues *et al*. (2018) arguing that existing LCA approaches generally do not address uncertainty [89,90]. During the third round of literature retrieval, a total of eight potential solutions, namely, MCS, sensitivity analysis, pedigree matrix and data quality indicators (DQI), fuzzy related method, Taylor series expansion and analysis of variance (ANOVA), decision support diagram, structured under-specification, and variants thereof (e.g., MCS mixed with pedigree matrix) have been identified. Notably, MCS is the most popular method (25 times) adopted to understand the uncertainties of WBLCA results, followed by sensitivity analysis (19 times), pedigree matrix and DQI (12 times), and fuzzy methods (3 times). Those mentioned only one time are categorised as 'other miscellaneous methods' hereinafter. The total number of times appeared is over 43 as some studies deployed more than one solution in a single study.

5.1 Monte Carlo Simulation

Compared with a single value assigned to each parameter (i.e., deterministic approach) [76], MCS is a tool through which uncertainty can be quantified (i.e., probability distribution of output parameters) by using random values of input parameters [22,91]. Within the identified WBLCA studies, it has been applied to different parts (e.g., brick/ fired-clay walls, insulation, flooring, etc.), phases (i.e., different system boundaries) and types (e.g., commercial and residential, traditional and contemporary) of buildings in different regions (e.g., Canada, Australia, Belgium) to address the result uncertainty caused by a variety of factors (e.g., materials, data, and model parameters). For example, MCS is employed by Rodrigues *et al*. (2018) and Rezaei *et al*. (2019) to compensate information shortage on materials at the early design stage of residential buildings in the South European Climate and Canada, respectively [90,92]. In this sense, designers can become aware of the EIs of their design and select materials that are environmental-friendly. Using MCS, Burek and Nutter [93] analysed the LCIA uncertainties of Walmart's distribution centres and confirmed electricity generation to be the biggest source of uncertainty. However, they consider only the uncertainties resulted from LCI input data while overlook the characterisation factors. The LCI data uncertainty was also examined by Hasik *et al*. [91] via MCS in three types of water systems of buildings and they attributed the uncertainties to a low number or large variability of samples and spatial and temporal scales. In addition, this uncertainty relates to how data are distributed (i.e., normally and uniformly). However, Pomponi *et al*. [94] argued that this relevance disappears in the MCS result after 104 random samplings from within the data variation range. There are other uncertain sources, such as material composition, transportation, energy usage, and service life prediction methods of materials that have been measured by MCS [65,95]. For instance, Robati *et al*. [22] predicted the EIs of each of 19 building materials for a 50-year building lifespan by considering uncertain variables such as materials' lifetime, CO_{2e} and transport distance.

5.2 Sensitivity Analysis

While there are solutions (e.g., MCS) aiming to understand the uncertainty of the LCA result, sensitivity analysis is commonly used to understand what parameters impact the result most [94]. Notably, a comprehensive list of the uncertainty types and their classification within the selected studies is presented in Section 4. This scenario-based approach is considered to be complementary to uncertainty analysis (sometimes even treated as the same, e.g., Walker *et al*. [96]) and a combination of them facilitates better decision-making (Roder *et al*., [97]). In the selected studies, we identify the most prevalent practice is a mixture of sensitivity analysis and MCS to target uncertainties in design features and background LCI data (Eckelman *et al*., [98]), foreground and background LCI data and transport (distance and types of vehicles) (Cuenca-Moyano *et al*., [99]), materials (Favi *et al*., [100]), commodity prices (Teh *et al*., [101]), key performance indicators (Walker *et al*., [96]), etc. An example is Ross and Cheah [102] adopted MCS to study LCA uncertainty of buildings' air conditioning systems resulted from different user behaviours and a subsequent sensitivity analysis identified system cooling and unoccupied room to be the highest influential factors. Similarly, maintenance frequency (frequent or periodic) and types (vacuum, sweep, or mop) can contribute to different LCA results of different floors. However, the sensitivity analysis in Minne and Crittenden [103] confirmed vacuuming's significant role in EIs. Aktas and Bilec [104] addressed the different lifetime of residential buildings in affecting their interior renovation energy consumption using MCS. Compared with the lifetime of carpet, ceramic, paint and Vinyl, residential building lifetime was found to be most significant using a sensitivity analysis. Different from the 'normal' procedure, Benetto *et al*. [105] firstly conducted a sensitivity analysis and then an uncertainty analysis through MCS. However, they only considered limited parameters in the sensitivity analysis and overlooked the uncertainties resulted from data recordings and data collection, which in turn jeopardise the accuracy of the final result. By contrast, the normal procedure followed in Su *et al*. [66] was able to examine all uncertain sources in the MCS and uncovered that physical parameters (i.e., conductivity and density) affect the LCA of building insulation materials most (i.e., 47% and 66.9%). Nevertheless, the use of hypothesis or empirical information in MCS can lead to this big uncertainty of physical parameters. In addition, Teh *et al*. [101] stated that the economy-wide system boundary embedded with the methodology resulted in higher GHG emissions. Obviously, these point out the importance of selecting appropriate uncertainty analysis methods *per se* and the awareness of their inherent uncertainty.

Sometimes (e.g., Cellura *et al*. [106], Walker *et al*. [96]), it is noted that sensitivity analysis is treated as the same as uncertainty analysis. This way, they tend to identify several variables that may be of high impact on the result and calculate their ‘uncertainties’ under a certain range (e.g., ±10%) or different scenarios (e.g., different impact assessment methods). For example, Cellura *et al*. [106] constructed different scenarios to study the uncertainties arisen from the secondary input data (i.e., transportation, electricity, and baking step) and methods (i.e., CML 2 baseline 2000, Ecoindicator 95, EDIP/ UMIP 97, IPCC 2007 and Impact 2002+) for roof tiles. However, problems can include: (1) it is not clear how these critical variables are identified; and (2) result shows the variables may not be critical, impeding a better understanding of the uncertainty. A case is, in Lu *et al*.’s study [107], three variables (change between -10% to +10) were presumably selected to check their uncertainties, and emissions from transportation processes was tested to be insensitive. In comparison, a hotspot analysis was undertaken by Wang *et al*. [108] to search the significant variables (i.e., transportation) and then calculated its variability. Therefore, it signifies not only the awareness of variances between uncertainty methods as mentioned above but also the careful selection of a single method with different types. As stated in Pannier *et al*. [109], different types of sensitivity analysis, such as screening and global ones, can present different relative influences of uncertain factors.

5.3 Pedigree Matrix and Data Quality Indicators

Pedigree matrix is introduced to ensure the reliability and applicability of LCA results by managing data quality. It encompasses five indicators, such as reliability, completeness, temporal correlation, geographical correlation, and further technological correlation, which have a score of 1 to 5, to adapt the actual data to a specific data quality goal [72]. In the target literature, we have witnessed the synergies of pedigree matrix, MCS and sensitivity analysis to estimate uncertainty and almost a half of them in CO_2 emission and embodied energy. Zhang *et al*. [110] used DQI and MCS to cope with parameter uncertainty followed by a scenario analysis to treat scenario uncertainty (e.g., different system boundaries and energy efficiency) and model uncertainty (e.g., different transformational relationships and distribution selection) for building life cycle carbon emission. The identical approach was applied in Zhang *et al*. [110] but for carbon emission during building construction. Similarly, the GHG emission during the construction was computed in Hong *et al*. [71] by combining MCS and DQI to ascertain input data that were deemed highly uncertain. The addition of MCS to DQI can mitigate the subjective evaluation and lower the calculation cost. However, compared with statistical methods, the result is not accurate. Therefore, a hybrid MCS-DQI-statistical method was proposed by Wang and Shen [111] for whole building embodied energy analysis and more accurate result and cheaper cost were observed than pure DQI and statistical methods, respectively. Moreover, recognising DQIs do not always contribute equally, a weighting mechanism is considered in the sole use of the pedigree matrix. For example, the analytical hierarchy process was employed by Wang *et al* [112] to determine the weighting of each DQI and estimate better probabilistic values of embodied energy intensity for concrete, steel and glass. Similarly, Taborianski and Prado [113] and Henriksson *et al*. [114] considered the weighting level of each life cycle stage and data's central value when multiple reported values are available, respectively.

In addition to the MCS and DQI to address absolute accuracy of the final LCA result, it is common to compare the uncertainty between scenarios, such as different earth-retaining walls [115], fired-clay bricks produced by different manufacturers [116], contemporary and traditional housing [117] and country-wide clay hollow brick walls [58]. According to Piroozfar *et al*. [117], the pedigree matrix showed that uncertainty for traditional houses is higher than contemporary houses, but the LCA results stimulated by MCS presented better EIs in the traditional houses. On the one hand, it challenges the environmental-friendly materials (e.g., limestone and lime mortar) as touted in the contemporary houses. On the other, it reinforces the importance of recording real data relating to building materials and methods that would otherwise generate uncertainties. This meaningful comparison perhaps corroborates Blengini and Carlo's [89] statement on the relatively more accurate comparative LCAs due to a higher correlation within scenarios' uncertainty.

5.4 Fuzzy-related Methods

Fuzzy-related methods (e.g., fuzzy rough sets, fuzzy variables, fuzzy logic approach and intuitionistic fuzzy sets) have been performed to counter the uncertainties in variables/ parameters and input data of LCA. For example, Li *et al*. [118] applied fuzzy rough sets to study the LCA uncertainty of a distributed renewable energy system derived from its power plant capacity, annual operation hours, and upstream Technosphere performance. Due to the different results from a sensitivity analysis, they believed that fuzzy rough sets are a new way of addressing uncertainties. However, how the different results impact decision-making should have been made clear. In the wind energy sector, intuitionistic fuzzy sets have been adopted by Gumus *et al*. [119] to examine uncertainties in indicators and lifecycle span of energy planning alternatives. In essence, a survey conducted by Lloyd and Ries [76] indicated that fuzzy data sets are ranked as the third most commonly used uncertainty method in addition to stochastic modelling (e.g., MCS) and scenarios. However, this does not appear to hold in the context of WBLCA in this research because there were only two articles that were qualified for review. Nevertheless, their applications in other areas shed light on how the fuzzy concept can potentially be mobilised in WBLCA.

Using linguistic rules, fuzzy set theory assumes the elements of a set following a membership function with the value ranging from 0 to 1 rather than binary terms [120]. This can solve the problem where an arbitrary number is assigned to a variable or where precise values are not available in WBLCA. As such, Ardente *et al*. [121] proposed a software based on fuzzy logic to define uncertain data on their age, underlying technology, statistical and geographic representativeness. In the case of plaster materials, it allowed WBLCA practitioners to view the whole calculation process and describe the sensitivities of each solution. More recently, Kaziolas *et al*. [122] chose two most uncertain variables, namely the end transport and recycling rate as fuzzy variables to calculate the EIs of a timber residential building and a steel building, respectively. A common feature of these two studies is that the fuzzy application to WBLCA requires expert knowledge and judgement, indicating the importance of experienced experts.

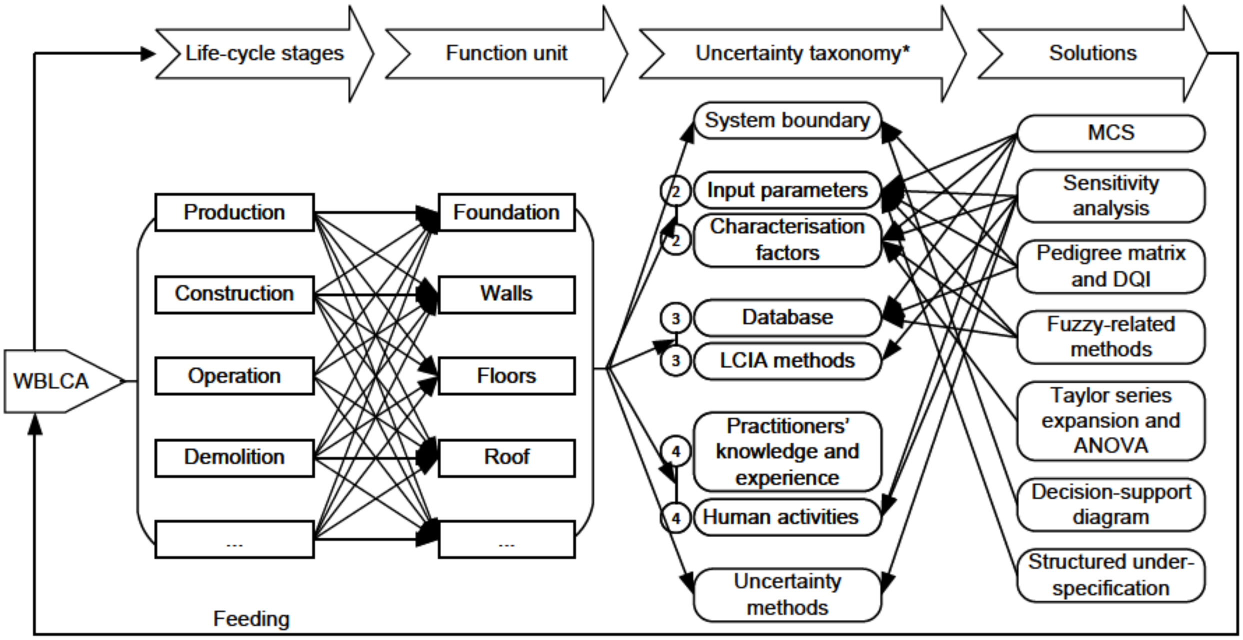
5.5 Other Methods

Through the literature review, a variety of 'non-mainstream' methods have been identified, which however, have provided a new stream of solutions to tackle uncertainties of LCA. For example, Hoxha *et al*. [123] adapted the Taylor series expansion and ANOVA to depict uncertainties (represented by mean value and the variance) in impact coefficient, density, mass and service life of building materials (see Hoxha *et al*. [124] p. 56 and Scherre [125], p. 534 for equations of the two methods). One benefit of this mixed method lies in that the Taylor series method can only calculate the mean value and the variance of continuous variables while ANOVA complements this by serving the discrete variables (e.g., the number of uses of material). Targeting at the specific spatial dimension to reduce geographic uncertainty at every LCA stage, Patouillard *et al*. [126] developed an iterative decision-support diagram to guide the inventory regionalisation and inventory spatialisation process by considering existing approaches (e.g., GIS) in the literature. While this provides a portable tool for practitioners to minimise spatial uncertainty without having to develop new instruments, it is suggested that uncertainty contribution analysis (i.e., determine if the uncertainty comes from inventory data or spatial variability of characterisation factors) should be developed in the long-term. Standing at the early design stage when detailed information on the system under investigation is unavailable, Tecchio *et al*. [127] proposed the structured under-specification where a hierarchical data structure is established to classify building materials and assemblies with different levels of specificity. Harter *et al*. [23], on the other hand, shifted the specificity to different building development levels and used the variance-based method to quantity uncertain design parameters, such as geometry, technology, operational design and system efficiency. Primarily, they focused on decomposing the model output variance and calculating the first-order effect and total effect to indicate the importance and effects of a parameter on uncertainty. In this sense, it can be regarded as a form of sensitivity analysis.

There are some other advanced uncertainty calculation methods that can be considered in WBLCA. A germane example is the Polynomial Chaos (PC) expansion where Sepahvand *et al*. [128] demonstrated the use of orthogonal polynomials as the expansion base in various random variables to compute the parameter uncertainty. Compared with the sampling method (e.g., MCS), PC expansion represents the uncertain quantities as an expansion in a non-sampling and surrogate way, and proves to be more accurate and time efficient. In fact, it has been pioneered by Galimshina *et al*. [129] to understand the uncertainty value in LCA and life cycle cost of residential building renovation in Switzerland. In addition, Latin hypercube sampling and quasi-MCS, which employ the stratified sampling approach (i.e., the input parameters are more uniformly distributed) and quasi-random numbers, respectively, have been identified by Groen *et al*. [130] to be more accurate in calculating the sample mean than MCS in LCA. Bayesian approach is another parameter uncertainty quantification method applied in Liang *et al*. [131]. It features a posterior probability distribution of the parameter by combining prior information (i.e., existing knowledge) and the likelihood information (i.e., the proximity of simulated and observed data). While these methods may not be readily available in WBLCA, it explicitly implicates that WBLCA researchers and practitioners need to learn from other areas and adapt the methods to their own needs.

6 A Conceptual Framework

The WBLCA community is in urgent need of a clear understanding of uncertainties associated with WBLCA to underpin decisions for sustainable development [110,122]. However, despite the sporadic efforts as we have uncovered, a comprehensive taxonomy of WBLCA uncertain sources and corresponding solutions are far from being at the fingertips. Having in place a typology of uncertainties and promising solutions, therefore, is important as this proposed pathway (Figure 3): (1) configures life-cycle stages and function units to achieve true WBLCA; (2) considers an exhaustive list of uncertainties and categorises them based on different LCA stages; and (3) provides pinpoint solutions to treat each uncertainty. To better employ the framework, the practitioners first need to decide on whether a true WBLCA or a ‘fitness for purpose’ LCA (e.g., not all life-cycle stages and function units are assessed) is needed. With the determined goal in mind, they then need to understand the life-cycle stages, function unit and their corresponding uncertainty taxonomy and solutions as depicted in Figure 3. For example, if the ‘fitness for purpose’ scenario selects the ‘production to demolition’ stage for external walls, Figure 3 then makes it clear to the practitioners that there will be five categories of uncertainties along the assessment process that should be noticed and provides corresponding solutions to measure them.



*Note: the uncertainty is classified by the LCA stages. System boundary belongs to the goal and scope definition, 2 is in inventory analysis, 3 is in impact assessment, and 4 is in interpretation.

Figure 3. Conceptual framework for solutions to address WBLCA uncertainties

Current research tends to frame WBLCA into different stages, such as the construction stage [71] and the replacement stage [58], and specific parts and materials, such as walls [115], floors [108] and concrete and cement [101], rendering a somewhat 'quasi-WBLCA'. While it is difficult to obtain a complete LCI and best guess values have to be used, it is possible to create a 'true' WBLCA by integrating life-cycle stages and function units. For example, Hoxha *et al*. [123] calculated the EIs of a building by calculating the cumulative sum of materials' (or components') EI and energy's EI. Put simply, the WBLCA should consider every material and component and their associated impact over the life cycle. In a 'fitness for purpose' scenario, where true WBLCA is costly and time-consuming, the framework can be adapted to target components (e.g., materials and embodied energy) that may be of high impact. However, these components should be determined scientifically (e.g., a contribution analysis) as subjective choices can be counterintuitive [117]. To realise the true WBLCA or fitness-for-purpose, we underlie a feeding mechanism where information can flow and be recorded throughout the assessment of the present project and lessons can be transposed to future projects. Another element relies on the understanding of the uncertainties as part of the WBLAC process.

There are studies that have outlined the sources of uncertainties [71,76]. However, a degree of ambiguity resides with the taxonomy of uncertainties and the correlation between each uncertainty and each solution. Building on the LCA stages and the factors we identified from the review, the goal and scope definition stage can contain such uncertainties as system boundary and function unit and the inventory analysis stage can include parameter uncertainty. For the impact assessment stage, database and the LCIA methods are the main uncertain sources while human related factors (e.g., knowledge and experience) are evident at the interpretation stage. This classification allows LCA practitioners to be aware of the uncertainties and conveniently locate them throughout the assessment. More importantly, our framework suggests that the inventory stage and assessment stage are more uncertain than other stages with parameter uncertainty and database uncertainty being the prominent factors. To solve them, MCS, sensitivity analysis, DQIs and fuzzy related methods can be useful and MCS and sensitivity analysis are able to address a broader range of uncertainties. However, we argue these different solutions themselves can embed uncertainties (i.e., uncertainty methods). Similarly, Cellura *et al*. [106] contend that the EIs are different using different LCIA methodologies. This, again points out the importance of: (1) LCA practitioners' capability to select an appropriate LCIA method and uncertainty quantification method to minimise uncertainties; (2) using a mixture of uncertainty methods and developing new and effective tools; and (3) an accurate way of recording data in industry and academia as they are often the data source or benchmark of the LCA ('Three principles'). Hoxha *et al*. [123] and Feng *et al*. [14] have reported that environmental product declarations (EPD) is a good example of reliable material information as EPD records data directly from manufacturers and companies, and is developed strictly following ISO 21931 and EN 15643 at the building level. Equally, this conceptual framework demonstrates a pathway for a suitable uncertainty method to be chosen and new ones to be developed for LCA practitioners.

Nevertheless, we are cognisant of the harsh reality that sometimes research findings are not applied to practice and *vice versa* [132]. In our case, the solutions identified in Section 5 may not be easily implemented by 'new' researchers and practitioners in the LCA field. This could be because some studies (e.g., Morales *et al*., [58], Teh *et al*., [101], Su *et al*., [66]) only mentioned, for example, that MCS is employed to quantify uncertainties without detailing the procedure. To facilitate the convergence of knowledge (i.e., understanding WBLCA uncertainties) between two communities, we summarised in Table 5 some promising tools emerged from the review process to bridge this gap. Taking the SimaPro software as an example, Silvestre *et al*. [65] elaborate five steps (see Heijungs *et al*. [133]) to be taken when using MCS to incorporate the parameter uncertainty. With these tools, the problem becomes 'how to use them and how to interpret the results after clicking buttons'.

Table 5. Available tools to facilitate the application of uncertainty solutions/ methods

Tools	References
Microsoft Excel (generating a random sampling for input parameters)	Robati *et al*. [22]
SimaPro (different versions such as 8.4 and 8.0.2)	Burek and Nutter, [93], Cuenca-Moyano *et al*. [99], Almutairi *et al*. [95], Silvestre *et al*. [65], Minne and Crittenden [103], Piroozfar *et al*. [117], Mohajerani *et al*. [116], and Blengini and Carlo [89]

Open LCA software	Rezaei *et al*. [92] and Pons *et al*. [115]
Sobol's method	Favi *et al*. [100]
One Click LCA software	Petrovic *et al*. [134]
Discernibility analysis and independent sampling	Eckelman *et al*. 2018 [98]
@RISK package	Ross and Cheah [102], Aktas and Bilec [104], and Tushar *et al*. [135]
MATLAB R2015b (8.6.0) and Python 3.5	Pomponi *et al*. [94], Zhang and Wang [44], Zhang *et al*. [18], and Wang *et al*. [112]
Umberto 5.0	Benetto *et al*. [105]
Tally	Tushar *et al*. [135]
Hotspot analysis	Wang *et al*. [108]
Minimum-maximum sensitivity analysis, Morris screening, and Plackett and Burman design of experiment	Pannier *et al*. [109]
Sensitivity coefficient (the percentage change of emissions divided by the percentage change of each factor)	Lu *et al*. [107]
Crystal Ball software	Hong *et al*. [71]
Expert judgement	Hong *et al*. [71] and Piroozfar *et al*. [117]
Beta function	Wang and Shen [111]
Membership functions	Li *et al*. [118] and Kaziolas *et al*. [122]
F.A.L.C.A.D.E. software	Ardente *et al*. [121]
One at a time approach	Li *et al*. [118]
ImpactWorld+	Patouillard *et al*. [126]
MasterFormat structure	Tecchio *et al*. [127]

Note: Different from the uncertainty tools in Table 5, Al-Ghamdi and Bilec [56] provided a comparative review of existing WBLCA tools. Notably, some WBLCA tools (e.g., SimaPro and OpenLCA) are embbed with a function to perform an uncertainty analysis. A more recent review of the tools for visualising LCA results can be found in Hollberg *et al*. [136].

It has been noted by Blengini and Carlo [89] the existing tools have their respective characteristics that may (dis)encourage LCA researchers and practitioners from adopting them. For instance, generic tools (e.g., SimaPro) are considered to be flexible by modelling different kinds of systems and having access to powerful databases. They, however, may not be attractive to users who prefer less complex analysis and friendly operation interface as in some building-specific tools (e.g., ATHENA system). Similarly, Meex *et al*. [137] suggest that current LCA-based EI assessment tools have complex methodologies and cannot be easily adapted, which hamper their adoption in the early design stage by architects. Therefore, it is important for researchers and practitioners to learn and grasp skills (e.g., software operation) to undertake WBLCA. Alternatively, we concur with Güereca *et al*. [138] that proper guidance and training should be provided to ensure the quality of LCA. Akin to the feeding mechanism in Figure 3, the payoff for such investment will not be one-off as the knowledge can be passed down internally. Another benefit is that the increasing proficiency of LCA practitioners can counter the uncertainty caused by the users themselves as stated in Henriksson *et al*. [114]. In tandem, we need to reiterate that the solutions and relevant tools exist to help understand and reduce WBLCA uncertainties so that cautious decisions can be made. It would not be ideal to completely rely on the tools to extirpate the uncertainties as some of them cannot be reduced due to the natural randomness (see, Favi *et al*. [95]). In addition, the tools may embed shortcomings as Burek and Nutter [87] state that SimaPro 8.4 software cannot quantify the uncertainty of characterisation factors. This reinforces the awareness of the 'three principles' as we proposed above. What is more, the review results can shed light on further collaboration between policy-makers, researchers and practitioners into making sense of WBLCA uncertainties by demonstrating their sources, solutions, tools and pathways.

7 Conclusions

WBLCA results can be unreliable, and further undermine decisions made for sustainable building development due to the fragmented nature of the construction sector and the complexity of LCA. To address the paucity of research that investigates the comprehensive uncertain sources of WBLCA and their corresponding solutions, this study conducted a systematic review of WBLCA, its uncertainties and solutions and proposed a conceptual framework that depicts their typology for LCA practitioners. Our review on the *status quo* of WBLCA supports this research by suggesting that WBLCA is experiencing a bottleneck period due to the variety of LCA methods and the complexity of building structures, and thus more studies are needed to better understand its results. This study also indicates that while the importance of uncertainty is recognised, research does not follow the need for addressing or mitigating the uncertainty of WBLCA results.

Among the selected publications, we have identified that life-cycle stages, function unit, system boundary, input parameters, characterisation factors, databases, LCIA methods, practitioners' knowledge and experience, human activities and uncertainty methods can all be sources of the WBLCA uncertainties. Accordingly, there are a total of eight solutions and variants thereof that have been proposed with MCS and sensitivity analysis being the most common. Unlike previous examples, details on how they were employed to estimate uncertainties were analysed. Aiming to facilitate a true WBLCA and establish the correlation between uncertainties and their solutions, a conceptual framework juxtaposed with a feeding mechanism was developed. Its novel way of classifying a comprehensive list of uncertainties and solutions based on LCA stages allows LCA practitioners to be aware of the uncertainties and conveniently locate and appraise them throughout the WBLCA. Therefore, by answering the *known-what* (i.e., *status quo* of WBLCA and the uncertain factors) and *known-how* (i.e., uncertainty methods) questions, this paper sheds light on the WBLCA literature, in particular, provides a practical pathway for WBLCA practitioners to conduct uncertainty analysis.

There are limitations of this research, which could form the basis for future work. First, if a WBLCA is costly and time-consuming, a robust method should be developed to help select the components that may have high EIs rather than arbitrary judgement. Second, a case study can be conducted to demonstrate the application of the solutions identified in Section 5 (especially for the ones that have not been widely implemented in WBLCA), which adheres to the idea that guidance and trainings are important to demystify the 'black box'. Finally, the framework calls for an empirical comparison of the uncertainty methods *per se* and the development of new effective methods to evade the uncertainty resulted from the methods (i.e., solutions).

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