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Developing a tier-hybrid uncertainty analysis approach for lifecycle impact assessment of a typical high-rise residential building

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Abstract

Reducing embodied impacts of buildings has become urgent given its dramatically increasing contribution to the total lifecycle impact. The embodied impact is traditionally assessed through a deterministic lifecycle assessment (LCA) approach whose validity is impaired by existing uncertainties in the building lifecycle, so that uncertainty analyses are necessary to improve the validity of buildings LCAs. However, there are many limitations in current uncertainty studies such as biases in the use of a pure data quality indicator (DQI) approach, a lack of uncertainty analyses for lifecycle phases such as the end-of-life stage, and the incomprehensiveness in uncertainty parameters. To address these gaps, this study: (i) proposed a tier-hybrid uncertainty assessment approach to evaluate parameter uncertainties in the lifecycle of buildings; (ii) adopted proper assumptions to explore the impact of scenario and model uncertainties as well as investigate strategies to reduce the energy use and carbon emission. A case study is conducted to estimate uncertainties in building LCAs where end-of-life management strategies and alternative design materials are comprehensively explored to reduce energy and environmental impacts. It is revealed that the materials production stage causes the least uncertainties although it contributes the most impacts. Uncertainties in other lifecycle phases reduce in the order of transportation, maintenance to construction. Also, it is proved that the alternative design strategies and materials explored can effectively reduce the energy use and carbon emission by 19.91% and 15.23%, respectively. Therefore, the developed tier-hybrid approach can increase the comprehensiveness and reliability of building LCAs.

Keywords: Lifecycle assessment; uncertainty analysis; embodied energy; embodied carbon.

Nomenclature

Abbreviations

LCA	Lifecycle assessment
DQI	Data quality indicators
GFA	Gross floor area
BIM	Building information model

CED Cumulative energy demand

GWP Global warming potential

SD Standard deviation

CV Coefficient of variation

OPC Ordinary Portland Cement

GBFS Granulated Blast furnace Slag

PFA Pulverized Fly Ash

Symbols

EI_P Material production

EI_T Transportation

EI_C Onsite construction

EI_E End-of-life

Q_p Quantity of material

IC_p Impact coefficient of material production

wf Waste factor

Q_t Quantity of material or component to transported

$IC_{t,m}$ Impact coefficient for the transport mode

lf Load factor

Q_c Quantity of construction activity

T_t Time spent on construction activity

$IC_{c,e}$ Impact coefficient of the equipment

Q_d Quantity of building material or components (tonnes/GFA) to be demolished/sorted/recycled

σ_b^2 Basic uncertainties

$\sigma_{a,i}^2$ Additional uncertainties

σ_t^2 Total uncertainties

1. Introduction

Lifecycle assessment (LCA) has become a popular measure of sustainability in construction decision-making as it can be easily applied to evaluate the embodied impacts of buildings (Miatto et al., 2019; Pal et al., 2017). Since LCA is commonly performed to improve the energy use and carbon emission of buildings, it is vital to achieve an accurate decision-making process (Orsini and Marrone, 2019; Pomponi and Moncaster, 2016). However, there is a wide range of architypes such as residential, office, scientific, and educational buildings. Even within each architype, buildings might vary in design components, and therefore construction processes (Park et al., 2019). Furthermore, every component has different performance requirements and customizable materials (Meacham et al., 2005). Accordingly, the material production phase of a building is deemed a complex process. In the construction phase, each material transported to the site has different assumptions in transportation modes, loading factors, and energy requirements (Kamali et al., 2019). Also, onsite construction involves numerous construction processes and workflows with different equipment and amount of time based on the complexity of works to be accomplished (Chen et al., 2020). During the use phase, each material has varying technical performances, requiring different replacement schedules, based on their service life (Goulouti et al., 2020). At the end-of-life phase, different management strategies can be applied, assuming unique demolishing or deconstruction processes and recycling, landfill, or reuse (Fufa et al., 2018). These complexities in each lifecycle phase increase assumptions for processes in building LCA. Thus, there are many uncertainties in building LCA, posing great challenges to practitioners when conducting LCA without advanced tools. Improper quantification of uncertainties leads to propagation of large errors and unreliable building performances. Hence proper uncertainty quantification is critical for increasing the accuracy of building LCA in predicting the energy use and carbon emission of buildings.

Uncertainty analysis is an effective method that allows LCA practitioners to evaluate possible variations in LCA results using different parameters, scenarios, and models (Hong et al., 2016). In order to quantitatively evaluate variations in building LCA results, significant efforts are required to acquire a large and accurate material and construction process database in order to generate input probability distributions for uncertainty models. When lacking such data, alternative approaches such as data quality indicators (DQI) have been developed to describe probability distributions in a qualitative fashion (Weidema et al., 2013). However, human induced biases usually limit the validity of these approaches. Even though, DQI and other quantitative approaches have been integrated in building related uncertainty investigations, they were used for two different objectives: (i) DQI mostly for estimating the probability distribution of data descriptively and (ii) quantitative methods for stochastic modelling of LCA input data (Morales et al., 2020; Pomponi et al., 2017). A substantial amount of data is required to build the probability distribution underlying statistical modelling. This was previously impossible as a result of the inadequate data collected in the context of case studies. Moreover, this approach is time consuming and difficult to conduct as careful consideration is needed to collect data from similar cases within a common geographical and temporal context. Nonetheless, sufficient data accumulated through case studies open up opportunities to generate probability distributions for statistical modelling. To address this issue, this research proposes a novel tier-hybrid uncertainty analysis approach in which both quantitative and qualitative approaches are used to characterize probability distributions for stochastic modelling of LCA. This approach is distinguished from previous ones with an integration of quantitative and qualitative approaches to characterize uncertainties before applying stochastic modeling and thereby improve its reliability. On one hand, a significant amount of datapoints is retrieved from existing literature to quantitatively characterize the probability distribution for uncertainty parameters. On the other hand, DQI is applied to instances when it is practical to apply a qualitative approach. In addition, the impact of scenario and model uncertainties is investigated to reduce the energy use and carbon emission of buildings.

In summary, aims of this study include: (i) Apply a tier-hybrid approach to evaluate parameter uncertainties in building construction; (ii) Adopt assumptions to assess the influence of scenario and model uncertainties and investigate strategies to reduce the energy use and carbon emissions. The central hypothesis of this research is that pure statistical data from previous studies reflect the uncertainties in LCA results and statistical analysis can more accurately characterize and propagate the uncertainties in LCA results by retrieving these data. The research hypothesis presumes that a tier-hybrid uncertainty approach could increase the accuracy and efficiency of building LCAs through (i) qualitative and quantitative characterization of uncertainty parameters and (ii) uncertainty propagation with pure statistical methods. The remainder of this paper is presented as follows. Section 2 presents a comprehensive review of (i) uncertainties in building LCA; and (ii) strategies to reduce the embodied impact of buildings. Section 3 describes (i) the methodology used to perform deterministic and stochastic LCA; and (ii) assumptions to evaluate scenario and model uncertainties. Section 4 and 5 present a comparison of the base case and alternative cases with defined scenarios, while conclusions, limitations and recommendations for future studies are presented in Section 6.

2. Literature review

2.1. Uncertainties the lifecycle of buildings

Building LCA estimates the embodied impacts associated with various lifecycle phases of buildings: material production, construction, building operation and end-of-life phases (International Organization for Standardization, 2006a). Many studies have focused on the identification of major sources of embodied impacts, development of new materials, and minimization of building impacts whereas few studies address the uncertainties in the building LCA process (Hoxha et al., 2017). Recently, some studies have begun to address the reliability and uncertainties of building LCAs from the perspective of the whole building lifecycle, individual components/materials or a particular lifecycle phase.

2.1.1. Uncertainties in the material production phase

Many studies have either investigated the material production phase or the entire building life cycle phase but with a focus on the former due to its high contribution to the embodied impacts of buildings (Ansah et al., 2020). Building LCA studies focusing on the material production have addressed major uncertainty sources including material quantities, embodied coefficients, materials waste rates, technical densities and system boundaries (Robati et al., 2019; Su and Zhang, 2016; Teng and Pan, 2020; X. Zhang et al., 2019; Zhang and Wang, 2017; Zhang and Zheng, 2020). These studies indicate that despite the higher contribution of the material production to the total embodied impacts in buildings, uncertainties are lower compared to other life cycle stages due to the availability of LCA data. In the context of transportation, assumptions about the sources of materials or components as well as transportation modes when such data is lacking may lead to large uncertainties in the transportation stage of building lifecycle analysis (Zhang and Wang, 2017). The overall accuracy of the environmental impact of the transportation phase is contingent on the accuracy of input data which is hard to achieve due to massive components and materials used in each building (Opher et al., 2021). Given the simplifications applied to the transportation phase, a rigorous uncertainty analysis should be applied to improve the accuracy of LCA results.

2.1.2. Uncertainties in the maintenance phase

Addressing maintenance issues has become urgent due to the increasing demand of meeting building performance requirements, new maintenance techniques and complex maintenance cultures of building operators (Kwon et al., 2020). However, studies have indicated that there are high uncertainties associated with the maintenance phase in building LCA due to the complexities in evaluating the service life of building components (Morales et al., 2020). Recent studies have shown that many factors can influence the service life building components such as the material and quality of workmanship, maintenance level, internal and external climate of the building, building design, technological change, availability of replacement components, legal requirements, residual value of building and energy efficient renovations (Grant and Ries, 2013). Given the need to reduce such uncertainties, some studies have tried to improve the accuracy of service life modelling. For instance, Ferreira et al. (2021) developed a method to quantify the impact of maintenance actions on the components of building envelopes. A probabilistic approach through stochastic maintenance modelling reveals that a combination of maintenance activities such as cleaning and minor interventions with total replacement ensures the high performance of a building component through its service life. Marques et al. (2018) applied a factor method to predict the service life of ETICS through the visual inspection of case buildings and modelling of the characteristics and degradation of patterns. Shohet and Nobili (2016) developed a framework for a performance-based maintenance of public facilities which showed consistent improvement in the performance of facilities during implementation. Mousavi et al. (2017) developed a model for predicting the service life of natural stone cladding with direct fastening systems to aid the definition of maintenance strategies and rational management systems for heritage buildings. Another study presents a fuzzy inference system based on the expert knowledge for the prognosis of the functional service life of buildings (Prieto et al., 2017). Among these studies for maintenance uncertainties, two distinct themes are addressed: (i) approaches to predicting the service life of materials; and (ii) maintenance strategies. Three main approaches are identified in predicting the service life of building components: (i) accelerated life test in laboratories; (ii) factorial methods; and (iii) the reference service life based on the documented service life. Also, two maintenance approaches are identified: (i) planned and unplanned maintenance. Planned maintenance can be further categorized into preventive, corrective and improvement types. In order to achieve a realistic maintenance modelling, data accumulated from historical cases are required. In the absence of such information, most researchers apply the reference service life approach. Although the application of service life databases for building components is proven reliable, some of these databases may be outdated or based on different calculation methods. To overcome these challenges, the variations in the service life of building components and materials should be included as uncertainty parameters.

2.1.3. Uncertainties in the construction phase

The construction phase usually receives less attention due to its low contribution to the total embodied impacts (Dixit, 2017). Researchers often apply simplified approaches when quantifying the impacts of the construction phase (Zhang et al., 2019). One example of such simplification is the use of construction data from previous building projects which induce large uncertainties given the lack of standardization in construction processes. Hence, interest in uncertainty characterization of construction phases has been growing because unrepresentative data is often applied to its impact assessment.

2.1.4. Uncertainties in the end-of-life phase

The end-of-life phase is frequently overlooked when modelling building LCAs since it contribute least to the total embodied impacts. However, the large amount of demolition and recyclable materials from high-rise buildings provide numerous opportunities to improve the environmental performance of buildings. The uncertainties induced in the end-of-life stages often come from assumptions in end-of-life modelling such as recycling, and demolition strategies. Chau et al. (2017) and Hossain and Ng (2020) defined scenarios to evaluate the impact of end-of-life stages but failed to address intrinsic uncertainties of parameters and assumptions in modelling the end-of-life stages. Given the lack of reliable input data, rigorous statistical approaches are required for quantifying these uncertainties and increasing the reliability of LCA results.

Generally researchers have identified uncertainty sources including variability of data and characterization models (spatial and temporal), imperfect measurements, incompleteness of data, unrepresentativeness of inventory data, normative choices, selected scenarios, technical performance, functional units, estimation of uncertainties and mathematical relationships (Björklund, 2002; Igos et al., 2019; Lloyd and Ries, 2007; Mendoza Beltran et al., 2018). In summary, uncertainty sources can be classified into parameter, scenario and model uncertainties among which parameter uncertainty is the most commonly addressed.

2.2. Evaluating uncertainties in building LCA

To evaluate uncertainties in LCA, it is important to identify the methods to characterize uncertainties. Uncertainties can be generally characterized statistically using probability distributions although qualitative descriptions may be applied when historic data are insufficient. Hence, both quantitative and qualitative methods have been explored in previous studies. Clavreul et al. (2012) identified the fuzzy theory, Tylor series expansion, DQI, stochastic modelling, possibility theory, expect judgement and hybrid of two or more methods in their study. Although the performance of each method can vary depending on the nature of uncertainties, the positive review of DQI and stochastic modelling has identified its wide application in building LCA (therefore incorporated in this research). In the DQI method, a pedigree matrix is applied to model the underlying uncertainties in a semi-qualitative fashion, and then propagated quantitatively through stochastic modelling such as the Monte Carlo simulation (Jim and Guill, 2017). The advantages of this approach include easy implementation, little computational resource requirements and applicability to a wide range of problems. However, the solution may be low quality due to human biases in the DQI method.

There has been ample research integrating DQI and stochastic methods. For instance, Teng and Pan (2020) applied a semi-quantitative method which combined the DQI and stochastic simulation to propagate uncertainties in the LCA of a prefabricated high-rise building. Morales et al. (2020) investigated uncertainties in the maintenance phase of a building using several scenarios of repairs or replacements. Similarly, DQI is applied to describe input data uncertainties while Monte Carlo simulation is used to calculate the model output uncertainties. Di Giuseppe et al. (2020) analyzed the implication of data availability and quality on LCA of five insulation systems for historic buildings in Italy. Su et al. (2016) performed a probabilistic LCA of eight insulation materials to evaluate the uncertainties induced by variability of data such as in the density using the data quality analysis and Monte Carlo simulation. The study also implemented a sensitivity analysis which reveals that the variability and uncertainty of parameters can significantly affect LCA results. Robati et al. (2019) collected data to determine the probability distribution of the lifespan, embodied emission and transport distances of 16 materials. A Monte Carlo simulation is then applied to perform a global sensitivity analysis which reveals uncertainties in the studied materials. Heijungs and Lenzen (2014) compared two uncertainty propagation methods: sampling and analytical methods. Although the sampling method requires more input data such as the probability distribution and parameters, a detail output can be generated and subject to rigorous statistical analyses. On the contrary the analytical method only requires variances but yields very limited results. Nonetheless, the sampling method requires a huge computational time due to the generation of a huge number of random variables.

In general, most researchers have adopted semi-quantitative methods in which qualitative techniques are applied for uncertainty characterization while quantitative techniques are used for stochastic modelling of uncertainties. This is a progressing research domain due to the large number of parameters, scenarios and models available. Also, very few studies have considered using quantitative techniques alone or jointly with qualitative techniques to characterize uncertainties prior to stochastic modelling. With the significant increase in LCA data from case studies, it has become possible to adopt rigorous statistical techniques to provide highly accurate results.

2.3. Reducing embodied energy in building

Researchers have investigated the field of embodied impacts of buildings to identify strategies to reduce the energy use and carbon emissions. Orsini and Marrone (2019) reviewed literature and summarized the pros and cons of low carbon building strategies such as reusable materials, alternative materials, local materials, renewable energy sources, increased performances, correct applications and innovation of production processes. In this regard, some studies have explored these strategies to reduce the energy use and carbon performance of buildings. For instance, Teng and Pan (2019) and Teng and Pan (2020) conducted case studies to explore measures for reducing embodied carbon such as adopting low carbon concrete, optimizing the prefabrication rate, and changing the thickness of walls. The results underscores that replacing ordinary Portland cement with blast furnace slag cement yields the highest carbon savings. Hossain and Ng (2020) compared deviations between building construction emissions using a localized and generic database. Two emission reduction measures namely alternative concrete materials and end-of-life processes are explored and proven to effectively reduce carbon emissions. Gan et al. (2017) presented a method to explore the carbon reduction potential of procurement strategies including the steel manufacturing process, recycling scrap, alternative cement materials and transportation distances. The results underscore the use of fly ash or slag for cement in ready-mix concrete, and also the production of steel with high amounts of recycled scrap in an electric arc furnace.

Xiao et al. (2018) evaluated the potential embodied impact reduction by replacing natural aggregate concrete with recycled aggregate concrete in case study approach showing significant reductions in both the energy use and carbon emission. AzariJafari et al. (2019) investigated the potential environmental impacts of alternative concrete mixtures when exposed to high temperatures, where a reduction in environmental impacts was achieved by using pozzolanic materials. Kurda et al. (2019) presented an approach to optimize concrete mixes containing various recycled concrete aggregates and fly ash for different building architypes. Mavrokapnidis et al. (2019) assessed the impacts of structural systems on the environmental performance of tall buildings and proposed the use of recycled materials as a potential approach to improve building sustainability. Other studies have also utilized waste materials to reduce the energy and carbon emission of cement and concrete significantly (Hossain et al., 2017a, 2016; Kleijer et al., 2017). Hossain et al. (2017b) identified that an on-site sorting system could reduce energy use and carbon emissions significantly due to the higher recyclability of materials, with a comparison between onsite and offsite waste sorting strategies. Previous studies primarily focus on alternative materials for cement production. The achievable amount of carbon emission reduction is still limited to the practicality of strategies and availability of these alternative materials. For instance, the use of alternative materials may reduce energy and environmental impacts during material production, but their transportation over long distances may decrease the overall net benefit. Hence, exploring the impact of transportation is strongly recommended.

Practically, this study expands the above research domain by developing a novel tier-hybrid approach to quantify building LCA uncertainties. This approach integrates both quantitative and qualitative uncertainty methods to characterize parameter uncertainties for a Monte Carlo simulation. Moreover, the study contributes to knowledge by exploring scenarios, alternative design strategies and materials, as well as end-of-life management strategies to examine the impacts of scenario and model uncertainties and effective strategies of energy and carbon reduction for buildings. In addition, the study applies alternative probability distributions to evaluate the impact of analytical model uncertainties.

3. Methodology

The methodology presented in this study is a three-stage approach: (i) a method to perform deterministic assessment of the lifecycle energy and carbon performance of a building in order to identify the most energy and carbon intensive activities, (ii) a tier-hybrid approach to stochastically evaluate and quantify parameter uncertainties in the lifecycle assessment of buildings (iii) scenarios to evaluate model and scenario uncertainties in the lifecycle of buildings. In building LCA, the scope is commonly defined to cover the processes of material production, building construction, building operation (including maintenance and occupational uses) and end-of-life cycle phases. This study focuses on embodied impacts and excludes those from the operation phase such as lighting and air-conditioning, which have been widely addressed in existing literature. Embodied impacts are expressed as the Cumulative Energy Demand (CED) and Global Warming Potential (GWP) in this study. Figs. 1 and 2 illustrate the research framework and flow chart of the research methodology, respectively.

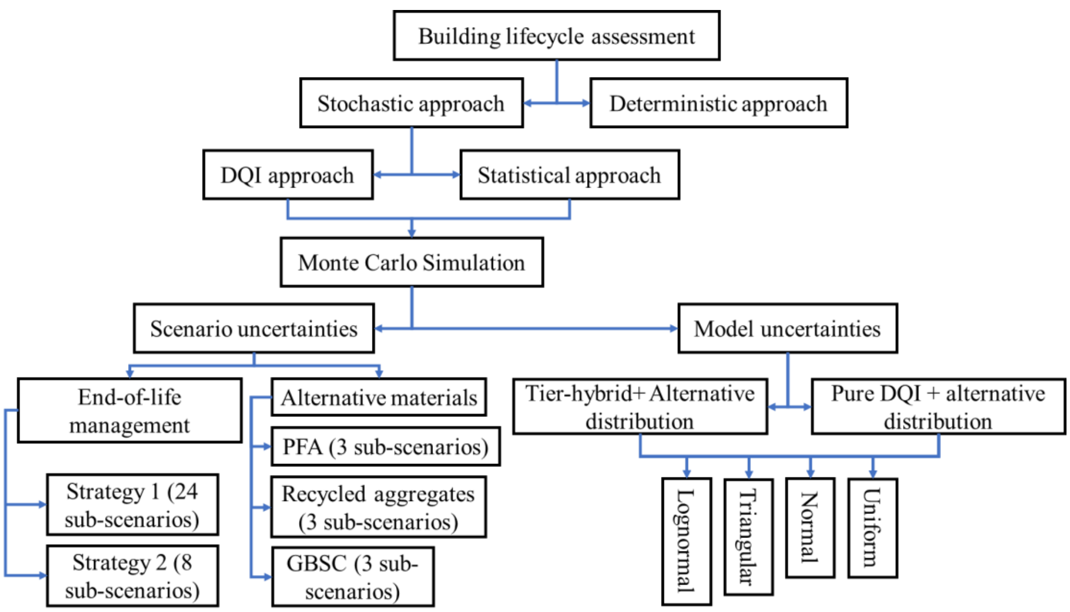


Fig. 1. Methodological framework.

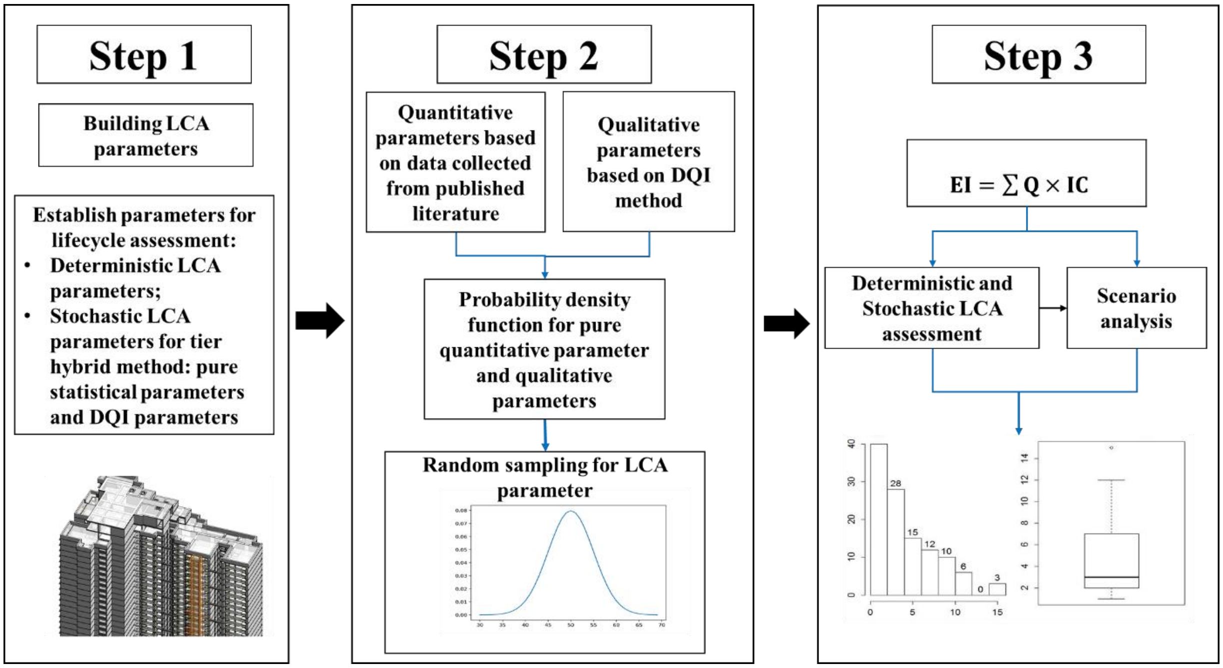


Fig. 2. Flow chart of the research methodology

3.1. Deterministic lifecycle assessment

The deterministic lifecycle assessment model is grounded on a process-based method defined by ISO 14040 and 14044 standards (International Organization for Standardization, 2006a, 2006b). It is founded on the premise that lifecycle impacts are equal to the product of the quantity/amount of an activity and its appropriate impact coefficient. Thus, two main types of data are required for each lifecycle phase: the quantity of materials/processes and an impact coefficient. For the material production phase, the quantity of building materials and components are retrieved from a building information model (BIM) of a case building which provided the types and strength grades of materials used. Supplementary information such as material's density and waste rates required to transform primary quantities to workable figures is sourced from literature and webpages of manufacturers. On the other hand, the impact coefficients for materials are obtained from the Ecoinvent database (Frischknecht et al., 2005). For the transportation phase, the quantity of activities denotes haulage of materials or components expressed in terms of weights and distances. At the construction stage, the quantity of activities is expressed as the electricity and fuel use for onsite construction equipment, temporary lighting, and office works. The energy use for onsite construction is estimated with reference to (Department Electrical and Mechanical

Service, 2006; X. Zhang et al., 2019) due to the unavailability of actual measured data. Relevant energy and carbon coefficients for electricity and fuel uses are acquired from literature. The end-of-life phase processes include demolishing, waste sorting, transportation and recycling. Impacts from demolishing are estimated as a product of the gross floor area (GFA) and the impact coefficient per square meter, while quantities of materials are used for waste sorting, transportation and recycling. The impact coefficients for demolishing and sorting are sourced from literature while those for recycling are obtained from the Ecoinvent database. Table 1 summarizes the calculation model and description for each lifecycle phase.

Table 1 Calculation model of lifecycle phases.

Life cycle phase	**Calculation**	**Description**
Material production (EI_P)	$EI_P = \sum_n Q_p \times IC_p \times wf$	where Q_p is the quantity of material *n*; IC_p is the impact coefficient of production *n*; *wf* is the waste factor
Transportation (EI_T)	$EI_T = \sum_m \sum_n Q_t \times IC_{t,m} \times lf \times wf$	Q_t is the quantity of material or component *n* (ton.kilometer) to be transported by the method *m*; $IC_{t,m}$ is the impact coefficient for the transport mode *m; lf* is the load factor
Onsite construction (EI_C)	$EI_C = \sum_k \sum_w Q_c \times T_t \times IC_{c,e}$	Q_c is the quantity of construction activity *w* which uses the equipment type k; T_t is time spent on activity; $IC_{c,e}$ is the impact coefficient of the equipment type *k*
End-of-life (EI_E)	$EI_E = \sum_e Q_d \times IC_{c,e}$	Q_d is the quantity of building material or components (tonnes/GFA) to be demolished, sorted and recycled or disposed which requires the energy type e; $ICc_{,e}$ is the impact coefficient of the energy type *e*

3.2. Tier-hybrid stochastic analysis

Uncertainties occur due to the lack of knowledge on the true value of a parameter. Normally, statistical approaches are used to determine a likely value when there is a sufficient amount of data points/observations. However, the nature of building LCA decreases the feasibility of collecting a large number of observations. To address this limitation, Weidema et al. (2013) proposed a DQI-based method which applies expert judgement to appraise the probable distribution of uncertainty parameters. However, subjective evaluation can reduce the validity of a pure DQI-based assessment. This study therefore proposes a tier-hybrid approach to improve the comprehensiveness and reliability of evaluating uncertainties in building LCA. The proposed approach follows a two-stage process: uncertainty characterization and uncertainty propagation.

3.2.1. Uncertainty characterization

Uncertainty characterization is implemented to determine the probability distribution of uncertainties in a parameter. The tier-hybrid approach used in this study is based on the integration of: (i) a pure statistical method and (ii) a DQI method prior to uncertainty propagation. Table 2 illustrates the sources of parameter uncertainties and the characterization approach used in this study. The pure statistical approach is applied when a sufficient number of datapoints could be retrieved to determine the probability distribution of the parameter. In the case where sufficient amount of data could not be collected, the DQI approach is implemented. For the statistical approach, data such as material densities and waste rates are retrieved from literature, websites and reports of manufacturers. Statistical methods are then applied to determine parameters such as the mean and standard deviation (SD) which are applied to characterize uncertainties of the retrieved data. The results of uncertainty characterization for pure statistics parameters are summarized in Appendix B.

The DQI approach used in this study is based on the method of Ecoinvent which categorize parameter uncertainties into basic and additional uncertainties expressed in terms of variance (Weidema et al., 2013). Basic uncertainties reflect the lack of knowledge on the exact value of a parameter (i.e. inconsistency in measurements) and additional uncertainties express imperfections in data (e.g. geographical and temporal variations). The total uncertainty is derived as a sum of basic and additional uncertainties. Ecoinvent provides a default variance (σ_b^2) for basic uncertainties based on expert judgement. Contrarily, additional uncertainties ($\sigma_{a,i}^2$) is estimated using a semi-qualitative approach incorporating a pedigree matrix with representative variances. As shown in Table 3, this pedigree matrix includes five data quality indicators. For each indicator, a score between 1 (highest quality data) and 5 (lowest quality data) is assigned. After determining the scores of an uncertainty parameter, representative variances with lognormal distributions are defined using Table 4. The results of DQI analysis are presented in Appendix A.

The total variance for the parameter is then estimated using Eq. (1):

$$\sigma_t^2 = \sigma_b^2 + \sum_{i=1}^{5} \sigma_{a,i}^2 \quad (1)$$

To extend the transformational relationship to other probabilistic distributions, the variance is converted to coefficient of variation (CV) using Eq. (2):

$$CV = \sqrt{\exp(\sigma^2) - 1} \quad (2)$$

Table 2 Uncertainty parameters and assessment methods.

Parameter	**Classification of uncertainty**	**Assessment method**
Material quantities	Parameter uncertainty	DQI and Monte Carlo simulation
Material densities	Parameter uncertainty	Statistical and Monte Carlo simulation
Onsite construction processes	Parameter uncertainty	DQI and Monte Carlo simulation
Building maintenance schedule	Parameter uncertainty	DQI and Monte Carlo simulation
Material waste rate	Parameter uncertainty	Statistical and Monte Carlo simulation
Transportation distances	Parameter uncertainty	Statistical and Monte Carlo simulation
Energy and emission factors	Parameter uncertainty	DQI and Monte Carlo simulation
Uncertainty model	Model uncertainty	Statistical and Monte Carlo simulation

Table 3 Data quality pedigree matrix.

Score	**Data quality indicators**				
	Reliability	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Further technological correlation**
1	Verified data based on measurements	Representative data from relevant parties over an adequate period	< 3 years	Field data	Data from enterprises, processes and materials under study

Score	Data quality indicators				
	Reliability	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Further technological correlation**
2	Verified data partly based on assumptions	Representative data from >50% of relevant parties over an adequate period	< 6 years	Data from similar area	Data from processes and materials under study
3	Unverified data partly based on qualified estimates	Representative data from <50% of relevant parties or >50% but from shorter periods	< 10 years	Regional data	Data from processes and materials under study but from different technology
4	Qualified estimate	Representative data from only one site relevant party	< 15 years	National data	Data on related processes or materials
5	Unqualified estimate	Unknown representativeness	≥ 15 years	Data from unknown ***or*** distinctly different area	Data on related processes or materials but different technology

Table 4 Variance of additional uncertainties.

Data quality indicator	Score				
	1	**2**	**3**	**4**	**5**
Reliability	0.000	0.0006	0.002	0.008	0.04
Completeness	0.000	0.0001	0.0006	0.002	0.008
Temporal correlation	0.000	0.0002	0.002	0.008	0.04
Geographical correlation	0.000	2.5×10^{-5}	0.0001	0.0006	0.002
Further technological correlation	0.000	0.0006	0.008	0.04	0.12

3.2.2. Uncertainty propagation

Uncertainty propagation involves propagating input uncertainties to calculate the overall uncertainty in the LCA result. Uncertainty propagation can be performed with an analytical method or a sampling method. The former produces limited results and is thus impractical for this study. On the contrary, the latter is more common and requires lesser computational resources.

Accordingly, the Monte Carlo simulation, a sampling method, is chosen to generate sample data from non-linear input uncertainties based on the pure statistical and DQI-based uncertainty characterization described in Section 3.2.1.

The Monte Carlo simulation is performed based on the algorithm developed by Pomponi et al., 2017). Equations 3 to 5 show the parameters and variables used to perform the Monte Carlo simulation in this study. Equation 3 is a vector *V* which represents the parameters for the evaluation of each lifecycle phase:

$$V = \{T_1 \dots T_h \dots T_i\} \tag{3}$$

where *i* represents the total number of processes *T* for a given lifecycle phase; *h* represents a vector *F* with a complete dataset for the stochastic evaluation of the embodied energy e in the process *T*.

For each process *T*, random variables can be chosen from the vector *F* for the Monte Carlo simulation in accordance with a given probability distribution. Vector *F* is given by Eq. (4):

$$F_h = \{f_{h,1} \dots T_{h,l} \dots T_{h,i}\} \tag{4}$$

The vector *F* represents two inputs as the outcome of the uncertainty characterization for the (i) pure statistical approach and (ii) DQI approach.

The two-input data are illustrated by the vector Q which contains a pair of inputs V_h and U_h as shown in Eq. (5):

$$Q = \{(V_1, U_1) \dots (V_h U_h) \dots (V_i, U_i)\} \tag{5}$$

In the case of pure statistical parameters, V_h, and U_h represent the mean and standard deviation of a normal distribution, whereas they represent the activity quantity and covariance for a lognormal distribution in a DQI-based case.

Different sets of Monte Carlo simulations are performed for different lifecycle stages and scenario analyses. For each simulation, 10,000 samples are generated. Each output generated represents the energy use or carbon emission associated with a lifecycle phase or scenario evaluated with randomly selected input variables.

3.3. Scenario analysis and Model analysis

Reasonable scenarios and models are utilized to individually appraise decision variables for clearly depicting changes in possible outcomes, while parameter uncertainties are evaluated simultaneously through Monte Carlo simulations. Four scenarios with seven sub-scenarios are defined to explore end-of-life strategies, alternative materials and analytical model assumptions as summarized in Table 5.

End-of-life scenarios explore the impact of end-of-life management strategies on the overall lifecycle impacts of buildings. Different combinations of demolishing practices, offsite/onsite waste sorting, recycling and landfilling can significantly vary the contribution of the end-of-life phase to the overall lifecycle impacts. Two strategies are therefore defined: EoL1 and EoL2. EoL1 considers an all-inclusive offsite sorting for demolishing wastes. After sorting, cementitious wastes and non-inert wastes (e.g. wood and paper waste) are disposed at public filling areas and landfills respectively, while steel scrap is recycled. Totally, 24 sub-scenarios are designed using alternative sorting, landfill and public filling areas to explore the impact of transportation. EoL2 considers a selective demolishing strategy in which wood wastes and aluminum in windows are sorted onsite. The remaining demolishing wastes are sorted offsite. This scenario also considers an extensive recycling approach in which timber and all metals including reinforcement steel, iron and aluminum are recycled. A recovery rate of 90% is applied to recycling materials. Cementitious wastes are however disposed at public filling areas. Totally, 8 sub-scenarios are designed to explore the impacts of transportation.

The use of alternative materials is considered an effective approach to reduce the embodied impacts of buildings as material production, especially concrete, contributes significantly to the lifecycle impact of buildings. Three scenarios are designed to replace virgin aggregates with recycled aggregates and Ordinary Portland Cement (OPC) with Granulated Blast furnace Slag (GBFS) or Pulverized Fly Ash (PFA). S1 explores the impacts of using recycled aggregates in both in-situ and precast concrete. Two sub-scenarios are also defined: sub-scenario 1 assumes that aggregates are recycled at a site with an equal transportation distance to the source of virgin materials whereas sub-scenario 2 assumes a recycling site 15 km away from the production site of concrete. Replacement rates of 50%, 70% and 100% are also explored for S1. S2 and S3 explores impact reduction from the use of GBFS and PFA respectively. Similarly, replacement rates of 50%, 70% and 80% are explored for both GBFS and PFA.

Assumptions about the analytical model is a crucial factor which may significantly change the results. Scenarios M1 and M2 are defined to explore model uncertainties. M1 investigates the impact of the probability distribution assumption on the proposed tier-hybrid method. In the base case (B2), a lognormal distribution is applied to the DQI components. Because other distributions such as normal, triangular and uniform could vary the results significantly, M1 explores the impacts of these distributions within the context of the tier-hybrid approach. M2 however is designed to compare the results of a pure DQI approach to the proposed tier-hybrid approach. To increase the comprehensiveness of assessments, all four probability distributions are considered in the pure DQI approach as well.

3.4. Case building

A typical public rental housing block in Hong Kong is selected as a case study, because such buildings accommodate over 40% of the local population (Hong Kong Housing Authority, 2019). Moreover, similar blocks are expected to be constructed to solve the increasing affordable housing challenge. The building is characterized by a reinforced concrete structure with prefabricated components. The gross floor area and total height are 12488 m^2 and 107 m, respectively. There are 36 habitable floors with 10 standardized flats on each. The ground floor and roof house electro-mechanical equipment. The design information and material specifications are acquired from a BIM model of the building as illustrated in Fig. 3.

Table 5 Summary of scenarios analysis.

Goal	Sub-type	Scenario code	Description
Basic case	Deterministic case	B1	Complete LCA based on primary data collected
	Stochastic case	B2	Complete LCA based on tier-hybrid method
Scenario analysis	End of life Scenario	EoL1	Off-site sorting; non-inert waste disposed at landfills; concrete disposed at public filling areas; scrap recycled *(generating 24 sub-scenarios)*
		EoL2	Onsite (waste wood) and offsite waste sorting (concrete and steel, waterproofing, etc.); maximum materials recycling *(generating 8 sub-scenarios)*
	Alternative materials	SC1	Use recycled aggregates (generating 6 sub-scenarios)

		SC2	Replace ordinary Portland cement with blast furnace slag cement *(generating 3 sub-scenarios)*
		SC3	Replace ordinary Portland cement with pulverized fly ash *(generating 3 sub-scenarios)*
Model uncertainties	Distribution selection	M1	Normal, triangular and uniform distribution applied to B2
	Pure DQI + distribution selection	M2	DQI only approach with Normal, lognormal, triangular and uniform distribution applied to B2

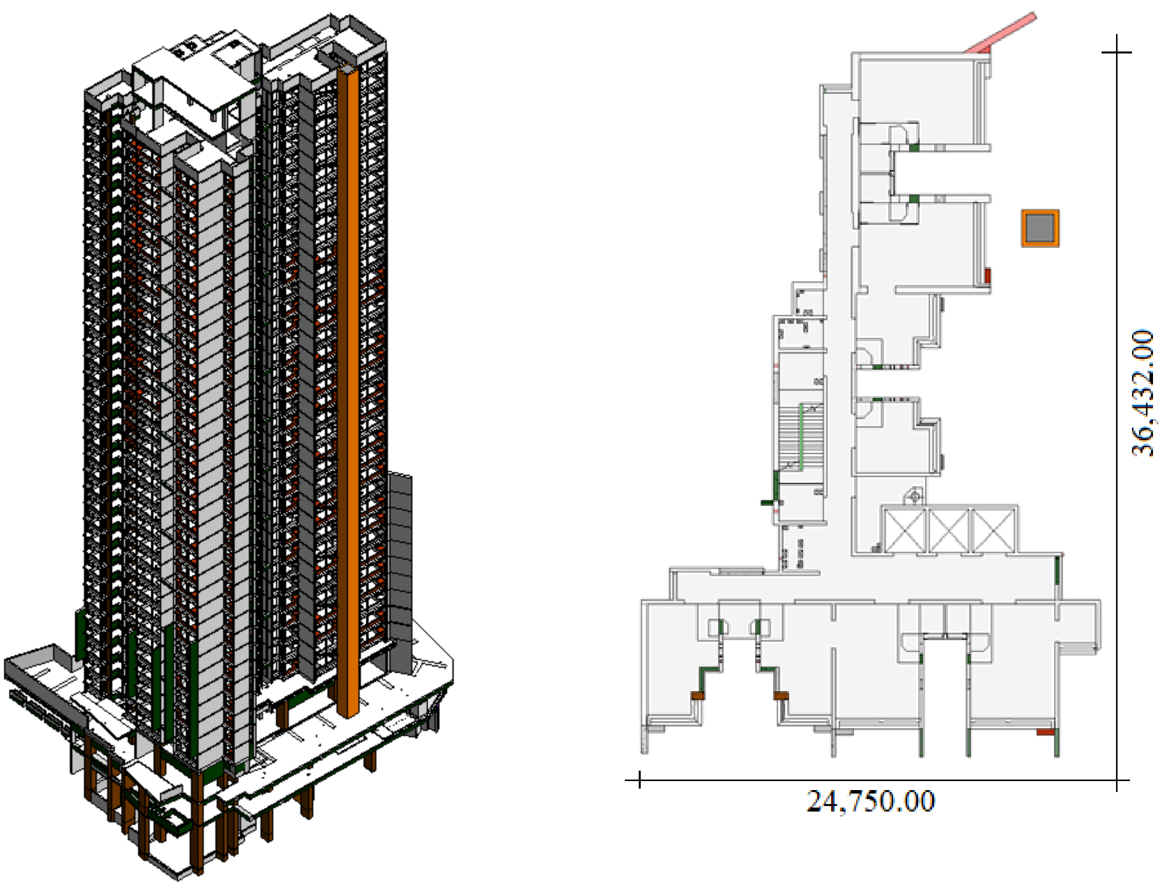


Fig. 3. BIM model and a typical floor plan of case building

4. Results and analysis

4.1. Assessment of embodied impacts

Deterministic and stochastic analyses are performed for each building material or process which is summed up for comparison in Tables 6 and 7. The mean overall lifecycle impacts (B2) are estimated as 6.86 GJ/m^2 and 638.28 kgCO_2/m^2, which are consistent with the deterministic results (B1). The minimum and maximum lifecycle impacts are 67.69% and 137.42% of the mean CED while 68.79% and 134.83% of the mean GWP. SDs of the overall CED and GWP are determined to be 0.76 GJ/m^2 and 71.75 kgCO_2/m^2 with corresponding CVs of about 11.79%.

Table 6 Comparison of the stochastic and deterministic cumulative energy demands.

Lifecycle phase	**Cumulative energy demand (GJ/m^2)**			
	Deterministic (B1)	**Stochastic (B2)**		
		Mean	**Minimum**	**Maximum**
Material production	4.99	4.99	3.62	6.67
Building maintenance	1.34	1.34	0.79	1.95
Transportation	0.30	0.29	0.09	0.80
Construction	0.23	0.23	0.15	0.23
Total lifecycle impacts	6.86	6.86	4.65	9.43

Table 7 Comparison of the stochastic and deterministic global warming potential.

Life Cycle Phase	**Global Warming Potential (kgCO2-eq./m^2)**			
	Deterministic	**Stochastic**		
		Mean	**Minimum**	**Maximum**
Material Production	494.91	495.78	357.84	647.16
Building Maintenance	87.56	87.52	53.12	124.57
Transportation	22.09	22.16	6.83	44.51
Construction	32.99	32.82	21.27	44.36
Total life cycle phase	637.56	638.28	439.05	860.60

Contribution analyses in terms of CED and GWP are presented in Figs. 4 and 5, respectively. It is observed that over 54% of CED and 66% of GWP are generated from the use of concrete and steel. Other materials also contributed significantly higher to both CED and GWP than reported in previous literature (Gan et al., 2017; Hossain and Ng, 2020; Teng and Pan, 2019). Particularly, windows, doors, composite mortar and ceramic tiles together contribute over 19% of both GWP and CED because of their high impact coefficient despite the low usage rate. From the perspective of uncertainties in material production, CV of each material ranges from 8.9 to 15.95 indicating a low dispersion around the mean. Materials yielding the highest uncertainties include windows, doors, aluminum, paint and formwork.

Fig. 6 illustrates a contribution analysis of the maintenance stage. It is assumed that public rental residential buildings have very limited opportunities of major renovations, so that building occupants have less influences over building maintenance. All maintenance activities throughout the lifecycle of the building is only to keep the required basic performance. Due to the complexities in modelling the actual degradation of components in high-rise buildings (e.g. challenges in visual inspection and lack of maintenance data), this study employs fixed cycles of replacement as applied in previous studies. The variations in the service life of building components and materials are counted as uncertainties in this lifecycle phase. From Fig. 6, it is observed that the majority of the impacts is from windows, doors and paint contributing 87.75% of CED and 82.28% of GWP. Composite mortar, glass, aluminum, PVC membrane and gypsum plaster correspondingly constituted 12.25% of CED and 17.69% of GWP. Although the latter contributed less, larger uncertainties are observed due to great variation in their maintenance schedules. The overall CV for the maintenance phase is found to be 24.59%. Given the contribution of these materials to both material production and maintenance, the comprehensiveness of system boundaries is critical for LCA results and therefore requires necessary adjustments especially when only primary materials are considered.

CVs of the transportation and construction phases are comparatively higher although their contributions to the total lifecycle impact are very low. Specifically, the overall CV of transportation is 29.73% due to the wide variation in the transportation distance of materials other than precast and insitu concrete. Similarly, the CV of construction phase is 19.47% owing to the assumption that construction process details are estimated based on previous literature. Nonetheless, the findings are coherent with Teng and Pan (2020) which recorded much higher uncertainties in the transportation and construction phases.

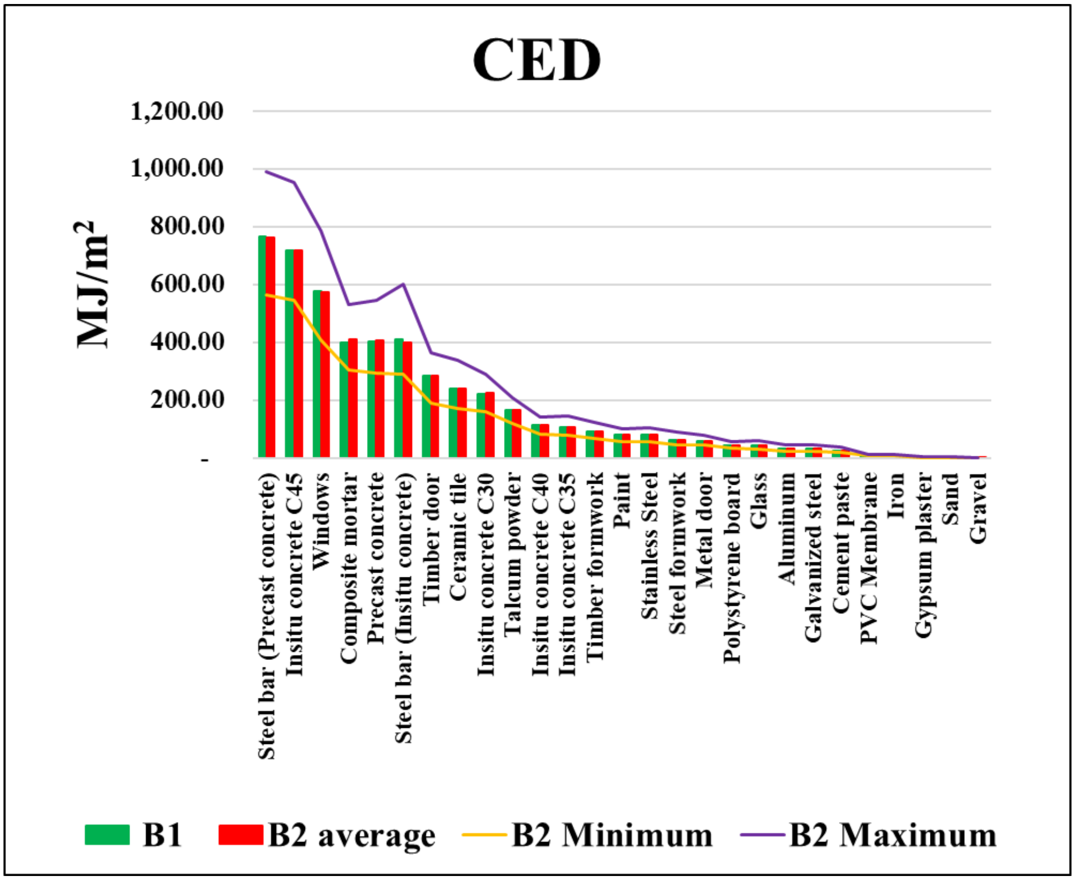


Fig. 4. Contribution analysis of material production phase (CED)

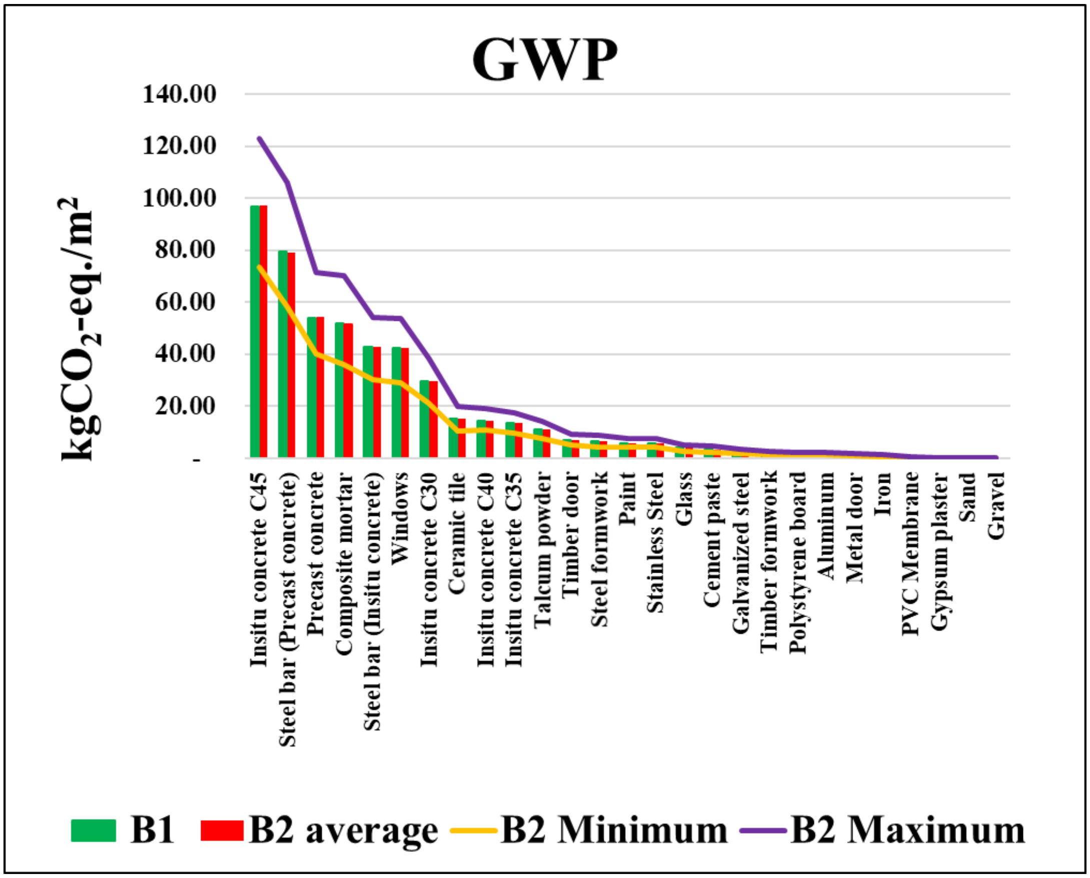


Fig. 5. Contribution analysis of material production phase (GWP).

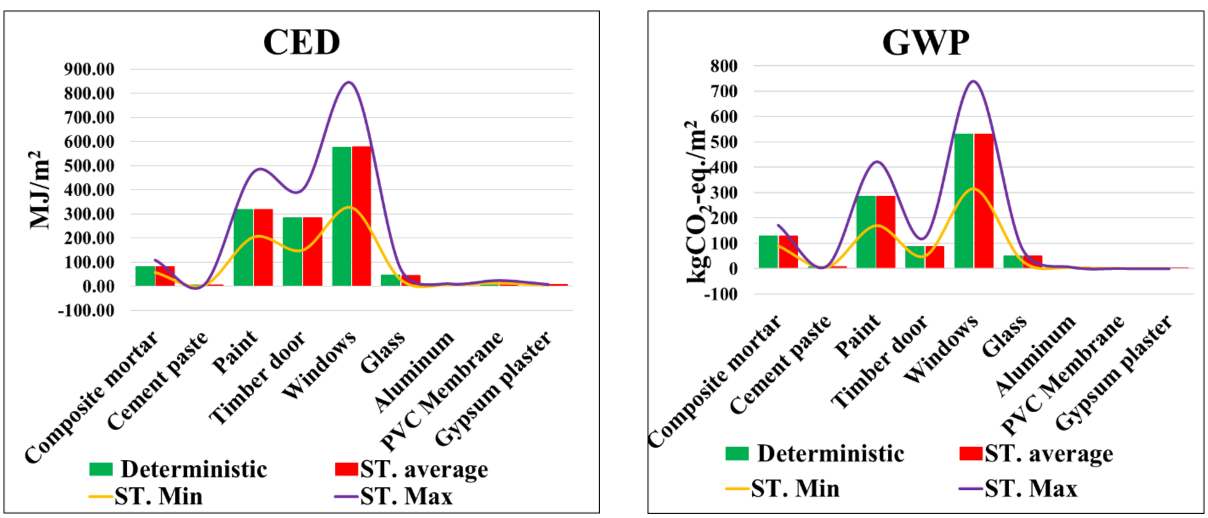


Fig. 6a. Cumulative energy demand **Fig. 6b.** Global warming potential

Fig. 6. Contribution analysis of building maintenance phase

4.2. Scenario uncertainties

4.2.1. End-of-life cycle strategies

Currently, recycling of demolished materials at the end of a building's life cycle is promoted in circular economy literature (Ghaffar et al., 2020). In this context, end-of-life management strategies such as selective demolishing, onsite or offsite sorting and recycling may increase the contribution of the end-of-life phase. Scenarios EoL1 and EoL2 consider two end-of-life management strategies.

In EoL1, demolished materials are transported to an offsite sorting yard, non-inert materials (e.g. wood and paper wastes) are landfilled and concrete is disposed at public filling areas, whereas steel is recycled. Embodied impacts from recycling are estimated using the impact coefficients of materials with an assumption of 100% recycled contents. As indicated in Fig. 7, the mean value for recycling alone results in a saving of 0.69 GJ/m^2 in CED and 33.10 kgCO_2/m^2 in GWP. Demolition, sorting and transportation jointly increase CED by 0.24 GJ/m^2 and GWP by 34.91 kgCO_2/m^2. In total, EoL1 results in a net CED saving of 0.45 GJ/m^2 but net GWP increase of 1.80 kgCO_2/m^2. The foregoing scenario assumes the shortest transportation distance for all activities. To further explore the impact of transportation, 24 other possible sub-scenarios generated by combining different sorting and public disposal/landfill sites in Hong Kong are presented in Fig. 8. The impact of transportation is highlighted as a combination of the longest transportation distances can increase CED by 2.7 times and GWP by 13.7 times.

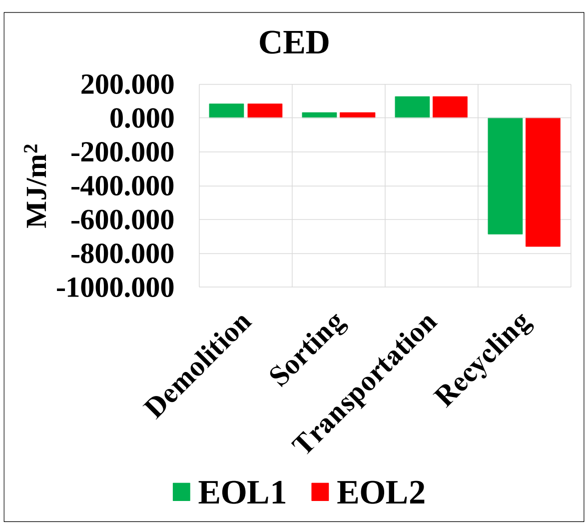


Fig. 7a. Cumulative energy demand.

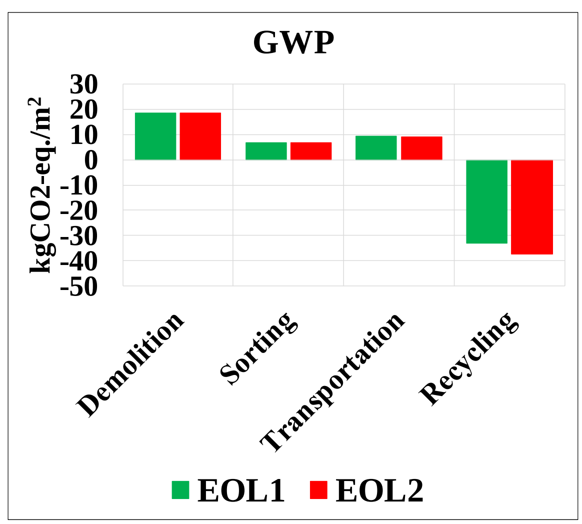


Fig. 7b. Global warming potential.

Fig. 7. Comparison of end-of-life management strategy 1 and 2.

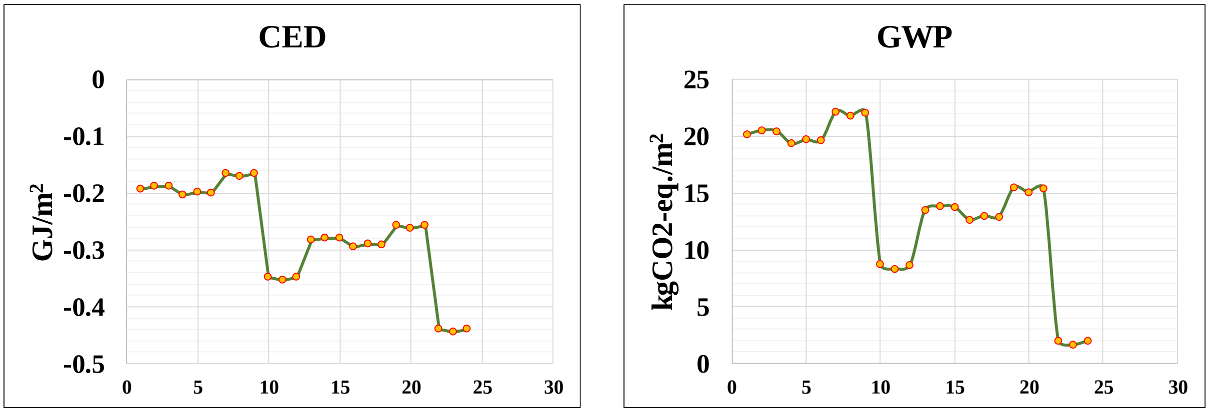


Fig. 8a. Cumulative energy demand. **Fig. 8b.** Global warming potential.

Fig. 8. Scenario analysis of end-of-life management strategy 1.

EoL2 considers a selective demolishing strategy in which wood wastes and aluminum in windows are sorted on-site while all other demolished materials are sorted offsite. This strategy is designed to include an extensive recycling of materials including aluminum, galvanized steel, iron steel and timber. Other materials such as concrete are disposed at public filling areas. The mean value for the recycling scenario indicates savings of 0.76 GJ/m^2 in CED and 37.34 kgCO_2/m^2 in GWP. The total mean values for demolition, sorting and transportation increase CED by 0.24 GJ/m^2 and GWP by 34.57 kgCO_2/m^2. Cumulatively, net savings of 0.52 GJ/m^2 in CED and 2.78 kgCO_2/m^2 in GWP are achieved. Also, the results from 8 sub-scenarios are shown in Fig. 9. It can be observed that the mean values of the base scenario EoL2 could be increased by 2.1 and 6.2 times for CED and GWP respectively given that the farthest sorting, landfill or public filling areas are used.

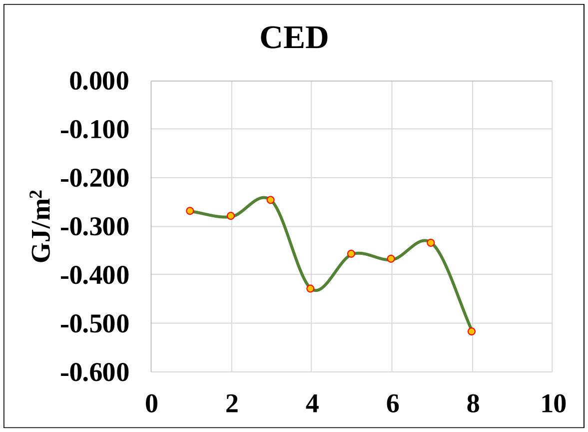


Fig. 9a. Cumulative energy demand.

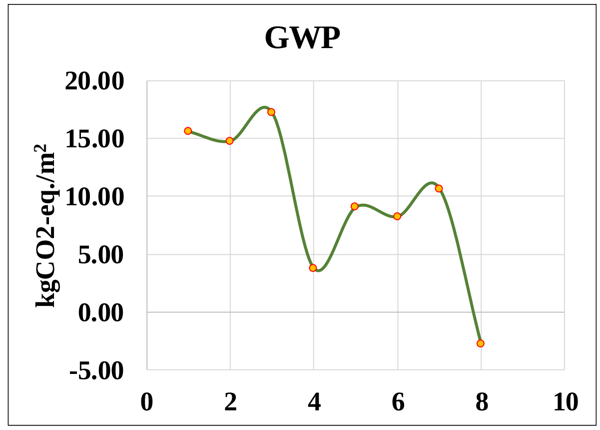
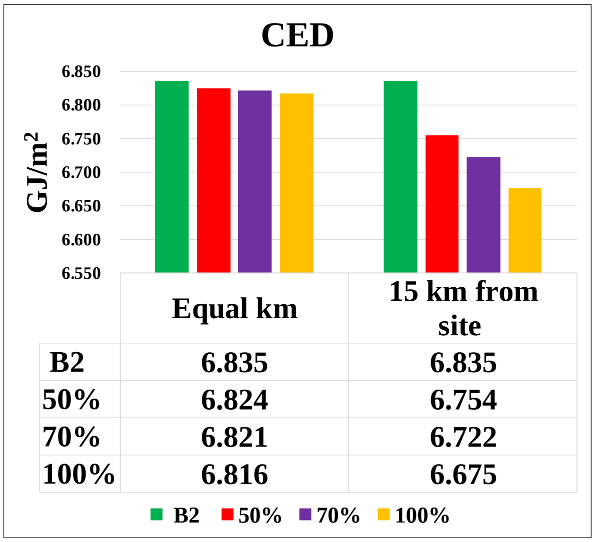


Fig. 9b. Global warming potential.

Fig. 9. Scenario analysis of end-of-life management strategy 2.

4.2.1. Alternative materials

The use of recycled aggregates is considered a strategy to reduce the energy use and carbon emission, so that SC1 is defined to evaluate the impact of recycled aggregates for concrete production. Furthermore, two sub-scenarios are defined to explore the impact of transportation within this context. The first sub-scenario assumes that aggregates are recycled at a site with an equal transportation distance to the production site of virgin aggregates. The second sub-scenario on the other hand considers a recycling site 15 km away from the insitu or precast concrete production site. For each sub-scenario, usage rates of 50%, 70% and 100% are considered for recycled aggregates. Fig. 10 presents a comparison between the two sub-scenarios and with B2. Considering an equal transportation distance, a very minor reduction in the total lifecycle CED is observed across the three usage rates (less than 1% for CED and 1.2% for GWP). Thus, increasing the usage rate of recycled aggregates yields insignificant impact on LCA results. For a recycling plant 10 km away from the concrete production site, a slightly higher impact is observed. The CED is reduced by 1.19%, 1.65%, 2.34% for 50%, 70% and 100% usage rates respectively. Similarly, the GWP is reduced by 0.92%, 1.35%, and 1.91%. It can be observed that LCA results are more sensitive to increases in the usage rate which can decrease transportation distances. Such observations echo with Ding et al. (2016), which explored the lifecycle impacts of recycled aggregates for concrete production in China.



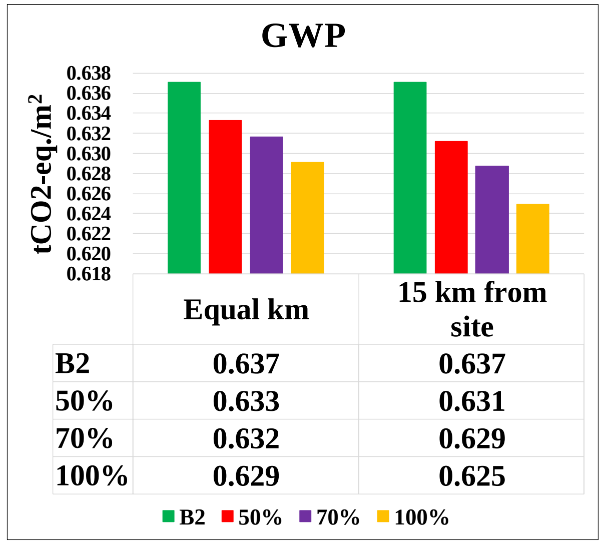


Fig. 10a. Cumulative energy demand. **Fig. 10b.** Global warming potential.

Fig. 10. Impact reduction from the use of recycled aggregates.

The use of cementitious materials is a major source of the energy use and carbon emissions, so that SC2 and SC3 are defined to replace OPC with GBFS and PFA respectively. Furthermore, replacement rates of 50%, 70%, and 80% are defined for both materials as sub-scenarios. Replacement of OPC is performed for three materials namely concrete, composite mortar and cement paste. Fig. 11 illustrates the reduction in CED and GWP for both GBFS and PFA in comparison to B2. It can be observed that the use of GBFS reduces the overall average CED by 8.11%, 11.34% and 12.95% for 50%, 70% and 80% replacement rates respectively. Comparatively, higher GWP reductions of 11.8%, 15.95% and 18.24% are achieved for the same replacement rates. With the use of PFA, 6.13%, 8.57% and 9.79% reductions in CED are achieved for 50%, 70%, 80% replacement rates respectively, while 8.65%, 12.13% and 13.88% reductions are achieved in GWP for the same replacement rates.

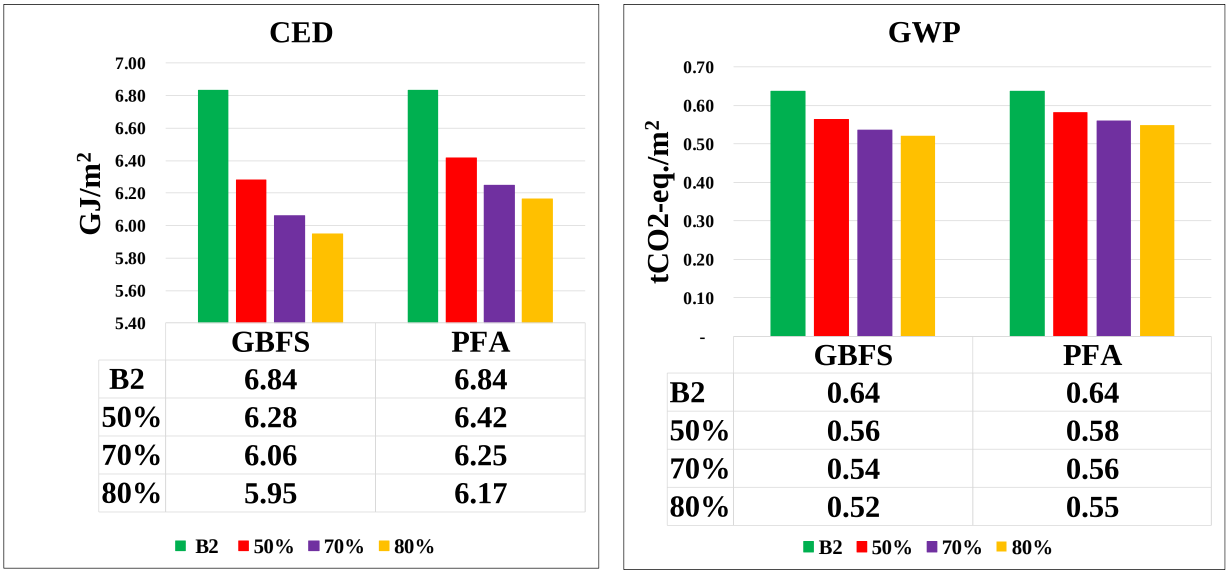


Fig. 11a. Cumulative energy demand. **Fig. 11b.** Global warming potential.

Fig. 11. Impact reduction from the use of alternative cementitious materials.

4.3. Model uncertainties

Scenarios M1 and M2 examine the effect of analytical model uncertainties for LCA results. For the baseline stochastic assessment (B2), a tier-hybrid approach is applied by incorporating a lognormal distribution for DQI components and normal distribution for statistical components. Alternative distributions such as triangular, uniform and normal are further coupled with the proposed hybrid method or a pure DQI approach to study their potential impact on LCA results. Table 8 presents a comparison of the overall mean impact of alternative distributions on the proposed tier-hybrid approach and pure DQI approach.

For scenario M1, it should be noted that only probability distributions of DQI-based parameters are modified whereas statistical parameters are held constant. In comparison to the lognormal distribution, the overall sample mean of uniform, normal and triangular distributions is about 6% lower with similar implication in their standard deviations. Moreover, the CV for each distribution does not vary significantly (about 11%).

In the case of M2, it can be observed that the mean overall lifecycle impact with lognormal distribution is slightly higher (1.6% for CED and 1.56% for GWP) than the base scenario (B2). Comparing the uniform, normal and triangular distributions to the lognormal distribution, decrements of about 3.5% are observed for both CED and GWP. From the perspective of CVs, the pure DQI approach yields a slightly lower value across all distributions (approximately 9%).

Table 8 Comparison of overall mean lifecycle impacts, standard deviation and coefficient of variation from different probability distributions.

Approach		**CED**			**GWP**		
	Distribution	**Mean (GJ/m^2)**	**Standard deviation**	**Coefficient of variation**	**Mean ($kgCO2$ $-eq./m^2$)**	**Standard deviation**	**Coefficient of variation**
Tier-hybrid (M1)	Lognormal	6.86	0.76	11.74	638.28	71.75	11.79
	Uniform	6.46	0.72	11.68	602.20	67.15	11.68
	Normal	6.47	0.72	11.53	601.52	67.10	11.68
	Triangular	6.46	0.72	11.64	602.00	67.39	11.73
Pure DQI (M2)	Lognormal	6.97	0.63	9.62	647.50	59.99	9.84
	Uniform	6.71	0.62	9.84	624.88	56.30	9.47
	Normal	6.70	0.62	9.73	624.17	57.45	9.75
	Triangular	6.68	0.61	9.32	623.99	57.37	9.73

5. Discussion

In general, few studies have evaluated uncertainties in building LCA. Among these studies, a semi-quantitative approach incorporating the DQI-based assessment and stochastic simulation is commonly used. A pure statistical distribution of uncertainty parameters could increase the reliability of DQI based assessments but has scarcely been applied in literature. This paper therefore applied a tier-hybrid approach integrating pure statistical distributions and DQI-based methods to evaluate uncertainties in the lifecycle CED and GWP of a case building in Hong Kong.

The reliability of the tier-hybrid approach is validated as the mean CED and GWP at different levels of assessments (e.g. individual materials and processes, lifecycle phases and overall impacts) are consistent with the deterministic results. Thus, it is validated for further discussion of the afore-described analysis. Considering the deterministic results alone could lead to misinterpretation of LCA results as it does not reflect potential variations in input parameters. From the perspective of lifecycle phases, the material production phase contributes the largest impact but the least uncertainty. On the contrary, transportation, construction and end-of-life phases with relatively lower impacts are embedded with very large uncertainties. High uncertainties in the transportation phase can be explained by the large variation in transport distances of modeled materials. High uncertainties in the construction phase can be attributed to poor quality input data based on assumptions and estimations from previous studies. Similarly, the rarity of end-of-life cycle modelling implies the use of unverified or unrepresentative input data. This study further explores the contribution of each material to the impact of the material production stage. As commonly reported, concrete and steel contribute the majority of building impacts, although lower than reported in previous studies. The contribution of other materials such as windows and doors is significant with even higher uncertainties than primary materials like steel and concrete. Wide variations are observed in the impact coefficient of the former group in comparison to the later. Future studies could explore the detailed sources of uncertainties in other lifecycle stages.

Based on the scenario analysis, essential approaches to reducing lifecycle impacts are identified. For the end-of-life management strategies, the demolishing, transportation and sorting process increases the overall lifecycle impact, but recycling strategies can reduce such impact especially when extensively adopted. As a proof, EoL2 reduces CED and GWP by 7.78% and 0.43% respectively, while much a higher GWP saving can be achieved with a cleaner fuel mix. Key attention must be given to transportation as the impact of end-of-life activities is highly sensitive to alternative sorting, landfill and public filling areas. From the perspective of alternative materials, maximum carbon savings are achieved by using GBFS and PFA to replace OPC with significantly higher energy and carbon coefficients. Specifically, up to 12.9% (CED) and 18.2% (GWP) savings can be achieved with GBFS while 9.8% (CED) and 13.79% (GWP) with PFA. On the contrary, using recycled aggregates yields very limited impact reductions of about 0.28% and 1.25% in CED and GWP respectively. By decreasing the transportation distance to the recycling site, the maximum CED and GWP savings can be increased to 2.34% and 1.91% respectively. Totally, up to 19.91% of the overall CED and 15.23% of the overall GWP can be saved through a combination of alternative materials and end-of-life management strategies.

The results of the model/analytical uncertainty imply that the final output uncertainty is highly correlated with defined probability distributions rather than the uncertainty characterization method. Hence integrating the pure statistical approach based on adequate data with the DQI method can reflect uncertainties more precisely. However, the proposed tier-hybrid approach can increase dispersion of LCA results as pure statistical distributions are collected from a wide range of sources. Finally, the selection of probability distributions can significantly vary statistical modelling outcomes, so that particular attention must be paid to the tier-hybrid approach when combining different probability distributions.

6. Conclusion

This study evaluates the uncertainties in the lifecycle assessment of buildings using a reliable tier-hybrid approach. The pure statistical and DQI approaches are integrated to increase the comprehensiveness and accuracy of uncertainty evaluations. A case study was performed on a typical public rental housing block in Hong Kong using both deterministic and stochastic approaches, where lifecycle impacts are expressed in terms of CED and GWP. The stochastic approach exemplifies the proposed tier-hybrid approach which can be adopted by LCA modelers in future. In this approach, pure statistical distributions are applied when rich information is available and complemented with expert judgement (DQI) where information is insufficient. Insights from the study provide a basis to interpret future LCA results in which multiple probability distributions are jointly applied in an analytical model. Hence the impact of arbitrarily assigning probability distributions due to data deficiency can be appropriately quantified.

The results of this study validates the initial hypothesis that a tier-hybrid method can improve the efficiency and accuracy of the uncertainty evaluation in building LCAs. Firstly, the results of this approach are proven valid because the mean stochastic outputs are almost the same as the deterministic results. It can be therefore concluded that the statistical characterization of uncertainties coupled with the DQI approach is an accurate method to characterize and propagate building LCA uncertainties. Secondly, the study further strengthens this approach by illustrating the effects of different probability distributions for the exploration of analytical uncertainties. It should be noted that the results vary slightly when the tier-hybrid approach is compared with the pure DQI approach. Lastly, the study illustrates the impacts of different probability distributions on the tier-hybrid approach in tandem with the impact of probability distribution on the pure DQI approach.

The main findings from evaluating scenario and model uncertainties can be summarized as follows:

- The material production stage yields the least uncertainties although it contributes the most to the overall lifecycle impact.
- The overall uncertainties in other phases are significantly higher than the material production stage, and decrease in the order of transportation, maintenance, to construction.
- An extensive end-of-life management strategy can produce significant CED savings which will be translated into a lower GWP using a cleaner fuel mix.
- Replacing virgin aggregates with recycled aggregates yields minor impact reduction, whereas replacing OPC with GBFS or PFA produces large CED and GWP savings.

Overall, this study provided deep insight into applying a tier-hybrid approach to evaluate the uncertainties in the lifecycle of buildings. In future research, the collection of data for pure statistical methods could be stratified to facilitate a more detailed estimation of uncertainties. Basic uncertainties can be processed as a function of pure measurement errors, while additional uncertainties can be processed as a function of geographical, temporal or technological differences.

Acknowledgement

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Appendixes

Appendix A Uncertainty characterization for DQI-based parameters

	Quantity	Unit	Data quality score		
Activity/Material			**Material Quantity**	**Energy use coefficient**	**Carbon emission coefficient**
Material Production					
Aluminum	2500.00	kg	3,2,1,1,1	4,4,5,3,4	4,4,5,3,4
Cement paste	160949.60	kg	3,2,1,1,1	2,2,1,4,2	2,2,1,4,2
Ceramic tile	232800.70	kg	3,2,1,1,1	3,3,1,4,1	3,3,1,4,1
Composite mortar	2431381.00	kg	3,2,1,1,1	3,2,2,4,2	3,2,2,4,2
Galvanized steel	9892.03	kg	4,2,1,1,1	3,2,2,4,1	3,2,2,4,1
Glass	44762.39	kg	3,2,1,1,1	3,4,3,3,2	4,4,3,3,2
Gravel	5966.79	kg	3,2,1,1,1	3,2,2,4,1	3,2,2,4,1
Gypsum plaster	30877.90	kg	3,2,1,1,1	2,2,1,4,2	2,2,1,4,2
Insitu concrete C30	1284.86	m^3	3,2,1,1,1	3,3,2,4,2	3,3,2,4,2
Insitu concrete C35	637.49	m^3	3,2,1,1,2	3,3,2,4,2	3,3,2,4,2
Insitu concrete C40	642.65	m^3	3,2,1,1,3	3,3,2,4,2	3,3,2,4,2
Insitu concrete C45	3487.75	m^3	3,2,1,1,4	3,3,2,4,2	3,3,2,4,2
Iron	6009.18	kg	4,2,1,1,1	3,2,2,4,1	3,2,2,4,1

Activity/Material	Quantity	Unit	Data quality score		
			Material Quantity	**Energy use coefficient**	**Carbon emission coefficient**
Metal door	507.22	m^2	4,2,1,1,1	3,2,3,4,5	3,2,3,4,5
Paint	9820.00	kg	3,2,1,1,1	4,4,5,3,4	4,4,5,3,4
Polystyrene board	8917.62	kg	3,2,1,1,1	3,3,2,4,1	3,3,2,4,1
Precast concrete	2424.37	m^3	3,2,1,1,1	3,3,2,4,1	3,3,2,4,1
PVC Membrane	1178.42	kg	3,2,1,1,1	3,3,2,4,1	3,3,2,4,1
Sand	440375.30	kg	3,2,1,1,1	3,2,2,4,1	3,2,2,4,1
Stainless Steel	14173.13	kg	3,2,1,1,1	3,2,2,4,2	3,2,2,4,2
Steel bar (Insitu concrete)	223378.60	kg	3,2,1,1,1	3,2,2,4,2	3,2,2,4,2
Steel bar (Precast concrete)	414845.90	kg	3,1,1,1,1	3,2,2,4,2	3,2,2,4,2
Steel formwork	31290.39	kg	3,2,1,1,1	3,3,1,4,2	3,3,1,4,2
Talcum powder	82265.29	kg	3,2,1,1,1	3,3,4,5,2	1,3,4,5,2
Timber door	2534.45	m^2	3,2,1,1,1	4,4,5,3,4	4,4,5,3,4
Timber formwork	395.67	m^3	3,2,1,1,1	4,4,5,3,4	4,4,5,3,4
Windows	3148.30	m^2	3,2,1,1,1	4,4,5,3,4	4,4,5,3,4
Onsite construction					
Electricity for temporary offices and onsite equipment	776502.60	kWh	3,4,3,4,4	3,4,2,4,5	3,4,2,4,5
Diesel for onsite vehicles and onsite equipment	31542.00	kWh	3,4,3,4,4	3,4,2,4,5	3,4,2,4,5
Building maintenance					
Aluminum	625.00	kg	3,2,1,4,3	4,4,5,3,4	4,4,5,3,4
Cement paste	32189.92	kg	3,2,1,4,3	2,2,1,4,2	2,2,1,4,2
Composite mortar	486276.20	kg	3,2,1,4,3	3,2,2,4,2	3,2,2,4,2
Glass	44762.39	kg	3,2,1,4,3	3,4,3,3,2	4,4,3,3,2
Paint	39280.00	kg	3,2,1,4,3	4,4,5,3,4	4,4,5,3,4
Windows	3148.30	m^2	3,2,1,4,3	4,4,5,3,4	4,4,5,3,4

Activity/Material	Quantity	Unit	Data quality score		
			Material Quantity	**Energy use coefficient**	**Carbon emission coefficient**
Timber door	2534.45	m^2	3,2,1,4,3	4,4,5,3,4	4,4,5,3,4
PVC Membrane	2356.84	kg	3,2,1,1,1	3,3,2,4,1	3,3,2,4,1
Gypsum plaster	61,755.86	kg	3,2,1,1,1	2,2,1,4,2	2,2,1,4,2

Appendix B Uncertainty characterization for pure statistical parameters

Material	Transportation distance (km)		Material waste rate (%)		Material density (kg/m^3)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Aluminum	200	18.49	5	0.51	2,710	142.06
Cement paste	25	1.06	10	0.93	1520	155.86
Ceramic tile	185	16.01	10	0.76	2200	117.13
Composite mortar	25	1.06	10	0.57	1650	87.85
Galvanized steel	200	18.49	5	0.56	7850	96.95
Glass	10	0.21	7	0.32	2450	56.97
Gravel	180	25.65	5	0.51	1520	155.86
Gypsum plaster	150	12.52	5	0.38	2320	74.47
Insitu concrete C30	25	3.81	5	0.51	2400	246.10
Insitu concrete C35	25	3.81	5	0.51	2400	246.10
Insitu concrete C40	25	3.81	5	0.51	2400	246.10
Insitu concrete C45	25	3.81	5	0.51	2400	246.10
Iron	250	28.14	5	0.51	6970	737.70
Metal door	200	16.96	2	0.05	-	
Paint	150	36.38	7	1.91	1350	106.46
Polystyrene board	150	15.00	3	0.30	28	2.80
Precast concrete	100	3.45	1	0.03	2400	138.84
PVC Membrane	100	13.24	5	0.66	1070	27.18
Sand	180	9.62	5	0.23	1680	183.05
Stainless Steel	120	11.08	10	1.06	7590	707.69
Steel bar (Insitu concrete)	150	11.79	7	0.15	7860	805.96
Steel bar (Precast concrete)	100	5.32	7	0.72	7860	805.96
Steel formwork	28	1.08	7	0.35	7860	418.55
Talcum powder	150	12.38	5	0.47	2650	271.73
Timber door	220	60.63	2	0.25	-	-

Material	**Transportation distance (km)**		**Material waste rate (%)**		**Material density (kg/m^3)**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Timber formwork	250	58.85	5	0.51	875	116.01
Windows	100	3.45	2	0.11	-	-