Estimating and minimizing embodied carbon of prefabricated high-rise residential buildings considering parameter, scenario and model uncertainties

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Estimating and minimizing embodied carbon of prefabricated high-rise residential buildings considering parameter, scenario and model uncertainties

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Abstract

Carbon emissions associated with high-rise buildings are expected to grow with the increasing population in high-density cities. As an environmentally friendly construction method, prefabrication should lead to reduced buildings' emissions. However, few studies have considered the uncertainty caused by errors in input parameters, scenario assumptions and choices of analytical uncertainty models when examining the embodied carbon of prefabricated high-rise buildings, leading to the misinterpretation of results. To address this, a five-level framework is developed for assessing the deterministic embodied carbon of prefabricated buildings using the process-based method. A Data Quality Index based Monte Carlo Simulation is applied for the uncertainty analysis using the SimaPro 9.0 software. A typical prefabricated high-rise residential case building in Hong Kong is examined. Seven scenarios are developed by varying system boundaries, materials used, partition wall thickness, waste rate, prefabrication rate, transportation distance, and analytical uncertainty model's transformation coefficients, to examine the influences of the scenario and model uncertainty. Results indicate that the embodied carbon of the case averages 561 kg CO_2/m^2. When considering both deterministic results and parameter uncertainty, the key processes are identified as being the production of concrete, steel and timber, as well as transportation activities. The results reveal that 31.6% of the embodied carbon is possibly reduced by combining the pre-defined scenarios. The selection of transformation coefficients in analytical uncertainty model significantly affects the variances of the results and should be carefully examined. This paper can better facilitate the uncertainty measurement of prefabricated buildings' embodied carbon assessment, for improving the reliability of results.

Keywords

Embodied carbon emission; prefabricated high-rise building; uncertainty analysis; scenario analysis; carbon reduction.

1. Introduction

Buildings are significant consumers of energy and materials, as well as significant contributors to global carbon emissions. As an innovative construction technology, prefabrication presents an opportunity to improve the effectiveness of construction in reducing material consumption and carbon emissions [1]. Prefabricated building products are manufactured initially in factories and then transported to construction sites for final assembly. The adoption of prefabrication should bring about environmental benefits, as only installation occurs on the construction site, with a lower waste rate. According to Lopez-Mesa et al. [2], carbon generated from precast concrete slabs was 12.2% lower than that of cast-in-situ slabs. However, prefabrication may have higher emissions during the transportation phase due to a higher delivery load. The evolution of carbon generated from prefabricated buildings is a complex problem that needs to be further addressed.

Previously, the Life Cycle Assessment (LCA) has been widely used in evaluating the environmental impacts of buildings over their life cycle. Life Cycle Carbon (LCCa) Assessment is similar to LCA but converts megajoules of energy to kilograms of carbon [3]. A building's life cycle is usually divided into several typical phases, including the production, assembly/construction, operation, maintenance, end-of-life, and upstream or downstream transportation activities. Over the last decade, LCA research on embodied carbon (from material manufacturing, transportation, and construction) analysis has considerably increased with the accelerated use of renewable energy and the adoption of low/zero carbon design. For example, Hollberg et al. [4] calculated the embodied carbon emissions of a residential building and found that they were responsible for two thirds of the emissions during the life cycle of 60 years. In particular, as Pan and Pan [5] revealed, embodied carbon was higher in import-dominated and high-density urban settings such as Hong Kong.

Hong Kong as a city has the highest density of population in the world and half of Hong Kong's 7.3 million population lives in public housing. The Hong Kong government has integrated a prefabrication strategy into the building design and construction of all public housing developments, which account for 30% of the total housing and benefit 44.7% of Hong Kong's population [6]. The construction demand for prefabricated residential buildings is expected to increase, which will consume a huge amount of raw materials and energy and thus produce various carbon emissions. Reducing the embodied carbon emissions of buildings, especially prefabricated high-rise residential buildings, is thus strategically important for reducing the overall environmental impacts of construction industry in Hong Kong.

Although several studies have investigated the embodied carbon of high-rise residential buildings, their reported results display significant variations [1,7]. The adoption of different system boundaries, assumptions, building design alternatives, and indicators, as well as the background data used by different LCA modelers, impose significant challenges to cross-case comparison and benchmarking [8,9]. Embodied carbon assessment incorporates a range of uncertainties associated with input parameters (e.g. the reliability of the data), the assumptions of scenarios, and choices of analytical uncertainty models that may result in misinterpretation of the results. However, few previous studies have explored these uncertainties in calculating embodied carbon emissions.

Compared with conventional construction, prefabrication involves the manufacture of building components or modules away from the construction site [10]. Prefabrication systems can be expressed at different levels based on the degree of prefabricated work completed in a factory (e.g. non-structural elements, structural elements, and volumetric elements). The highly standardized features determine the meaningfulness to report and compare the embodied carbon of prefabricated buildings at a higher unit of analysis directly (e.g. a piece of component or a standard flat). However, most studies failed to exploit these advantages of prefabrication, in which the embodied carbon was calculated by adding the engineering quantities of materials each time for each precast component. It is important to have a more systematic multi-level approach for effective calculation and reliable comparison.

This paper aims to examine the embodied carbon of prefabricated high-rise buildings in Hong Kong at multi-level units of analysis, considering the uncertainties caused by the errors in input parameters, and the different selections of scenarios and analytical uncertainty models. Based on this introduction, the paper reviews the previous research on carbon assessment methods and uncertainty analysis. It then conducts a case study to identify the carbon-intensive processes, considering both the deterministic results and corresponding parameter uncertainties during the production, transportation, and construction of buildings. Based on the Hong Kong situations, embodied carbon results are reported at five levels, i.e. material, component (e.g. a staircase), assembly (e.g. a volumetric precast bathroom), flat (a residential unit) and the entire building.

Seven scenarios are developed and compared for exploring the scenario and analytical model uncertainties. Possible embodied carbon reduction measures are explored by combining the pre-defined scenarios. The results are then discussed and suggestions given, followed by a summary of the conclusions drawn.

2. Carbon assessment of prefabricated buildings and uncertainty analysis

The environmental benefits of prefabrication have been demonstrated, one of which is reduced life cycle carbon emissions [11]. For example, Dong et al. [12] pointed out that carbon emissions of prefabricated concrete were 10% less than that of in-situ cast concrete measured per cubic meter. Ji et al. [13] found that the adoption of prefabrication helped to achieve a 3.1% carbon reduction compared with conventional construction. There are three typical methods for assessing buildings' embodied carbon, namely input-output (I-O), process-based, and hybrid methods. I-O covers nearly the whole system boundary involved in the supply chain of a product whereas it is blamed for the inaccuracy of detailed processes [14]. The process-based method delivers more detailed and reliable results by breaking down the product system into individual processes in the products life cycle. Although this method is known to suffer from a complex and time-consuming calculation process [15], it is the most widely used and recognized LCA technique. The hybrid analysis combines I-O and process-based methods but introduces risk of double counting [16]. Several standards and databases are therefore provided for improving the efficiency of embodied carbon assessment. However, there has not been a common protocol with appropriate data for all projects worldwide. To ensure that the emission factors match with the respective materials used under different manufacturing conditions and ingredients, further efforts such as interviews and questionnaires are required. Despite much attention being focused on the buildings' embodied carbon assessment, only a few studies have considered the relevant uncertainty during the calculation process, even though the ISO 14040 standard has pointed out the necessity of conducting uncertainty analysis to reinforce confidence in the results.

Uncertainty happens when using information that is unavailable, unreliable or when more than one value is available [17]. Generally, uncertainty in embodied carbon assessment is generated from three aspects: the unreliability of input parameters [18], the scenario assumptions [19] and the varied choices of uncertainty analytical models [20], namely parameter, scenario and model uncertainties. Parameter uncertainty is caused by data inaccuracy and incompleteness when using secondary input data. Scenario uncertainty results from the unavoidable assumptions, choice of system boundaries, waste-handling scenarios and expected technology trends [21], which is also expressed as the assumption uncertainty [17], cut-off uncertainty [22] or choice uncertainty [23]. The scenario alternatives can reflect the decision-maker preference, which can be assessed one by one using scenario analysis [17]. The analytical uncertainty models themselves may add to the uncertainty due to the different selections of mathematical relationships in the models (e.g. probability density function (PDF), the transformation relationship between the data quality grades and PDFs). These categories clearly identify specific modeling activities: defining parameters and calculation procedure, selecting scenarios, and constructing mathematical models for uncertainty analysis.

A range of uncertainty analysis tools have been examined previously based on the uncertainty types. In terms of parameter uncertainty, both qualitative and quantitative approaches have been applied. For example, the data quality index (DQI) method, first proposed by Weidema and Wesnaes [24] for LCA studies and then developed by Weidema [25] and Kennedy et al. [26], has been used as a qualitative assessment tool due to its high applicability. However, the pure DQI method has a weakness in its subjective evaluation, and thus remains of limited application

[27]. To reduce the bias, quantitative approaches have been advocated in previous studies, such as Bayesian methods [28], a neural network (NN) model [29], a fuzzy set method [30], an interval theory [31], possibility analysis [32], and stochastic analysis (e.g. Monte Carlo simulation (MCS) [33]. Compared with other methods, stochastic analysis is superior [21] as it can provide sufficient information. In particular, MCS is the most frequently used method of addressing uncertainty aggregated by various uncertainty factors with non-linear relationship [34]. However, pure statistical analysis has seldomly been used in building assessment as the information scarcity [18]. Therefore, some studies have proposed the benefits of integrating qualitative and quantitative approaches. For example, Kennedy et al. [26] combined DQI and MCS to evaluate the uncertainty by using descriptive information to obtain the probability distribution of data. The subjective judgment acts as a substitute when the actual data are lacking to estimate uncertainty ranges. The DQI-based method has also been advocated by Hong et al. [18], showing its efficiency in conducting the parameter uncertainty analysis. Although the parameter uncertainty has been addressed in some studies, the scenario or model uncertainty have seldomly been considered [17]. In addition, no studies have focused on prefabricated high-rise buildings' embodied carbon assessment in Hong Kong by considering the uncertainties.

3. Methodology

3.1 System boundary and study scope

The life cycle stages cover the cradle-to-end-of-construction, including raw material extraction (P1), transportation from extraction to factory (P2), manufacturing of construction materials (P3), prefabrication (P4), transportation to the site (P5), and onsite construction/assembly (P6). Auxiliary materials like the timber formwork are also included, and their turnover frequency can be collected from the interviews. Construction activities include the fuel and electricity consumption of construction machinery and temporary lighting. The production, abrasion loss, maintenance and disposal of vehicles and roads are also considered in transportation carbon emissions.

3.2 Research method

The analysis presented in this paper follows a four-step process (Fig.1): (1) conducting a deterministic embodied carbon analysis of prefabricated buildings at five levels for identifying the most carbon-intensive processes; (2) employing stochastic analysis to identify the greatest uncertainties caused by errors in input parameters; (3) identifying the critical processes based on the previous two steps; and (4) exploring the influences of possible scenarios on the embodied carbon results, thus indicating the scenario and model uncertainties caused by different choices. A typical prefabricated high-rise residential building in Hong Kong was selected as the base case for verification and comparison.

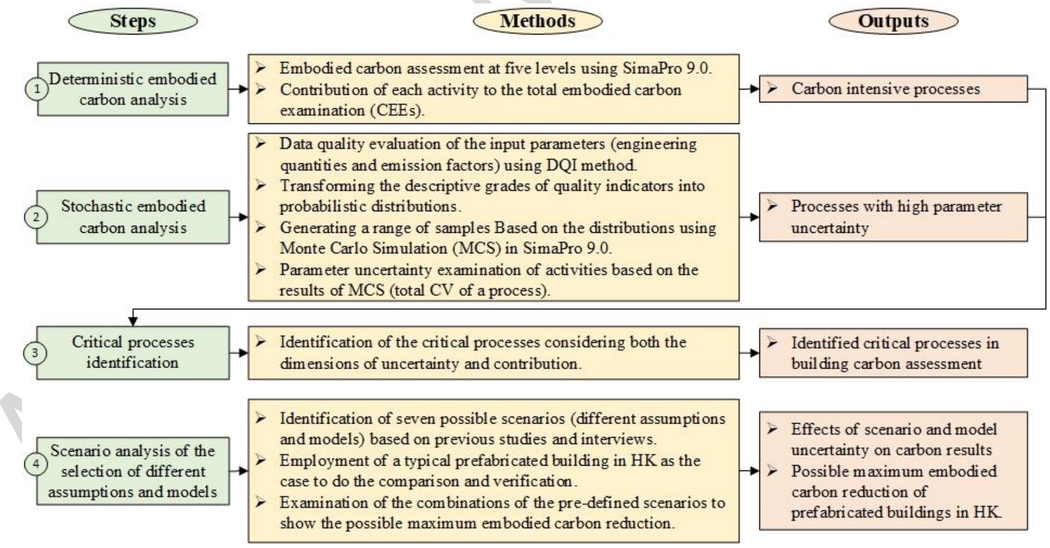


Fig.1 Framework of the four-step analysis for this present study

3.2.1 Deterministic embodied carbon analysis of prefabricated buildings

The deterministic analysis is conducted based on the process-based method provided by ISO 14044 standards [35], PAS 2050 [36] and EN 15978 [37], and the basic concept is that emissions are equal to a product's quantity multiplied by the relevant emission factor of its production process. Two kinds of data are needed: engineering quantities and emission factors. Data on the material consumption, waste rate, detailed information of precast elements, concrete ingredients, supplier lists, transportation modes can be directly collected from the bills of quantities (BoQ), building drawings, disposal records, and personal interviews with the designers, precast manufacturers, and contractors. The transportation distances will be determined using Google map according to the locations of prefabrication factories, material suppliers and construction site. Fuel and electricity consumed in the precast factory and construction site will be calculated based on the catalog, capacity and running time of the machinery. Emission factors can be obtained from sources like literature, official reports, databases or site surveys. The detailed calculation models are presented in Table 1. The five levels unit of analysis proposed by Pan et al. [38] is adopted as the functional unit considering the standardized features of prefabrication. The contribution to the total Embodied Emissions (*CEE*) of each activity is calculated using Eq. (4), which acts as the reference for identifying the carbon-intensive processes.

Table 1 Calculation model of deterministic embodied carbon analysis

Source	Phase	Equation
EC_m	Material and precast product manufacturing carbon	$\mathrm{EC}_m = \sum Q_m \times e_m$ (1)
EC_t	Transportation carbon	$\mathrm{EC}_t = \sum Q_m \times D_{mt} \times e_{mt}$ (2)
EC_c	On-site assembly carbon	$\mathrm{EC}_c = \sum Q_r \times e_r$ (3)

Footnote: EC_m, EC_t, EC_c indicate embodied carbon generated from material manufacturing, transportation and construction stages; Q_m denotes the engineering quantities of material m (kg or t or m^3); e_m is the carbon emission factor ((kgCO_2/kg or kgCO_2/m^3)) generated by producing a unit of material m; D_{mt} indicates the distances of transportation of material m (km); e_t is the carbon emission factor of vehicles for transporting material m (kgCO_2/tkm); Q_r represents the consumption quantity of resource r (MJ or kWh); e_r denotes the carbon emission factor of r consumption (kgCO_2/MJ or kgCO_2/kWh).

$$\mathrm{CEE}_p = \mathrm{E}_{D,p}/\mathrm{EC}_D \qquad (4)$$

where CEE_p denotes the contribution of process p to the total embodied emissions; $\mathrm{E}_{D,p}$ denotes the deterministic embodied carbon from process p; EC_D denotes the total embodied carbon emissions.

3.2.2 Stochastic embodied carbon analysis of prefabricated buildings

The stochastic analysis is implemented by combining the DQI method and the MCS procedure. Ecoinvent 3.4 in SimaPro 9.0 software is adopted to conduct the DQI analysis. It classifies the parameter uncertainty into “basic” uncertainty (uncertainty due to the stochastic error of the parameters) and “additional” uncertainty (uncertainty due to the use of imperfect data, e.g. estimated data or temporal conditions) [39], where the overall total uncertainty can be derived as the sum of basic and additional uncertainties. The default variances (σ_b^2) for basic uncertainty are directly derived from Ecoinvent with respect to a lognormal distribution of data [39]. The additional variances (σ_a^2) can be determined by a DQI-based two-step semi-quantitative approach as follows. First, the data quality indicators are initially determined based on the characteristics of the data inventory. To code the qualitative judgments into numerical scales, the pedigree matrix approach is used considering five types of criteria in Table 2 [24, 25]. The quality of each indicator is graded from 1 to 5 based on the standard descriptions (high grades indicating higher data quality), resulting in a 5 × 5 matrix (Table 2). Second, these descriptive grades of indicators are then transformed into probability profiles. The variance ($\sigma_{a,h}^2$) for each indicator *h* *(h=1…5)* is obtained from Table 3. For example, the engineering quantities of cement can be collected from BOQ by contractors through on-site survey. The completeness of data is therefore described as “representative data from an interest party” and can be graded as “4” according to Table 2. The corresponding additional variance ($\sigma_{a,1}^2$) is proposed as 0.0001 based on Table 3. The variance for total uncertainty (σ_t^2) can be obtained from Eq. (5), assuming that each indicator is independent.

Table 2 Data quality pedigree matrix based on studies of Weidema (1998)

Score	Data quality indicators				
	Completeness (Source)	Reliability	Temporal correlation	Geographical correlation	Technological correlation
5	Representative data from an independent source	Verified data based on consistent measurements	< 3 years	Field survey/measured data	Data from a process with the same technology
4	Representative data from interest party	Data based on measurements with some assumptions	< 6 years	Average data from the area with a similar condition	Data from a process with similar technology
3	Unrepresentative data from an independent source	Data partly from qualified estimation	< 10 years	Regional data	Data from a process with different technology
2	Unrepresentative data from irrelevant enterprise	Data from qualified estimation (e.g. by the industrial expert)	< 15 years	National data	Data from a related process with similar technology
1	Unrepresentative data from an interested party	Non-qualified estimated data	> =15 years	International data	Data from a related process with different technology

Table 3 The variance of additional uncertainty (lognormal distribution) by converting the data quality indicators of the pedigree matrix (Weidema et al., 2013)

Data quality indicator	Score				
	1	2	3	4	5
Completeness	0.0080	0.0020	0.0006	0.0001	0
Reliability	0.0400	0.0080	0.0020	0.0006	0
Temporal correlation	0.0400	0.0080	0.0020	0.0002	0
Geographical correlation	0.0020	0.0006	0.0001	2.5×10^{-5}	0
Technological correlation	0.1200	0.0400	0.0080	0.0006	0

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

where $\sigma_t^2, \sigma_b^2, \sigma_{a,h}^2$ denote the variances of total, basic and additional uncertainty for indicator *h*.

To achieve a universal measurement, the variances of the basic and additional uncertainty for indicator *h* ($\sigma_b^2, \sigma_{a,h}^2$) are converted into the coefficient of variations (CV_b, $CV_{a,h}$) using Eq. (6)

and Eq. (7) so that the lognormal case can be extended to other distribution functions [40]. The additional and total uncertainty can be calculated using Eq. (8) and (9), respectively.

$$CV_b = \sqrt{e^{\sigma_b^2} - 1} \qquad (6)$$

$$CV_{a,h} = \sqrt{e^{\sigma_{a,h}^2} - 1} \qquad (7)$$

$$CV_a = \sqrt{\prod_{h=1}^{5} CV_{a,h}^2 + 1) - 1} \qquad (8)$$

$$CV_t = \sqrt{CV_a^2 + CV_b^2} \qquad (9)$$

MCS is then adopted to generate samples of input data in SimaPro 9.0 software (including engineering quantities and the corresponding emission factors) based on the distributions obtained using the DQI method. In summary, the DQI-based MCS is conducted flowing the following steps: (1) Identify simulation inputs based on the process-based embodied carbon assessment model; (2) Determine the probability distributions of these variables; (3) Generate samples of input data (e.g. consumption of materials and energy, and emission factors) based on the distributions assessed in the DQI analysis. The sampling process is conducted by using Latin hyper-cube sampling (LHS) method, which is a famous for its convenient implementation [41]; (4) Run the simulation model *N* times using SimaPro 9.0 to generate corresponding output values; (5) Conduct further analysis such as median, sample mean, Standard Deviation (SD), and CV. After this, the stochastic value (EC_S) and deterministic value (EC_D) are compared for the verification of the results using relative error (RE) (Eq. (10)):

$$RE = (EC_S - EC_D)/EC_D \times 100\% \qquad (10)$$

3.2.3 Identification of critical processes in building embodied carbon assessment

The critical processes in embodied carbon assessment of buildings are identified simultaneously considering the dimensions of uncertainty and contribution, with the CV (to decide the uncertainty of a process) and CEE (to indicate the contribution of an activity) represented in the horizontal and vertical coordinate axes. The importance of each process is evaluated according to their relative positions on the coordinate axes, where upper right parameters should be concerned compared with the lower left ones.

3.2.4 Scenario analysis of the selection of different assumptions and analytical uncertainty models

Scenario analysis is then conducted to investigate the uncertainties caused by the selection of different assumptions and analytical uncertainty models. This method is selected as it does not require complex statistical mathematics, making it more appropriate to be applied within the construction industry to model alternative outcomes. Seven possible scenarios, along with nine sub-scenarios, during the cradle-to-end-of-construction period are then developed (Table 4).

Table 4 Scenarios considered in this paper

No	Scenario	Code	Sub-scenarios
1	Different system boundaries	S1a	Simplified system boundary
		S1b	Extended system boundary
2	Low carbon material selection	S2a	Adopting additives (pulverized fly ash (PFA))
		S2b	Adopting low carbon cement
3	Material minimization	S3	Decreasing the concrete amount of internal wall
4	Material waste reduction	S4	Material waste rate based on good practice
5	Varied prefabrication rate	S5	Increased prefabrication rate
6	Transportation optimization	S6	Assuming local production is adopted
7	Transformation relationship	S7	Using averaged additional transformation coefficients of variations (CVs) for additional uncertainty

Scenario S1 determines the influences of different system boundaries. A large number of materials and energy are consumed during the cradle-to-end-of-construction phases, so including or excluding them might significantly influence the results [8]. S1a and S1b will consider simplified and extended system boundaries, respectively. The transportation carbon generated from the production, abrasion loss, maintenance and disposal of vehicles and roads are excluded in S1a. Apart from the emissions considered in the base case, labor transportation-related carbon will be included in S1b.

The importance of material selection in reducing emissions generated from high-rise buildings has been highlighted in previous studies. For example, González and Navarro [42] showed that a 30% carbon reduction of a building could be achieved by replacing conventional materials with low carbon materials. Negishi et al. [43] emphasized the importance of using less impactful materials in the manufacturing process. Among a range of construction materials, great attention has been paid to concrete [44]. Therefore, scenario S2 is designed to examine the effects of selecting different low carbon materials on the embodied carbon of prefabricated buildings. Two sub-scenarios will be considered based on the Hong Kong regulations, namely, adding additives and adopting low carbon cement. It is assumed that 25% of pulverized fly ash (PFA) will be added to both precast and cast-in-situ concrete in scenario S2a. In scenario S2b, the original ordinary Portland cement will be replaced with blast furnace slag cement.

Some scholars have also pointed out that an emission-optimized design under the technical and performance requirements could help to reduce buildings' embodied carbon. For example, the study of Eleftheriadis et al. [45] showed that a changed design of buildings could achieve as high as 20% embodied carbon reduction. However, some of these significant changes are not applicable to Hong Kong (e.g. the thickness of semi-precast slabs has already reached the considered minimum). The potential reduction through emission-optimized designs based on Hong Kong's situation is thus discussed in Scenario S3. Based on the interviews with structural engineers in Hong Kong, a slight reduction in the thickness of load bearing concrete walls and non-structural concrete block walls that would not jeopardize the structural stability of the building is acceptable. Therefore, S3 examines carbon reduction of a decreased use of concrete in internal walls.

In addition, some studies indicated that embodied carbon could be reduced by reducing the waste rate [46]. According to Aye et al. [47], concrete structure buildings could see a carbon reduction of up to 32.3% if the reusability of materials was considered. Another study conducted by Hossain and Poon [48] indicated that as high as 90% of the embodied carbon could be reduced by directly reusing of the steel panels and products in hoarding construction. In particular, prefabrication has been acknowledged as being a method with waste avoidance benefits [47] due to a controlled factory environment. Exploring the influences of reduced waste rate on embodied carbon reduction through the adoption of prefabrication is meaningful. Scenario S4 therefore examines reducing waste rates under good practice situations.

The impact of transportation to the embodied carbon reduction of buildings has also been emphasized. The main factors affecting transportation carbon include the amount of transported materials, the distance, and mode of transport [49]. In particular, the transportation carbon of prefabricated buildings has seen a significant increase [44], showing a higher carbon reduction potential if local manufacturers are selected. Therefore, scenario S6 examines the effects of different transportation distances on embodied carbon results.

Based on the studies of Teng et al. [1] and Mao et al. [50], the adoption of prefabrication is environmentally friendly compared with traditional construction methods. Scenario S5 is conducted to explore the influences of a higher prefabrication rate on the total embodied carbon value.

The transformation relationship between the data quality grades and the probabilistic distributions of parameters is also an important factor in modeling [40]. In the base case, different weights of CVs for the five indicators are suggested based on the calculation principle of Ecoinvent. Therefore, scenario S7 will be discussed by using averaged additional CV ($\mathrm{CV}_{a,h}^2$) (Eq. (11)) for calculating additional uncertainty.

$$(\mathrm{CV}_a^2 + 1)^5 = \prod_{h=1}^{5}\left(\mathrm{CV}_{a,h}^2 + 1\right) \quad (11)$$

In order to explore the potential maximum embodied carbon reduction of prefabricated high-rise residential buildings in Hong Kong, possible combinations of the six sub-scenarios (S2a, S2b, S3, S4, S5, S6) defined in Table 4 are analyzed. S1 and S7 are excluded as these two scenarios only affect the embodied carbon calculation processes but have no influence on the selection of carbon reduction measures.

3.2.5 Case study

The case building refers to that in the previous study by Teng and Pan [44] and is a 30-story public rental housing (PRH) block developed by the Hong Kong Housing Authority (HKHA). The gross floor area (GFA) of the case building is 39501 m^2. The main body of the building employs a reinforced concrete structure with a standard layout which is regarded as the ‘Slab (Link I=180^o)’ type. It represents the status quo of the typical high-rise public housings in Hong Kong.

Engineering quantity related data were collected through face-to-face interviews and site surveys in the precast factory in Huizhou, China, and the construction site in Hong Kong. This factory supplies the precast concrete elements for the case building, and is a main factory for producing precast products for PRH in Hong Kong. Site survey in the factory included examining the manufacturing procedures of the precast products, the factory layout, the delivery routes among production lines, loading ways of each precast product, etc. Quantities of materials for each component, catalog of precast products, transportation distance and mode were collected from the relative documents. An interview was conducted with three production line workers and a factory manager for further investigating the carbon reduction potentials (e.g. selecting low carbon materials, changing the transportation mode or distance) from the technical and economic feasibility aspects. Similarly, another site survey on the construction site in Hong Kong was conducted to obtain data such as the material quantities, suppliers' address, the catalog and capacity of machinery, building drawings, BOQ, waste rate records. A followed interview was held with two structural engineers and a construction manager to determine the carbon reduction strategies during the construction stage (e.g. selecting local suppliers, the potential of reducing waste rate). Followed by the two-site surveys, a semi-structured interview was conducted with the design team for determining the building design-related carbon reduction potential (e.g. changing the thickness of walls or building layout). Emission factors were determined using Ecoinvent database embedded in the SimaPro software with adjustment of specific processes or parameters using local data (Table 5).

Table 5 Processes or parameters adjusted in SimaPro 9.0 database

Parameters	Specification	Adjustment
Electricity and Fuel	In-plant electricity consumption	Adjust the fuel mix of electricity in Mainland, China (China Energy Statistics Yearbook), and Hong Kong (CLP).

	In-plant fuel consumption	Select the process of 'Diesel, burned in building machine/GLO U' and adjust the amount of diesel consumption.
Transportation	Transportation distance	Adjust the transportation distance according to the suppliers' locations.
	Transportation mode	Select the transportation modes as 'Transport, lorry 3.5~16t', 'Transport, lorry, 16~32t', and 'Transport, refuse truck' for materials, precast products, and construction waste, respectively.
Construction materials	Concrete	Adjust the amount of gravel (aggregate), cement, tap water. Establish a 'precast concrete' parameter.
	Cement	Adjust the cement type to 'Portland cement, strength class Z 52.5, at plant/ CH U'.
	Steel	Establish the 'Steel framework of components' parameter.

4. Results and analyses

4.1 Analysis of the deterministic and stochastic embodied carbon

The deterministic embodied carbon of the case building is calculated at five levels of units of analysis, i.e. material, component, assembly, flat and building (Fig.2). The results show that the majority of the embodied carbon is generated by the production of cast-in-situ concrete (39.8%), steel (20.1%), and precast concrete (19.4%). It strengthens the importance of optimizing the manufacturing process of concrete and increasing the reusability of steel. This finding has also been strengthened by Cao et al. [11] and Teng et al. [1]. At the component level, staircases generate the highest embodied carbon per unit (average of 722 kg CO_2), followed by connecting slabs (average of 495 kg CO_2 per unit), slabs (average of 277 kg CO_2 per unit), and internal partitions (average of 217 kg CO_2 per unit). However, slabs and connecting slabs have a higher embodied carbon in total due to the higher number of them used throughout the building. At the assembly level, kitchens generate the largest amount of carbon emissions per element (average of 3156 kg CO_2 per unit), whereas facades and bathrooms have higher embodied carbon in total, since only a small number of kitchens are designed for the whole building. At the flat level, 2B has the highest contribution to the total embodied carbon (47%). However, 1B as the most embodied-carbon-friendly flat among the four types with averaged embodied carbon emissions as 418 kg CO_2/m^2. In total, the embodied carbon from material production and prefabrication, transportation, and onsite construction activities are 18383, 2062, and 1732 tCO_2, accounting for 82.9%, 9.3% and 7.8% of the total impacts respectively. The average embodied carbon of the case building is calculated as 561 kg CO_2/m^2. Transportation-related carbon in this paper is calculated higher than in other studies (e.g. 4.5% in the study of Zhang and Wang [51]; and 5% in that of Sandanayake et al. [52], which is caused by the increase in carbon generated by delivering precast products.

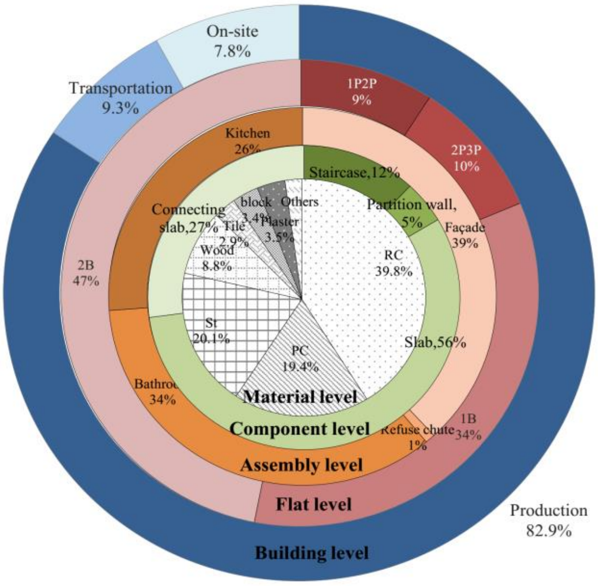


Fig.2 Deterministic embodied carbon percentage of the case building at five levels of unit of analysis

The deterministic embodied carbon results of this present paper were verified by cross-case comparison with the results of previous studies. Table 6 summarizes the embodied carbon results of high-rise concrete buildings in literature, including 8 residential buildings and 3 office buildings. The result (561 kg CO_2/m^2) obtained in this study is in line with the range of residential buildings with concrete structure provided in previous studies (336-836 kg CO_2/m^2), despite a small difference due to different system boundaries selection. For example, the embodied carbon of high-rise residential building in Hong Kong analyzed by Langston et al. [53] is 836 kg CO_2/m^2, much higher than that of other studies. This is due to the fact that a hybrid method used in this study is usually much higher than process-based results due to the systemic completeness and the risks of double counting. In addition, the buildings' carbon emissions estimated by Gan et al. [54] were lower than that reported in this paper because Gan et al. [54] only considered cradle-to-gate stages and structural materials. Should we subtract on-site assembly related emissions and carbon generated from non-structural materials, the embodied carbon of our study could decrease from 561 kg CO_2/m^2 to 410 kg CO_2/m^2, which is only 1% more than that reported by Gan et al. [54] (406 kg CO_2/m^2). The comparisons show that the results of this study are highly consistent with the results reported in literature.

Table 6 Embodied carbon emissions of high-rise concrete buildings

Year	Location	Type	Height	Floor area (m^2)	Embodied carbon (kgCO2/m2)	Method	Ref.
2019	Milan, Italy	R	44	20,000	413	P	[55]
2019	Chengdu, Mainland China	O	17	14431.3	488.53	P	[56]
2019	Guangdong, Mainland China	O	36	192,181	546	P	[57]
2018	Hong Kong	R	N.A.	25477	836	Hybrid	[53]
2018	Hong Kong	R	40	38360	406	p	[54]
2018	Hong Kong	R	40	33078	686.5	P	[58]
2017	London, UK	O	11	15,590	487.2	P	[59]
2016	Gaziantep, Turkey	R	13	7445	737	P	[60]
2015	Hong Kong	R	30	2880	669	P	[12]
2013	Shenzhen, Mainland China	R	N.A.	216,000	336	P	[50]
2011	Seoul, South Korea	R	35	14,424	462	P	[61]

Notes: R: residential building; O: office building; P: Process-based method; N.A.: Not specified.

The results of data quality evaluation are presented in Appendix A. Based on Table 3 and equations (6), (7), (8) and (9) the calculated variances and CVs are adopted to conduct the MCS implemented in the SimaPro 9.0 software (Fig. 3). According to Nguyen and Reiter [41], the sample size for MCS should be large enough but not be so significant to avoid the delay. The sample sizes are changed from 100 to 12000 with LHS according to data of the case building to develop the proper size. Based on the repeated sampling results (Appendix B) and previous studies [18, 19], a 10,000-sample size is used as the standard error of mean (SEM) is estimated as only 1% of SD. Overall, the SD of the embodied carbon of the total building is 2010 tCO_2, and the 95% confidence interval of the sample mean is [18800, 26600] tCO_2. The total CV within the embodied carbon assessment of the case building is 9% due to the parameter uncertainty, with CVs of 10.2%, 33.3%, and 21.2% for the processes of material manufacturing and prefabrication, transportation and construction, respectively. The relative error (RE) is 0.55%, showing that the calculated deterministic value is acceptable. The comparisons of sample mean of the stochastic analysis and deterministic results are presented at five levels in Fig.4, and these indicate that no significant error occurred during the simulation process.

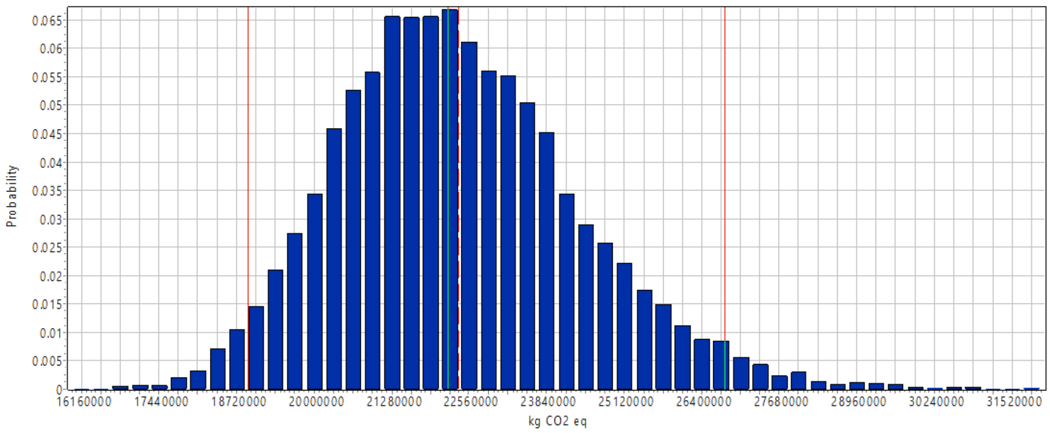
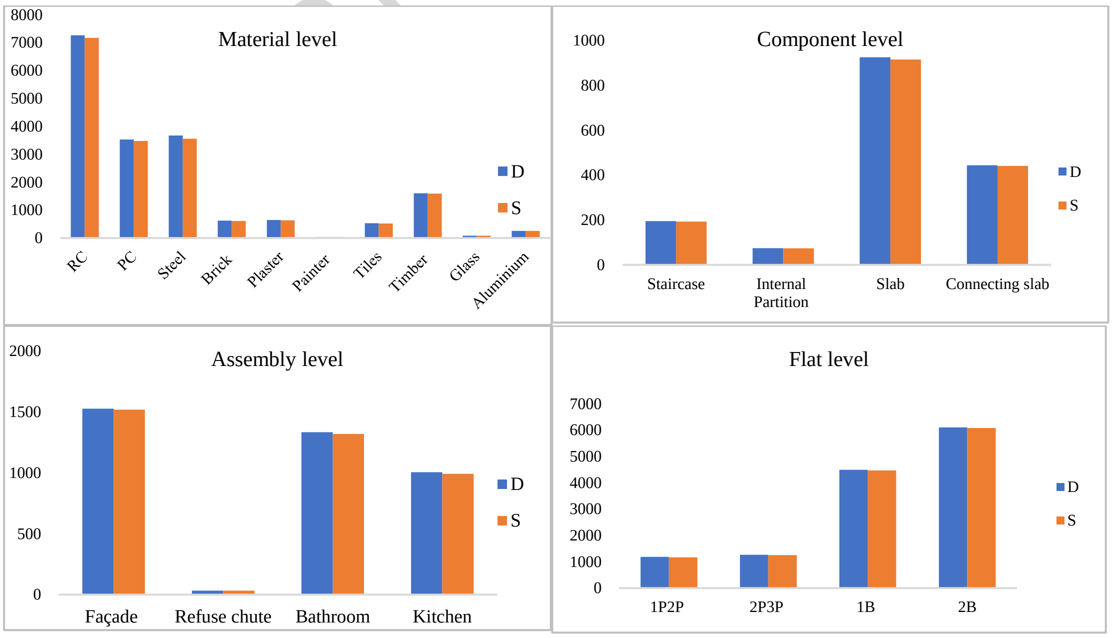


Fig. 3 Stochastic embodied carbon results of the case building (tCO_2)



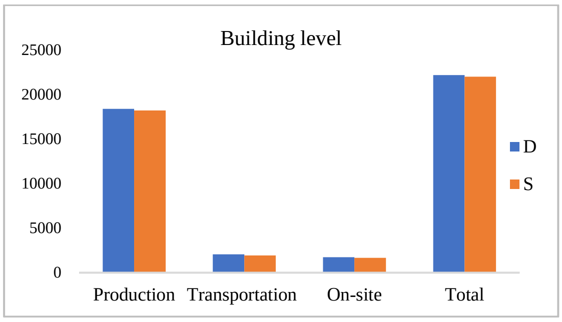


Fig. 4 Comparisons of stochastic sample mean and deterministic results at five-level unit of analysis (tCO_2)

4.2 Critical processes of building embodied carbon assessment

The critical processes, sorted by levels of material, component, assembly, flat and building, are identified in Fig. 5. At the material level, the manufacturing of concrete sees higher uncertainty (with the CV 15.6% for cast-in-situ concrete and 15.3% for precast concrete) since the ingredients of the concrete are different among companies in different regions and with different technologies. In addition, the CVs of steel and timber production are also higher than other materials, except for the concrete. Unlike other materials where the engineering quantities are directly collected from the BOQ, the quantities of steel and timber formwork are estimated by the managers through interviews. Therefore, when collecting the steel and timber data, attention should be paid to the parameter uncertainties. At the component level, the CVs of the four precast components are similar, whereas the slabs and connecting slabs generate a higher carbon within the whole building. At the assembly level, although the refuse chutes generate a much lower proportion of total embodied carbon, they suffer higher uncertainties than the other three elements. This is due to the fact that the refuse chutes have a higher ratio of concrete to steel. At the flat level, the CVs of the four residential units are similar, although they contribute differently to the total embodied carbon. At the building level, although the transportation and on-site assembly processes account for a lower carbon proportion, they are burdened with higher uncertainties. In particular, the CV of transportation carbon is as high as 33.4%, showing that greater attention should be paid when considering its data reliability. These findings are in line with the results proposed by Hong et al.[18] and Zhang and Wang [19], who highlighted the greater uncertainties in construction material and equipment transportation processes.

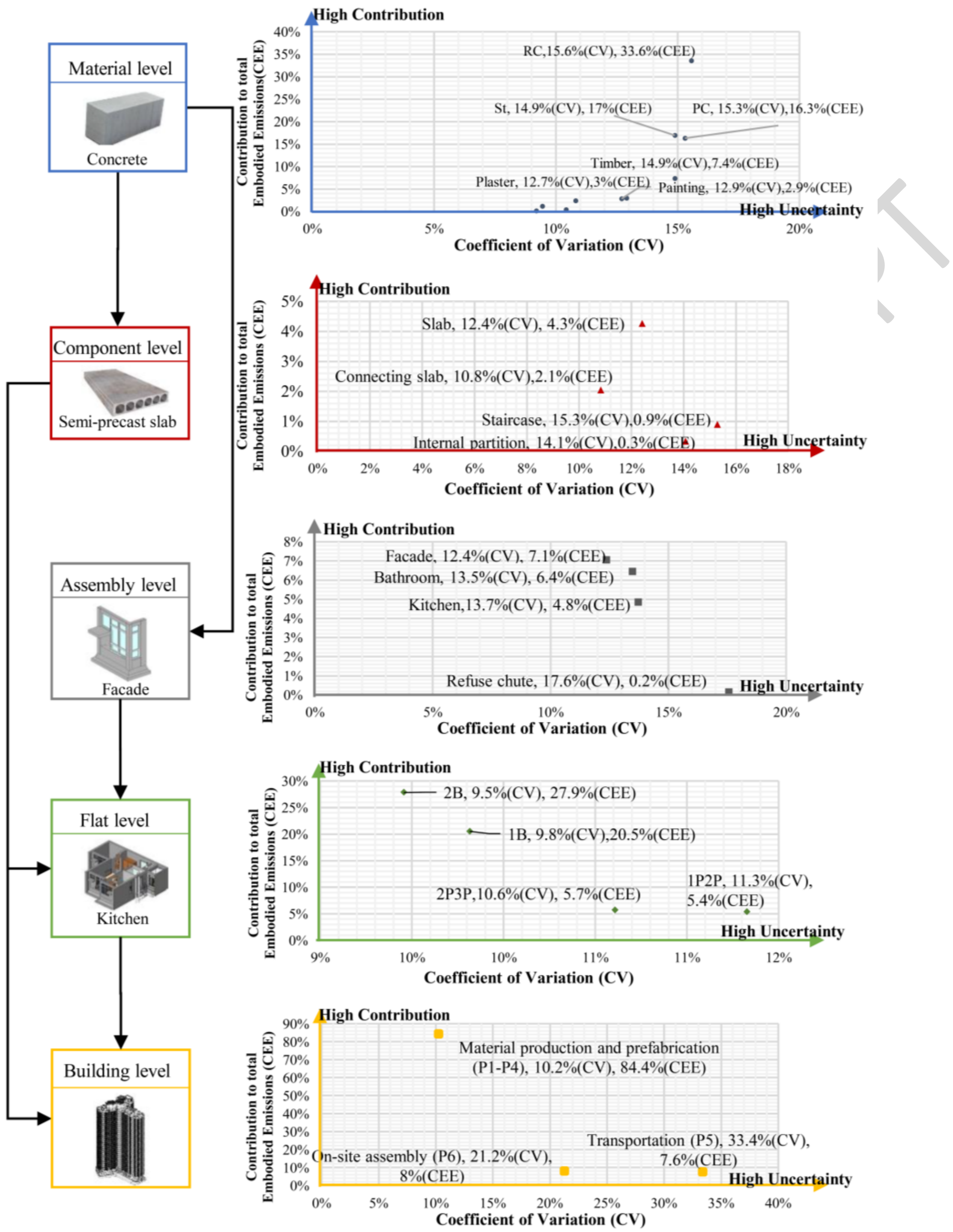


Fig.5 Critical process identification at the five levels of unit of analysis

4.3 Scenario analysis

The total embodied carbon of S1a is calculated as 21,330 tCO_2, which is 3.7 % lower than that of the base case, whereas the CV of S1a (9.2 %) is similar to that of the base case (9 %). This change causes underestimation of carbon emissions from production and transportation by 2.5% and 17.1%, respectively. S1b calculates an extended system boundary, which saw only 0.4% increased carbon because of the smaller impact of labor transportation, with parameter uncertainty calculated as 9%. This is the reason that emissions generated from human activities during transportation were scarcely considered in previous studies [62].

The results of S2a show that replacing 25% of the cement with PFA for concrete results in a 9.8% reduction in embodied carbon without increasing the parameter uncertainty (8.7%). In scenario S2b, by replacing ordinary Portland cement with blast furnace slag cement, a maximum 22.8% embodied carbon reduction can be achieved (with CV 9.2%).

In scenario S3, the results indicate that 1.9% embodied carbon reduction could possibly be achieved (with CV 9%) by decreasing the thickness of non-structural concrete block walls from 150 mm to 125 mm, and the thickness of load-bearing reinforced concrete walls from 200 to 175 mm, within the requirements of the Buildings Ordinance of Hong Kong.

The potential carbon reduction from a reduced waste rate results from the technological progress of prefabrication. The general waste rates under the baseline and good practice situations in the construction industry can be extracted from the Net Waste Tool developed by WRAP [63] (Table 7). Net Waste is a freely accessible web-based tool, where data are collected, summarized, and validated by using the combined methods including workshops with manufacturers/installers, professional reports, and questionnaires. Baseline wastage rates are from the professional judgments based upon the nature of the materials and application in the construction process, which are the figures for achieving minimum standards. Usually, these sources provide a range of values between which wastage rates are expected to fall without a fundamental change in working practice and are cost neutral, and these have been interpreted as providing 'good' practice wastage rates. Assumed waste rate under the good practice situation is achieved in Scenario S4, and the results show that embodied carbon is reduced by 5.3% (with CV 8.9%).

Table 7 Waste rates for materials at baseline and good practice

Material	Base Case	Baseline	Good practice
Aluminum	5%	15%	5%
Cast-in-Situ concrete	5%	5%	2.5%
Ceramics Tiles	10%	8%	5%
Concrete block	10%	20%	5%
Glass	7%	15%	5%
Gravel	5%	10%	5%
Other metal	5%	15%	5%
Painter	7%	5%	2.5%
Plaster	10%	5%	2.5%
Precast concrete	1%	1%	0%
Steel	7%	15%	5%
Timber	7%	10%	5%

Scenario S5 explores the influences of a higher prefabrication rate on the embodied carbon. However, this scenario shows less carbon reduction potential (1.5%) of the case building (with CV 9 %), when the prefabrication rate is increased from 35% to 45% (without significantly changing its structural stability).

Scenario S6 examines the carbon reduction potential when changing the transportation distance. Currently, prefabricated products for the case building are manufactured at different locations in Mainland China and then converge at the site in Hong Kong for installation. Therefore, Scenario 6 is designed by assuming that local manufacturers are selected for both the precast factory and construction site. Results indicate that a 7.8% reduction can be achieved when local suppliers are selected (with CV 7.9%).

Scenario S7 considers the effects caused by analytical uncertainty models. By adopting the averaged additional CV defined in Eq. (11), the mean value of S7 is nearly the same with the base case (Fig.6). However, the SD of sample results for S7 is 2,840 tCO_2, which is 41% higher than that of the base case, leading to results with different dispersion degree. Therefore, these transformation coefficients need to be carefully studied, and a unified standard should be developed to better quantify the uncertainties. The two-sample Kolmogorov-Smirnov (K-S) test is conducted to determine whether the difference of the two datasets is statistically significant. The two samples are combined and sorted to compute the empirical cumulative distribution function (CDF). The maximum absolute difference of the two observed distribution functions is calculated as 0.0995 (Appendix C).

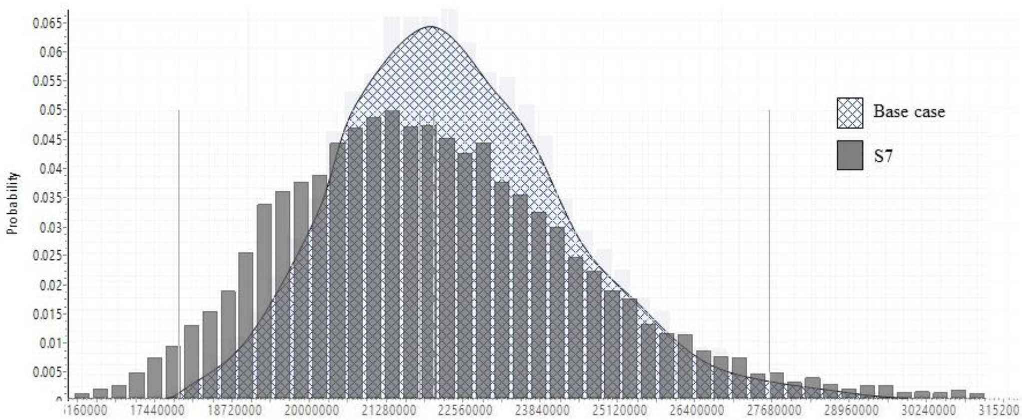


Fig.6 Comparison of the distribution of embodied carbon (tCO_2) of the base case and S7

4.4 Possible maximum embodied carbon reduction of prefabricated buildings

The possible combinations generate 41 different situations (Fig.7), and their carbon reduction ranges are analyzed in Fig.8. Fig.7 presents the embodied carbon results of these combinations from the manufacturing and prefabrication, transportation and construction, respectively. The areas in Fig.8 indicate the sensitivity of the values from the six pre-defined scenarios (S2a, S2b, S3, S4, S5, S6) and 41 situations to the total embodied carbon of the case building. The results show that the embodied carbon reduction range can be from 1.5% to 31.6%. The higher reduction potential is achieved mainly through decreased carbon generated from material manufacturing and prefabrication, as well as transportation, whereas on-site assembly has a smaller impact.

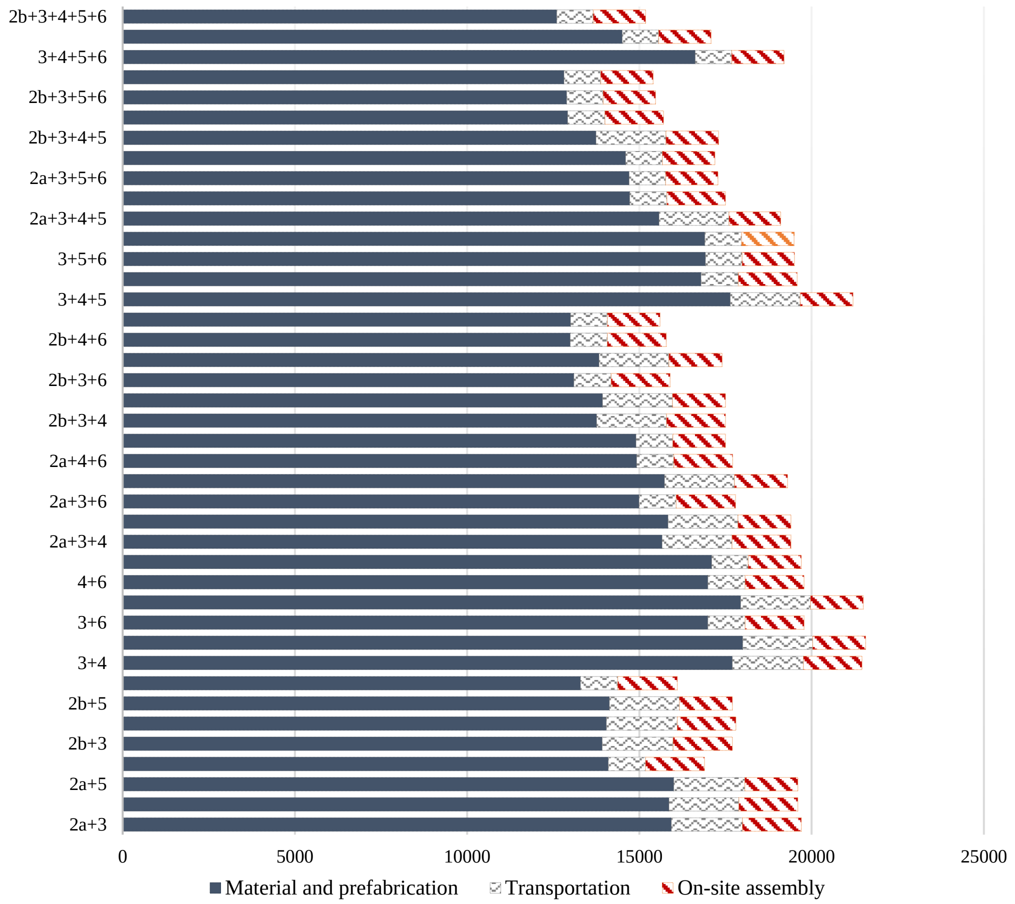


Fig.7 Embodied carbon results of different combinations; (Codes used in Table 4)

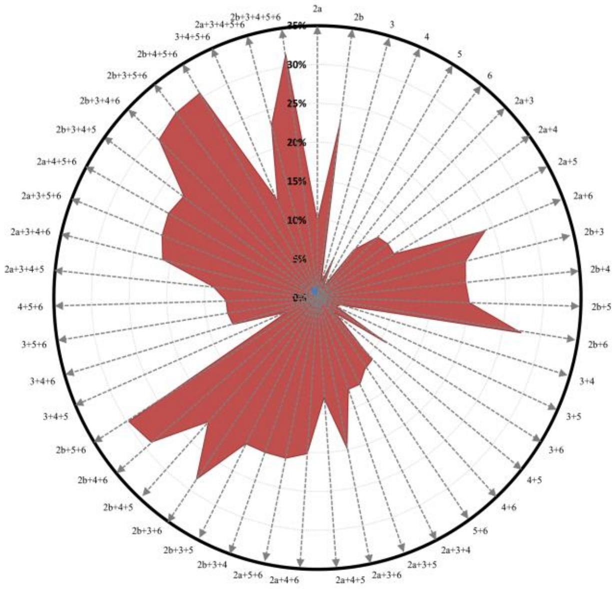


Fig.8 Sensitivity of the embodied carbon of buildings under different scenarios and combinations

5. Discussion

Traditionally, critical carbon-intensive processes are identified solely based on their contributions to the total embodied carbon. However, the uncertainties caused by errors in input parameters, as well as the selection of different assumptions and analytical uncertainty models, have seldom been considered. This paper examines the embodied carbon of prefabricated high-rise buildings in Hong Kong at five-level units of analysis, taking the uncertainties (i.e. parameter, scenario, and model uncertainty) into consideration. To elicit the findings, the results are discussed below.

First, conducting parameter uncertainty analysis in embodied carbon assessment is helpful to avoid misinterpretation of the results. Traditionally, the production of concrete and steel have both been recognized as critical carbon contributors [64] due to their carbon-intensive manufacturing activities and high volumes used. This paper indicates that timber is also an important parameter when considering uncertainty, as timber formwork engineering quantities were estimated through interviews, and were based on their turnover rate. In addition, calculated transportation emissions present higher uncertainty (33.4%), although they contribute only 7.6% to the total embodied carbon. However, such transportation-related activity is ignored previously due to its lower proportion [50].

Second, the different selections of scenarios result in a wide range of alternative outcomes for embodied carbon assessment, hindering efficient comparison between different studies. In particular, the selection of materials significantly affects the carbon results with only a part of their ingredients is changed [65]. A remarkable variability still exists among different embodied carbon assessment studies. For example, Pomponi and Moncaster [66] point out that variations between the embodied carbon of concrete and recycled steel, as shown in previous case studies, has been as high as 894% and 1044%, respectively. Such variations may be caused by the different technological and geographical correlations of the collected data, as well as the ingredients of specific materials, for which suitable adjustment and modifications should be considered to reduce the misinterpretation when different cases are directly compared. In particular, the regional specificity of emission factors has seldomly been considered, which presents weaknesses in geographical representativeness if there is no relevant adjustment made. The applicable situations of the emission factors should be appropriately indicated and an official emission factor database applicable within Hong Kong is thus needed.

Third, the uncertainty analytical model uncertainty analyzed in this paper (S7) implies that the results of uncertainty analysis are highly influenced by the transformation coefficients between the data quality index (DQI) and the distribution parameter. Although semi-quantitative DQI-based uncertainty analysis is feasible for the embodied carbon assessment of prefabricated buildings, transformation coefficients have to be carefully studied, evaluated, and standardized according to the unique situation of Hong Kong. To better quantify such uncertainties, it is urgent that a unified standard is set by a widely recognized organization or by the Hong Kong government.

Fourth, there is great potential for reducing the high-rise buildings' embodied carbon in Hong Kong (as high as 31.6%). The maximum carbon reduction can be achieved by together replacing ordinary Portland cement with blast furnace slag cement (S2b), decreasing the thickness of walls (S3), reducing the waste rates of materials based on good practice (S4), increasing the prefabrication rate (S5) and adopting local suppliers (S6). The results indicate that adopting low carbon concrete has higher carbon reduction potential compared with other measures, which has also been advocated by a range of previous studies [67]. Limited reduction potential can be achieved by emission-optimized design (1.9% reduction for decreased thickness of non-structural concrete block walls and load-bearing reinforced concrete walls, and 1.5% reduction for an increased prefabrication rate) if the structure or layout of a building has not been significantly changed. Although previous studies have pointed out that optimization of the layout design (e.g. columns dimensions and reinforcement bar diameters and spacing) [68] and selection of structural forms (e.g. core-outrigger structural form for high-rise buildings) might have higher embodied carbon reduction potentials [69], these measures were rejected during the on-site interviews with structural engineers since they did not currently want to take the risks. The selection of local suppliers has a considerable carbon reduction potential (7.6%). This measure was also highlighted by Zhang and Wang [19], showing that transportation emission is 5.6 times higher when changing from local suppliers to those in another city. However, the adoption of local manufacturers will be challenging in the short term, since moving the production lines of precast products to Hong Kong is difficult. A balance has to be made in choosing a low carbon option by comprehensively considering the availability of low carbon materials and their transport requirements. Reducing the waste rates of materials has a 5.4% carbon reduction potential, and this finding is consistent with that of Hong et al. [18], who proposed that carbon savings from waste reduction and building quality improvement could range from 4% to 14%. This strengthens the importance of waste management, not just from the aspect of cost reduction, but for the environmental benefits too. However, close attention should also be paid when integrating different measures together. For example, obtaining low carbon materials from sources far away may actually lead to higher emissions.

6. Conclusions

This paper examines the impacts of parameter, scenario, and analytical model uncertainty on the embodied carbon assessment of typical prefabricated high-rise residential buildings in Hong Kong. The average embodied carbon of the case building during the cradle-to-end-of-construction phases is calculated as 561 kg CO_2/m^2, mainly generating from the material manufacturing and prefabrication processes.

The paper first concludes that the five-level framework, that is, material, component, assembly, flat and building, promotes a systemic way for calculating and reporting on the embodied carbon of prefabricated buildings. Traditionally, a building's embodied carbon is calculated by adding together each time all the emissions generated from materials and energy consumption, which is inefficient and makes it difficult to compare with other cases. This complicated calculation process hinders the willingness of designers to consider embodied carbon reduction as an indicator during the design stage. This paper pushes the embodied carbon assessment of prefabricated buildings in a new and innovative direction, and lays a theoretical foundation for the government to establish a multi-level carbon inventory or database of prefabricated buildings for achieving more accurate and effective comparisons and benchmarking.

The paper's second conclusion is that a combined data quality index (DQI) based Monte Carlo Simulation (MCS) method can better facilitate analysis of parameter uncertainty in a building's embodied carbon evaluation, which should help to improve the reliability of embodied carbon assessment. The results of parameter uncertainty analysis are presented following the five-level framework, and these show that certain other activities need to be further examined, even though they have a low contribution to the total emissions. The paper explores the feasibility of semi-quantitative methods to conduct an uncertainty analysis of a prefabricated building's embodied carbon assessment at different levels. It also examines key activities that have been overlooked in traditional contribution-oriented analyses.

The third conclusion is that a wide range of alternative outcomes will be caused due to the uncertainties within different scenarios and analytical uncertainty models, which hampers effective cross-case comparison and unification. However, the parameter uncertainty is usually the only type of uncertainty addressed in previous studies due to its most commonly recognized form, whereas the scenario and model uncertainty of embodied carbon assessments have not been satisfactorily considered. In particular, decisions concerning material selection will significantly affect the total embodied carbon. However, in a wide range of studies the specific ingredients, the clear technological and geographical data about the materials, were seldom presented, thus increasing the risk of misinterpretation of the results, which should thus be carefully handled before doing the comparison studies. The model uncertainty analysis indicates that variance between the carbon results is highly correlated with the transformation coefficient between the DQIs and the distributions. for conducting an uncertainty analysis. It is thus necessary to explore a unified uncertainty analysis model of a prefabricated building in Hong Kong. Overall, the results of scenario analyses will be useful for the decision making involved in selecting system boundaries, analytical mathematical uncertainty models, and will therefore provide new insights into emission reduction policies and benefit the application of uncertainty analysis.

The fourth conclusion is that the embodied carbon of prefabricated buildings in Hong Kong can potentially be reduced as much as 31.6% by combining the influences of six pre-defined sub-scenarios. It should be noted that, although 41 possible measures are discussed, it is not suggested to make decisions in a particular sequence (e.g. from the highest carbon reduction situation to the lowest one). Designers should consider the practical situations case by case (e.g. the availability of low carbon materials, the feasibility of accessing a local supplier). However, the paper provides possible directions for reducing embodied carbon, and also examines the potential extents of reduction. Government and practitioners can evaluate the efforts and effects when adopting various low carbon measures. This will help to accelerate the establishment of a policy to integrate low carbon indicators into building design decision making. In particular, Hong Kong has set an ambitious carbon intensity reduction target of 65% to 70% (26%~36% absolute reduction) by 2030, using 2005 as the base, and to reach nearly net-zero around 2050 for fulfilling its obligations under the Paris Agreement. Current decarbonization plans in Hong Kong mainly include phasing down coal-fired fuel mix for electricity generation (from 48% to 25%) and replacing it with natural gas, which will enable Hong Kong to reduce its carbon intensity by 50% (20% absolute reduction) by 2020. However, achieving the net-zero target is still challenging, and thus requires sustained efforts from all the sectors in various aspects over the decades. The explored embodied carbon reduction measures will help to fill the gaps to some extent, since embodied carbon accounts for around 15% to 20% within the life cycle carbon emissions of residential buildings in Hong Kong.

Future research should further investigate the statistical distributions of the critical parameters with a view to improving the reliability of model uncertainty results. Exploration of the dynamic relationships between different low carbon measures is also recommended. Furthermore, exploration of high-tech integrated tools for automated data collecting and processing can accelerate embodied carbon calculation, which is currently labor-intensive. This will support the implementation of regulations to incorporate carbon reduction as a criterion in building design decision making.

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8. References

[1] Y. Teng, K. Li, W. Pan, T. Ng, Reducing building life cycle carbon emissions through prefabrication: Evidence from and gaps in empirical studies, Build. Environ. 132 (2018) 125–136.
[2] B. Lˇpez-Mesa, A. Tomßs, T. Gallego, Comparison of environmental impacts of building structures with in situ cast floors and with precast concrete floors, Build. Environ. 44, no. 4 (2009) 699-712.
[3] G.F. Menzies, S. Turan, P.F. Banfill, Life-cycle assessment and embodied energy: a review. *Proc. Inst. Civ. Eng - Constr. Mater.* 160, no. 4 (2007) 135-143.
[4] A. Hollberg, T. Lützkendorf, G.J.B. Habert, Top-down or bottom-up? How environmental benchmarks can support the design process, Build. Environ. 153 (2019) 148–157.
[5] W. Pan, M. Pan, A dialectical system framework of zero carbon emission building policy for high-rise high-density cities: Perspectives from Hong Kong. J. Clean Prod. 205 (2018) 1-13.
[6] THB. 2013. Modular Flat Design for public housing development of the Hong Kong Housing Authority, Legislative Council Panel on Housing, *Transport and Housing Bureau*, Hong Kong.
[7] P. Chastas, T. Theodosiou, K.J. Kontoleon, D. Bikas, Normalising and assessing carbon emissions in the building sector: A review on the embodied CO2 emissions of residential buildings, Build. Environ. 130 (2018) 212–226.
[8] W. Pan, K. Li, Y. Teng, Rethinking system boundaries of the life cycle carbon emissions of buildings. Renew. Sustain. Energy Rev. 90 (2018) 379-390.

[9] M.N. Nwodo, C.J. Anumba, A review of life cycle assessment of buildings using a systematic approach. Build. Environ. (2019) 106290.
[10] A. G. GIBB, Off-site fabrication: prefabrication, pre-assembly and modularisation, *John Wiley & Sons, (1999).*
[11] X. Cao, X. Li, Y. Zhu, Z. Zhang, A comparative study of environmental performance between prefabricated and traditional residential buildings in China. J. Clean Prod. 109 (2015) 131-143.
[12] Y.H. Dong, L. Jaillon, P. Chu, C.S. Poon, Comparing carbon emissions of precast and cast-in-situ construction methods–A case study of high-rise private building. Constr. Build. Mater. 99 (2015) 39-53.
[13] Y. Ji, K. Li, G. Liu, A. Shrestha,J. Jing, Comparing greenhouse gas emissions of precast in-situ and conventional construction methods. J. Clean Prod. 173 (2018) 124-134.
[14] O.F. Kofoworola, S.H. Gheewala, Environmental life cycle assessment of a commercial office building in Thailand. Int. J. Life Cycle Assess.13, no. 6 (2008) 498.
[15] Z. Yeo, R. Ng, B. Song, Technique for quantification of embodied carbon footprint of construction projects using probabilistic emission factor estimators. J. Clean Prod. 119 (2016) 135-151.
[16] J. Hong, G.Q. Shen, C. Mao, Z. Li, K. Li, Life-cycle energy analysis of prefabricated building components: an input–output-based hybrid model. J. Clean Prod. 112 (2016) 2198-2207.
[17] M. Huijbregts, R. Heijungs, S. Hellweg, Complexity and integrated resource management: Uncertainty in LCA. Int. J. Life Cycle Assess. 9, no. 5 (2004) 341-342.
[18] J. Hong, G.Q. Shen, Y. Peng, Y. Feng, C. Mao, Uncertainty analysis for measuring greenhouse gas emissions in the building construction phase: a case study in China. J. Clean Prod. 129 (2016) 183-195.
[19] X. Zhang, F. Wang, Stochastic analysis of embodied emissions of building construction: A comparative case study in China. Energy Build. 151(2017) 574-584.
[20] E. Cherubini, D. Franco, G.M. Zanghelini, S.R. Soares, Uncertainty in LCA case study due to allocation approaches and life cycle impact assessment methods. The Int. J. Life Cycle Assess. 23, no. 10 (2018) 2055-2070.
[21] S.M. Lloyd, R. Ries, Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: A survey of quantitative approaches. J. Ind. Ecol. 11, no. 1 (2007) 161-179.
[22] E. D. Williams, C. L. Weber, T. R. Hawkins, Hybrid framework for managing uncertainty in life cycle inventories. J. Ind. Ecol. 13, no. 6 (2009) 928-944.
[23] M. Cellura, S. Longo, M. Mistretta, Sensitivity analysis to quantify uncertainty in life cycle assessment: the case study of an Italian tile, Renew. Sustain. Energy Rev. 15, no.9 (2011) 4697-4705.
[24] B.P. Weidema, M.S. Wesnaes, Data quality management for life cycle inventories—an example of using data quality indicators. J. Clean Prod. 3-4 (1996) 167-174.
[25] B.P.Weidema, Multi-user test of the data quality matrix for product life cycle inventory data. Int. J. Life Cycle Assess. 3, no. 5 (1998) 259-265.
[26] D.J. Kennedy, D.C. Montgomery, B.H. Quay, Data quality. Int. J. Life Cycle Assess. 1, no. 4 (1996):199-207.
[27] R. Coulon, V. Camobreco, H. Teulon, J. Besnainou, Data quality and uncertainty in LCI. Int. J. Life Cycle Assess. 2, no.3 (1997) 178.
[28] S. De Wit, G. Augenbroe, Analysis of uncertainty in building design evaluations and its implications. Energy Build. 34, no. 9 (2002): 951-958.
[29] J.D. Silvestre, A. Silva, J. de Brito, Uncertainty modelling of service life and environmental performance to reduce risk in building design decisions. J. Civ. Eng. Manag. 21, no. 3 (2015): 308-322.

[30] A. Weckenmann, A. Schwan, Environmental life cycle assessment with support of fuzzy-sets. Int. J. Life Cycle Assess. 6, no. 1 (2001) 13.
[31] J.L. Chevalier, J.F. Le Téno, Life cycle analysis with ill-defined data and its application to building products. Int. J. Life Cycle Assess. 1, no.2 (1996) 90-96.
[32] R.R.Tan, A.B.Culaba, M.R. Purvis, Application of possibility theory in the life-cycle inventory assessment of biofuels. International Journal of Energy Research. 26, no. 8 (2002) 737-745.
[33] X. Zhang, R. Zheng, F. Wang, Uncertainty in the life cycle assessment of building emissions: A comparative case study of stochastic approaches. Build. Environ. 147 (2019) 121-131.
[34] M.A. Huijbregts, 1998. Application of uncertainty and variability in LCA. Int. J. Life Cycle Assess. 3, no. 5 (1998) 273.
[35] ISO. BSI EN ISO 14044: Environmental management – life cycle assessment – requirement and guidelines; 200 (2006).
[36] BSI, 2011. PAS 2050. Specification for the assessment of the life cycle greenhouse gas emissions of goods and services. British Standards Institution, London. 2011.
[37] BSI, BS EN 15978. Sustainability of construction works– assessment of environmental performance of buildings–calculation method. British Standards Institution, London. 2011.
[38] W. Pan, K. Li, Y. Teng, Life-cycle carbon assessment of prefabricated buildings: challenges and solutions. Proc. Inst. Civ. Eng-Eng. Sustain. 172, no.1 (2018) 3-8.
[39] B.P. Weidema, C. Bauer, R. Hischier, C.Mutel, T. Nemecek, , J. Reinhard, C.O. Vadenbo, G. Wernet, Overview and methodology: Data quality guideline for the ecoinvent database version 3. (2013). Available at: https://www.ecoinvent.org/files/dataqualityguidelineecoinvent_3_20130506.pdf (Accessed: January, 2020).
[40] S. Muller, P. Lesage, A. Ciroth, C. Mutel, B.P. Weidema, R. Samson, The application of the pedigree approach to the distributions foreseen in ecoinvent v3. Int. J. Life Cycle Assess. 21, no. 9 (2016): 1327-1337.
[41] A.T. Nguyen, S.Reiter, December. A performance comparison of sensitivity analysis methods for building energy models. Build. Simul. 8, no. 6 (2015) 651-664.
[42] M.J. González, J.G.Navarro, Assessment of the decrease of CO2 emissions in the construction field through the selection of materials: practical case study of three houses of low environmental impact. Build. Environ. 4, no. 7 (2006) 902-909.
[43] K. Negishi, A.Lebert, D. Almeida, J. Chevalier, L. Tiruta-Barna, Evaluating climate change pathways through a building's lifecycle based on Dynamic Life Cycle Assessment. Build. Environ. 164 (2019)106377.
[44] Y. Teng, W. Pan, Systematic embodied carbon assessment and reduction of prefabricated high-rise public residential buildings in Hong Kong. J. Clean. Prod. 238, (2019) 117791.
[45] S. Eleftheriadis, P. Duffour, P. Greening, J. James, B. Stephenson, D. Mumovic, Investigating relationships between cost and CO2 emissions in reinforced concrete structures using a BIM-based design optimisation approach. Energy Build. 166 (2018) 330-346.
[46] S. Martinez, M. del Mar Delgado, R.M. Marin, S. Alvarez, The Environmental Footprint of the end-of-life phase of a dam through a hybrid-MRIO analysis, Build. Environ. 146 (2018) 143-151.
[47] L. Aye, T. Ngo, R.H. Crawford, R. Gammampila, P. Mendis, Life cycle greenhouse gas emissions and energy analysis of prefabricated reusable building modules. Energy Build. 47 (2012) 159-168.
[48] M.U. Hossain, C.S. Poon, Global warming potential and energy consumption of temporary works in building construction: A case study in Hong Kong, Build. Environ. 142 (2018) 171–179.

[49] A.Meneghelli, Whole-building embodied carbon of a North American LEED-certified library: Sensitivity analysis of the environmental impact of buildings materials. Build. Environ. 134 (2018) 230-241.
[50] C. Mao, Q. Shen, L. Shen, L. Tang, Comparative study of greenhouse gas emissions between off-site prefabrication and conventional construction methods: Two case studies of residential projects, Energy Build. 66 (2013) 165-176.
[51] X. Zhang, F. Wang, Analysis of embodied carbon in the building life cycle considering the temporal perspectives of emissions: a case study in China. Energy Build. 155 (2017) 404-413.
[52] M. Sandanayake, G. Zhang, S. Setunge, A comparative method of air emission impact assessment for building construction activities, Environ. Impact Assess. Rev. 68 (2018)1-9.
[53] C. Langston, E.H. Chan, E.H. Yung, Hybrid input-output analysis of embodied carbon and construction cost differences between new-build and refurbished projects, Sustainability. 10(9) (2018) 3229.
[54] V.J. Gan, M. Deng, K.T. Tse, C.M. Chan, I.M. Lo, J.C. Cheng, Holistic BIM framework for sustainable low carbon design of high-rise buildings, *J. Clean. Prod.* 195 (2018) 1091-1104.
[55] E. Sicignano, G. Di Ruocco, R.J.S. Melella, Mitigation Strategies for Reduction of Embodied Energy and Carbon, in the Construction Systems of Contemporary Quality Architecture, Sustainability. 11(14) (2019) 3806.
[56] M. Sandanayake, W. Luo, G.J.S.C. Zhang, Direct and indirect impact assessment in off-site construction—A case study in China, Sust. Cities Soc. 48 (2019) 101520.
[57] H. Li, Q. Deng, J. Zhang, B. Xia, M. Skitmore, Assessing the life cycle CO2 emissions of reinforced concrete structures: Four cases from China, *J. Clean. Prod.* 210 (2019) 1496-1506.
[58] S.Y. Yim, S.T. Ng, M. Hossain, J.M. Wong, Comprehensive evaluation of carbon emissions for the development of high-rise residential building, *Buildings*. 8(11) (2018) 147.
[59] A. Azzouz, M. Borchers, J. Moreira, A. Mavrogianni, Life cycle assessment of energy conservation measures during early stage office building design: A case study in London, UK, Energy Build. 139 (2017) 547-568.
[60] A. Atmaca, Life-cycle assessment and cost analysis of residential buildings in South East of Turkey: part 2—a case study. Int. J. Life Cycle Assess. *21*(7), pp.925-942.
[61] S. Tae, C. Baek, S. Shin, Life cycle CO2 evaluation on reinforced concrete structures with high-strength concrete, Environ. Impact Assess. Rev. 31(3) (2011) 253-260.
[62] M.K. Dixit, C.H. Culp, J.L. Fernández-Solís, System boundary for embodied energy in buildings: A conceptual model for definition. Renew. Sustain. Energy Rev. 21 (2013)153-164.
[63] WRAP, Net Waste Tool. http://nwtool.wrap.org.uk/Documents/WRAP%20NW%20Tool%20Data%20Report.pdf , 2008 (Accessed: January, 2020).
[64] M.L. Pannier, P. Schalbart, B. Peuportier, Comprehensive assessment of sensitivity analysis methods for the identification of influential factors in building life cycle assessment, J. Clean Prod.199 (2018) 466-480.
[65] P. Wu, Y. Song, J. Zhu, R. Chang, Analyzing the influence factors of the carbon emissions from China's building and construction industry from 2000 to 2015, J. Clean Prod. 221 (2019) 552-566.
[66] F. Pomponi, A. Moncaster, Scrutinising embodied carbon in buildings: The next performance gap made manifest. Renew. Sustain. Energy Rev. 81 (2018) 2431-2442.
[67] V.J. Gan, J.C. Cheng, I.M. Lo, A comprehensive approach to mitigation of embodied carbon in reinforced concrete buildings, J. Clean Prod. 229 (2019) 582-597.
[68] T. Malmqvist, M. Nehasilova, A. Moncaster, H. Birgisdottir, F.N. Rasmussen, A.H. Wiberg, J. Potting, Design and construction strategies for reducing embodied impacts from buildings–Case study analysis. Energy Build. 166 (2018) 35-47.

[69] V.J. Gan, C.M. Chan, K.T. Tse, I.M. Lo, J.C. Cheng, A comparative analysis of embodied carbon in high-rise buildings regarding different design parameters, J. Clean Prod.161 (2017) 663-675.