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Quantification of uncertainty in product stage embodied carbon calculations for buildings

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Abstract

Decarbonisation of the energy industry and enforcement of strict targets for operational energy consumption means that non-operational greenhouse gases (GHG) emissions, also known as embodied carbon (EC), will soon represent the majority of whole life carbon associated with buildings. EC assessments are often presented as deterministic, single-point values but contain a high degree of variability which is typically unacknowledged. Common sources of uncertainty are variability, data gaps, measurement error and epistemic uncertainty such as absence of detailed material specification (e.g. manufacturer, concrete mix, recycled content etc). Particularly during early design stages when such information is unconfirmed, average material data is used by necessity. While some material databases and LCA software can provide ranges of embodied carbon coefficients (ECC) between some materials and/or the uncertainty within individual manufacturers' carbon data, the practice of reporting this is uncommon and has limited practicality for whole building assessments.

This paper presents a simple procedure that selects the highest impact materials of the EC of an asset and implements a Monte-Carlo simulation to estimate the uncertainty behind the product stage EC assessment. Material coefficients of variation (CoV) are obtained from database values where available, and interpolated values are used in the absence of such data.

A product stage EC assessment of a UK educational building, initially undertaken using single data points for each material, gave an EC prediction of 525 $kgCO_2e/m^2$ GIFA. Two scenarios were then assessed using our proposed procedure: 1) the full building scope and 2) substructure and superstructure only.

It was demonstrated that, for scenario one, the EC can range from 50-140% of the original result when considering the extreme results from the Monte-Carlo simulation. Scenario one (considering the full building scope) resulted in an average EC value (mean ± CoV) of 526 $kgCO_2e/m^2$ GIFA±10.0%. The second scenario (sub- and super-structure only) resulted in an average EC value of 312 $kgCO_2e/m^2$ GIFA ± 11.9% with a full range of 45-155% of the original result.

This paper shows that a straightforward uncertainty analysis procedure can support designers in understanding the possible range of asset product-stage EC and, therefore, inform construction product selections at an early stage where detailed information is not known. The variation also gives a degree of confidence/caution in the average EC prediction in lieu of a single-point result. The construction product CoV results can be used to set target ECCs on projects to help ensure reliable low-carbon products are specified. If these target ECCs were met, a minimum of 29% and 33% (excl. EPD uncertainty) in product stage EC reductions could be achieved. Future work should extend this method to include additional life cycle assessment (LCA) stages and other uncertainty factors. And, the method could be applied to comparative life cycle assessments and optioneering exercises, as well as including more specific construction product variability data.

1 Introduction

In order to achieve the Paris Climate agreement targets by 2050, the UK construction sector must drastically reduce its greenhouse gases (GHG) emissions. The GHG emissions associated with buildings refer to only 100-year global warming potentials (GWP) measured in kilograms of carbon dioxide equivalent (kgCO2e) and are divided into operational and embodied impacts. In this paper, GHG emissions are referred to as “carbon”, as defined in PAS 2080 (BSI, 2016). Decarbonisation of the energy supply system and the improvement of building energy performance means that operational carbon are decreasing, and that non-operational carbon (embodied carbon) will soon represent the majority of whole life carbon associated with buildings. For example, embodied carbon (EC) can make up 67% of the whole life carbon of a typical office building (RICS, 2014). This shift in focus will require assessments to demonstrate whether assets are net zero carbon, as defined by Twinn et al. (2019), with clear reporting of assumed assessment scope, material data sources, life cycle assessment (LCA) boundary and reference study period (RICS, 2017).

Each of these estimations introduces variability into EC predictions, but assessment results are often reported as a single deterministic value without acknowledging the range of uncertainty. Other sources of uncertainty in life-cycle assessments (LCA) include, but are not limited to, data accuracy, data gaps unrepresentative data, spatial and temporary variability and epistemic uncertainty (Björklund, 2002), and can broadly be categorised into three categories - parameter (input data such as quantities and material carbon data), scenario (normative choices such as future scenarios) and model (mathematical relationships) (Lloyd and Ries, 2007).Uncertainty can refer to both random and systematic error (measurement uncertainty) and unknowns caused by limited data and knowledge (epistemic uncertainty) (Björklund, 2002). Variability can be linked to geographical, environmental and temporal differences and can be improved by better sampling but not reduced (Björklund, 2002). In addition, errors due to simplified calculations (including incomplete scopes and LCA boundaries) and approximations are also sources of uncertainty. For a comprehensive list of uncertainty types, please refer to Björklund (2002) and Lloyd and Ries (2007). This paper deals with epistemic uncertainty where detailed material information (such as specification, manufacturer, performance characteristics) is unknown and/or unavailable.

Carbon assessments, in accordance with BS EN 15978:2011 (BSI, 2011) for buildings (currently under revision) and BS EN 15804:2012+A2:2019 (BSI, 2019) for products, are becoming more common amongst practitioners. This has been driven, in part, by the release of industry guidance documents with a focus on whole life carbon assessments for buildings (RICS, 2017) and the incorporation of EC into client briefs (UKGBC, 2017). Best practice relies on the comparison against EC case studies and industry databases to benchmark and verify the performance of projects. However, this is challenging due to a sparsity in both case studies and sufficiently detailed reporting, including material data sources. Within the material carbon data, there is also a lack of consistent environmental product declarations (EPDs), despite the presence of product category rules (PCR). Consequently, access to data, lack of standardisation and data transparency have been identified as issues with EC assessments for buildings (Giesekam and Pomponi, 2017), and mean that quantification of uncertainty is rare.

In order to accurately inform reduction strategies on projects, designers require a good quality baseline estimate of EC and, ideally, an appreciation of the potential variation in EC results. This is important both in cases where the design is “fixed” (during or post-tender) and most products and materials are confirmed but also in early stage estimates where the final material information is unknown and there are multiple design options (e.g. steel vs. concrete frame). In the latter case, designers may apply a specific manufacturer EPD upfront before this is confirmed. There is substantial variation in manufacturing global warming potential (GWP in kgCO_2e per functional unit) of common structural material EPDs, with the ratio of maximum to minimum GWP ranging from 284 - 1044% in different materials and can be due to regional, process and material specification differences (Pomponi and Moncaster, 2018). In addition, oversight (quality control), inconsistent functional units, allocation rules and transparency have been identified as key reasons for the lack of comparability (and, hence, variation) in EPDs (Gelowitz and McArthur, 2017).This can lead to unrealistic predictions of EC in comparison to the final constructed building and incorporating a range of EPD data into assessments, by using statistical measures of uncertainty such as coefficient of variation (CoV), would help to mitigate this.

Product stage EC, emissions associated with raw material extraction and manufacturing, often represents the majority of EC across multiple building typologies over 60-years (Zhang and Wang, 2016, Pomponi et al., 2018, London Energy Transformation Initiative, 2020). Building elements with high in-use replacement rates, such as services and equipment, can make up a significant proportion of whole life carbon – particularly where long life spans are considered (Sturgis, 2017, Pomponi et al., 2018). However, the structure (sub-structure and superstructure) is often the largest contributor to product stage EC in new buildings, (Kaethner and Burridge, 2012, London Energy Transformation Initiative, 2020, Dimoudi and Tompa, 2008, Pomponi et al., 2018). Although, it is worth noting that this is dependent on the primary structural material as timber structures have significantly lower carbon. And, as shown above, the variation in structural material embodied carbon coefficients (ECCs) is large.

Structural design choices, such as span length, main structural material, flooring solution etc, can have a large impact on EC (D'Amico and Pomponi, 2020, Dunant et al., 2021). Therefore, highly variable comparative structural LCA studies could result in differing conclusions and, consequently, recommendations on projects. In addition, the material quantities during early stages can be uncertain and reinforcement rates, connection allowances are used prior to detailed design. ECC and mass parameter variation have been incorporated into parametric tools for use in early stage steel frame design (D’Amico and Pomponi, 2018). For an 8-storey steel structural frame a CoV of 24.8% was found when used as part of a mass optimisation procedure (D’Amico and Pomponi, 2018).

This paper provides a methodology to quantify uncertainty in EC assessments for product stage carbon only. Mendoza Beltran et al. (2018) has previously reviewed a broad range of different statistical analyses that could be applied to compare the relative impacts of multiple LCA assessments, but this is beyond the scope of this paper. The uncertainty analysis method proposed here is applied to a single building assessment and builds on the method from Pomponi et al. (2017) and uses a Monte-Carlo simulation, as the uncertainty propagation method. However, the process could also be applied to multiple assessments or design options and could be used for comparisons.

1.1 Structure

This paper investigates a UK educational building case study and assesses the potential range of results in product stage EC based on the uncertainty of ECCs. An uncertainty analysis procedure using Monte-Carlo simulation was developed and tested on a case study, in two scenarios - 1) full building and 2) substructure and structural frame. The availability and range of data for the most impactful materials were gathered from Hammond and Jones (2019) and used for the analysis. The paper finishes with a discussion, conclusions and recommendations for future EC assessments and research outputs.

2 Methodology

This paper describes a methodology, built on techniques from Pomponi et al. (2017), to estimate parameter uncertainty through simulation, designed to be performed as part of a LCA assessment using material inventory data from Hammond and Jones (2019) and calculated CoV, Figure 1. Stochastic modelling is the most common method for uncertainty propagation; therefore, a Monte-Carlo simulation is used in this study (Lloyd and Ries, 2007). Monte-Carlo simulations facilitate uncertainty analysis for multiple design variables using basic statistical parameters (European Commission, 2010). The analysis method, described here in further detail, is as follows:

1. Perform LCA assessment for product stage only (Modules A1-A3), in compliance with BSI (2011).
2. Rank the EC results by material, from highest impact to lowest GWP impact (kgCO_2e)
3. Maintaining the rank order, select the materials that contribute 80% of the estimated EC.
4. For each of the selected materials:
    a. Extract, where possible, the mean and standard deviation of the material ECC from the ICE material inventory (Hammond and Jones, 2019). In the absence of material data, the average CoV of the other materials is used.
    b. Using the values above, calculate CoV and plot a corresponding normal distribution.
5. For pragmatic reasons, sum the remaining 20% of the EC to include in the simulation and apply the average CoV.
6. Perform a Monte-Carlo simulation with N number of iterations. During each iteration, a random value is selected from each material normal distribution. Sum these to produce a building total EC. Total EC is summarised as mean, standard deviation, CoV and range.

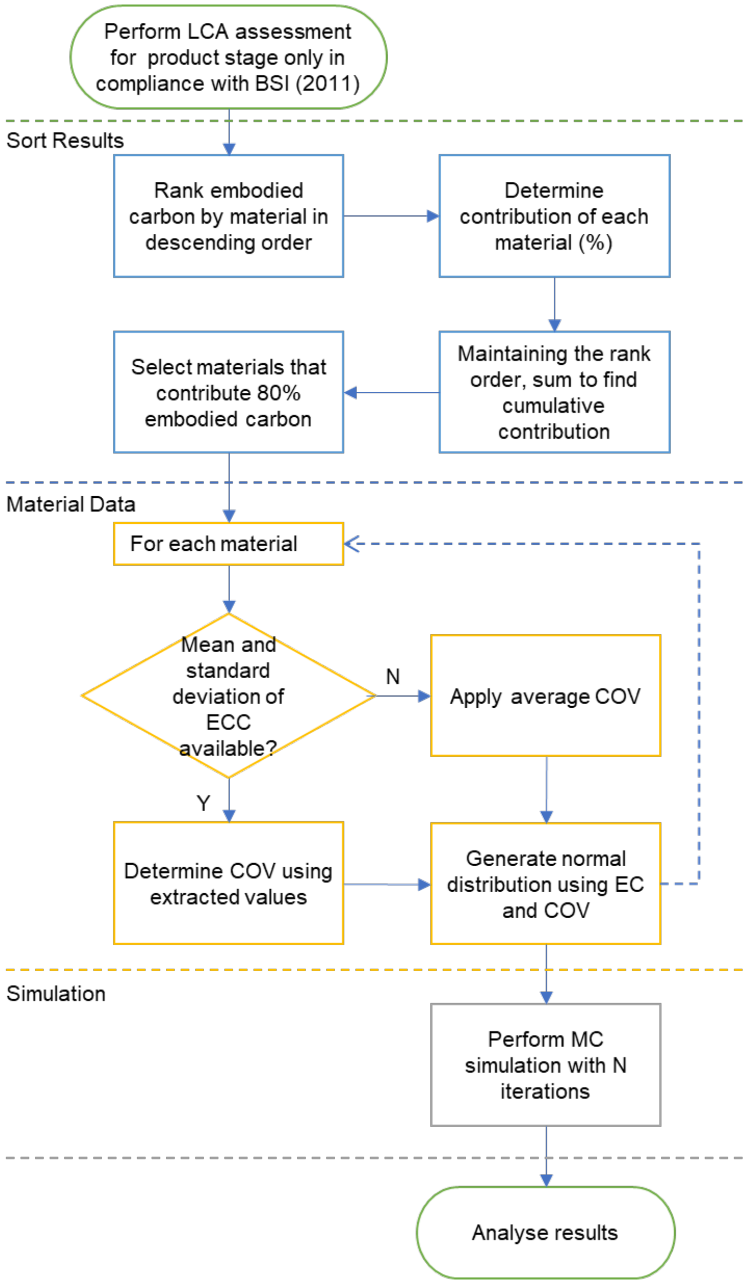

Figure 1 Uncertainty methodology flow chart

The methodology is software agnostic and simply applies a variation in material (Cradle-to-Gate) EC parameters. As a result, a distribution of building total EC helps to indicate the range and standard deviation, as well as providing a total estimated CoV for the assessment. Where a standard deviation value was unavailable for material parameters, the average CoV of the other materials was used. The calculated CoVs and Monte-Carlo simulation can be used to inform on materials with the highest variability and their impact on the assessment. As a result, the CoVs can be used to inform decisions on ECC targets for EPDs to achieve carbon reductions.

During each iteration of the MC simulation, a random material ECCs is generated from an assumed distribution defined by the mean and standard deviation. For this assessment, it is assumed that the possible range of ECCs of each material are best represented by a normal distribution. However, additional analysis is conducted applying the methodology using two alternative distributions (uniform and truncated normal). Normal and triangle distributions are the most common distribution used for uncertainty studies (Lloyd and Ries, 2007) and is discussed in more detail later in the paper.

The method is used for the EC of LCA Modules A1-3 only (product stage), as per BSI (2011). The methodology could be applied to assessments of different scope boundaries, if CoVs are available, such as those applied in Hoxha et al. (2017). The ICE database (Hammond and Jones, 2019), used in this study, only provides ECCs for product stage. Alternatively, the assessor could choose to collect EPDs manually and calculate standard deviations and means, or consult with experts to determine the variability of the material data. However, this can be time-consuming (Pomponi et al., 2017). The Ecoinvent (Ecoinvent, 2015) and EC3 (Labs, 2019) databases display uncertainty for Cradle-to-Gate ECCs and could also be used. However, EC3 (Labs, 2019) EPDs are predominantly American products and therefore the ICE database, consisting of UK EPDs, (Hammond and Jones, 2019) is deemed better suited to the UK case study building and reflects the uncertainty in UK products.

The treatment of biogenic carbon in the amendment to EN-15804 (2019), which will become mandatory in 2022, uses the -1/+1 approach - where the carbon uptake occurs during product stage A1 and the carbon release occurs at the end-of-life (C3) stage. Biogenic GWP will need to be reported alongside fossil GWP and LULUC (Land Use and Land Change) GWP. It also requires that materials that contain biogenic carbon must declare modules product (A1-3), end-of-life (C1-4), and D stage benefits. However, IStructE (2020) suggests reporting carbon sequestration separately when presenting assessments results to practical completion (A1-A5). This follows the more widely used 0/0 approach that the carbon uptake is equivalent to the carbon release at the end of life and ensures that product stage carbon is not under reported. As per RICS (2017), biogenic carbon has been excluded from the product stage results in this study because end-of-life impacts are not considered and were beyond the assessment scope. Arehart et al. (2021) and Hoxha et al. (2020) provide a detailed review of carbon sequestration and storage treatment in LCAs.

The post-processing method was written in Python 3.8.1. In order to check the optimum number of iterations to generate accurate simulations whilst limiting runtime, a sensitivity check is conducted. Measures of runtime, central tendency and variance (average and standard deviation) are evaluated whilst increasing the number of iterations (1,000 to 2,000,000 iterations) in the Monte-Carlo simulation. Test-retest reliability of the methodology is assessed by performing 25 identical simulations and calculating CoV, expressed as a percentage of the mean.

2.1 Application

2.1.1 Case Study Building

This section summarises the scope of an EC assessment for an educational building in the UK using the RICS methodology (RICS, 2017). Material quantities were obtained from the Bill of Quantities. The project parameters are summarised below in Table 1**.** The full assessment contained 93 individual materials. The product stage EC represented 77% of the whole life carbon emissions. The results for the product-stage only are summarised below.

It should be noted that the following case study includes both products (assemblies such as windows and doors) and raw materials (i.e. concrete and steel). From this point forward, the term “constuction products” will refer to both products and raw materials. Concrete 1 represents the concrete used for substructure only and has a different specification from Concrete 2.

Table 1 Assessment summary, adapted from reporting temple provided in RICS (2017)

Project Type	**New build**
Assessment Objective	EC only
Property type	Educational
Size	Gross internal floor area (GIFA) – 1760 m^2
Project design life	60-year design life
Assessment scope	A1-3 (Product stage only)
Data sources	Material quantities - Bill of Quantities Carbon data – OneClickLCA (Bionova Ltd, 2020) Coefficient of variations (CoV) - ICE database (Hammond and Jones, 2019) and OneClickLCA ((Bionova Ltd, 2020) using methodology from EC3 (Labs, 2019))

Building elements included, and excluded, in the analysis are displayed in Table 2**.** Two scenarios have been evaluated – superstructure (structural i.e. NRM 2.1-2.4 (RICS, 2017)) plus substructure and the full building analysis. Due to a lack of data, services other than lifts were excluded from the study. Services can have a high replacement rate and are often made from high impact materials therefore the services results will be underestimated across all LCA stages.

Table 2 Building elements included in assessments (two scenarios)

	Scenario One – Full Scope	Scenario Two – Substructure and Superstructure (2.1 – 2.4) Only
1 Substructure	Y	Y
2.1 Frame	Y	Y
2.2 Upper floors	Y	Y
2.3 Roof	Y	Y
2.4 Stairs and Ramps	Y	Y
2.5 External Walls	Y	N
2.6 Windows and External Door	Y	N
2.7 Internal Wall and Partitions	Y	N
2.8 Doors	Y	N
3 Finishes	Y	N
5 Services (Lifts only)	Y	N

3 Results

3.1 Case Study – Product stage EC Assessment from Bill of Quantities

Table 3 indicates the product stage EC (absolute, $kgCO_2e$, and $kgCO_2e/m^2$ GIFA), by building element, for the full building. The full superstructure (NRM 2.1-2.8) accounts for 54.6% of the product stage EC with the structural frame (NRM 2.1-2.4) contributing 21.5%. The second largest contributor is the substructure (38%) and, therefore, the structural frame and substructure account for 59.2% of the total EC, Figure 2.

Table 3 Product stage EC, scenario one i.e. full scope, by building element.

	Scenario One ($kgCO_2e$)	Scenario One - ($kgCO_2e/m^2$ GIFA)	Percentage contribution to total (%)
1 Substructure	350,000	198	37.7%
2.1-2.4 Superstructure **2.1 Frame** **2.2 Upper floors** **2.3 Roof** **2.4 Stairs and Ramps**	200,000	113	21.5%
2.5-2.6 Superstructure **2.5 External Walls** **2.6 Windows and External Door**	227,000	128	24.4%
2.7-2.8 Superstructure **2.7 Internal Wall and Partitions** **2.8 Doors**	80,800	45.9	8.74%
3 Finishes	58,800	33.4	6.36%
5 Services (Lifts only)	11,600	6.59	1.26%
Total $kgCO_2e$	928,000	525	-

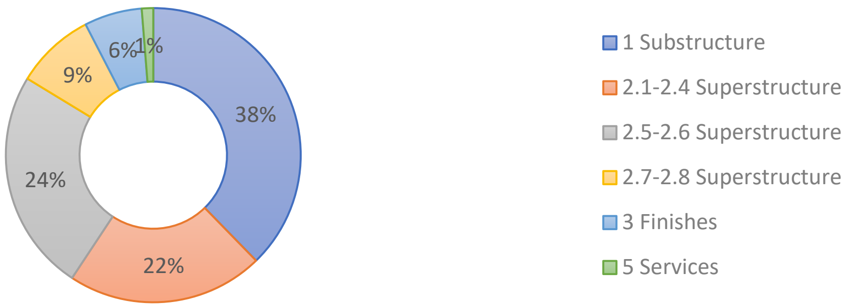

Figure 2 Product stage embodied Carbon (EC), by building element

3.2 Uncertainty Analysis Results

3.2.1 Scenario One – Full Scope

This section presents the result of the post-assessment uncertainty analysis. This includes a discussion of the initial construction product inputs for the analysis and their contribution to the building total. The CoV from the extracted values are also shown, followed by the corresponding results. Fifty thousand iterations were deemed adequate for the analysis with respect to running time, sensitivity and repeatability, discussed at the end of this section.

The highest impact construction products, contributing up to 80% of total product-stage EC were identified, as shown in Table 4. Their total and cumulative contribution to the whole building total was calculated. In rank order, the top five construction products account for 58.0% of the estimated total building product stage EC. All thirteen construction products listed represent 80.1% of the estimated total.

Table 4 Product stage embodied carbon (EC) by construction product, ordered by impact. Percentage contribution to total EC and cumulative percentage contribution also shown. Average and standard deviation ECC from (Hammond and Jones, 2019) . Calculated coefficient of variation (CoV).

Construction product description	Absolute EC ($kgCO_2e$)	% Total EC	Cumulative EC %	Average EC coefficient ($kgCO_2e/kg$)	Standard deviation EC coefficient ($kgCO_2e/kg$)	Coefficient of variation , CoV (± %)
Concrete 1	187,000	20.1%	20.1%	0.112	0.028	25.0%
Red brick	111,000	11.9%	32.0%	0.225	0.045	20.0%
Concrete 2	99,200	10.7%	42.7%	0.112	0.028	25.0%
CLT	90,900	9.79%	52.5%	1.20	0.136	11.3%
Steel 1	50,800	5.48%	58.0%	2.37	0.645	27.2%
Reinforcement	31,200	3.36%	61.3%	1.09	0.707	64.9%
Window 1	29,800	3.21%	64.6%	N/A	N/A	N/A
Structural steel profiles	27,000	2.90%	67.5%	2.10	0.940	44.8%

Lime mortar	23,600	2.55%	70.0%	0.737	0.319	43.3%
Window 2	21,800	2.35%	72.4%	N/A	N/A	N/A
Glazed door	19,800	2.13%	74.5%	N/A	N/A	N/A
Glulam	19,600	2.11%	76.6%	0.896	0.361	40.3%
Insulation	17,400	1.87%	78.5%	N/A	N/A	N/A
Precast concrete	14,800	1.59%	80.1%	0.152	0.075	49.3%
All remaining items	184,000	19.9%	100%	N/A	N/A	N/A

The CoV for the construction product EC has been calculated using the extracted values from the ICE database (Hammond and Jones, 2019), Table 4. Using these values, a normal distribution of possible EC impacts for each construction product was produced. Figure 3 shows a bar chart for each construction product with CoV error bars indicated. The average of the overall calculated CoV is 35% and has been applied to all remaining items and construction products where variability information was not available, i.e. window 1, window 2, glazed door and insulation.

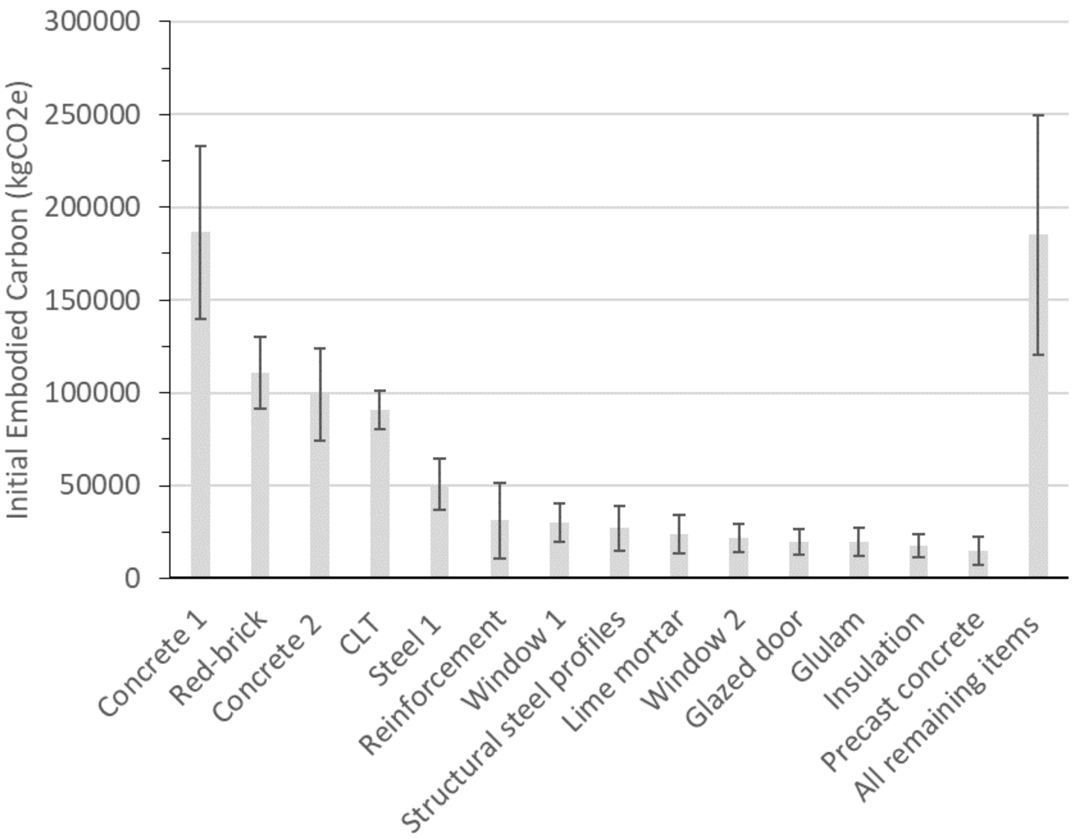

Figure 3 EC (kgCO2e) for scenario one by construction products

Uncertainty analysis was performed on a simulation of 50,000 iterations for the full building. The average EC was 930,000 $kgCO_2e$, with a standard deviation of 93,000 $kgCO_2e$ (± 10.0%). The results varied from 513,000 $kgCO_2e$ to 1,300,000 $kgCO_2e$, Figure 4. The vertical axis represents the probability and the histogram bin size is 10,000 $kgCO_2e$.

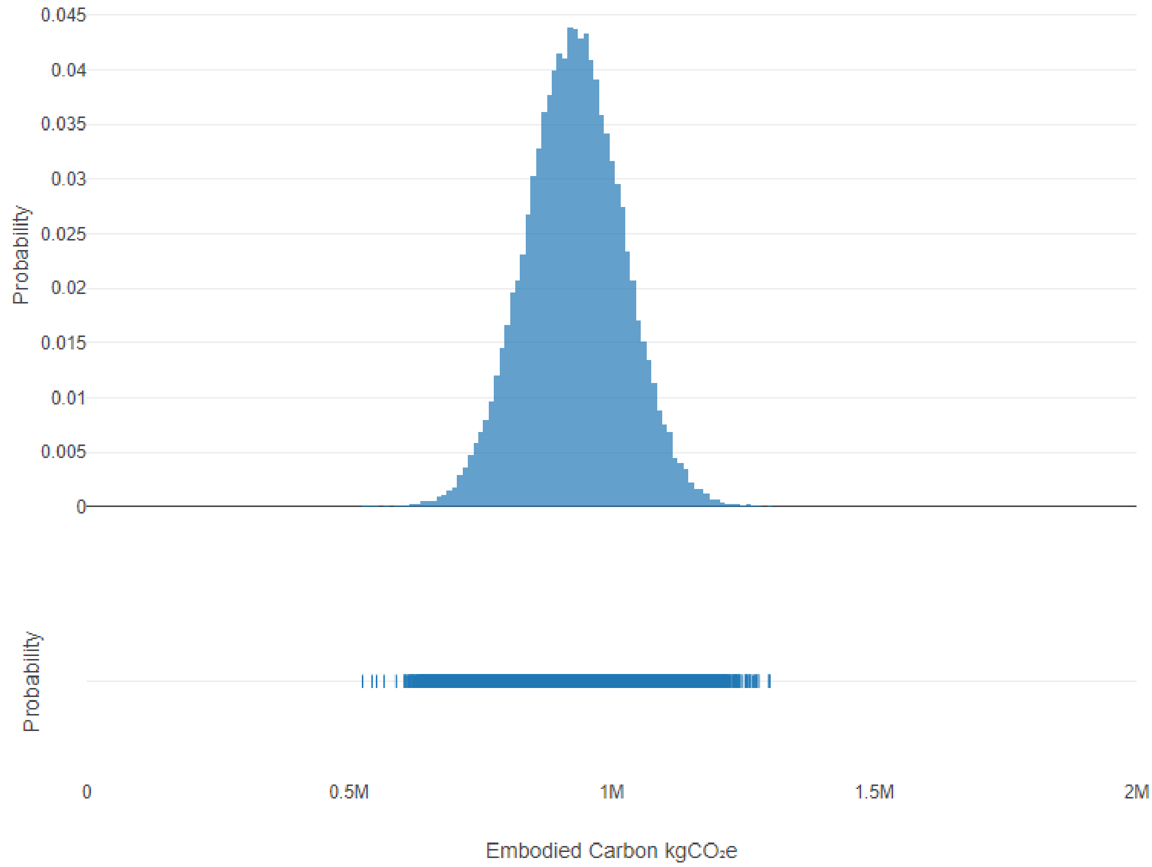

Figure 4 Histogram of total product stage EC (kgCO2e) for 50,000 iterations

3.2.2 Scenario Two – Substructure and Superstructure (NRM 2.1-2.4)

The highest impact construction products, for substructure and superstructure, contributing up to 80% of total product stage EC, are listed in Table 5. The top five construction products represent 82.2% of the estimated total product stage EC. The average of the calculated construction products CoV is 31% and has been applied to all remaining items in scenario two.

Table 5 Embodied Carbon (EC) by material, ordered by impact, scenario two. Percentage contribution to total EC and cumulative percentage contribution also shown. Average and standard deviation ECC from (Hammond and Jones, 2019). Calculated coefficient of variation (CoV)

Construction product description	**Absolute EC ($kgCO_2e$)**	**% Sup. + Sub EC**	**Cumulative EC %**	**Average EC coefficient ($kgCO_2e/kg$)**	**Standard deviation EC coefficient ($kgCO_2e/kg$)**	**Coefficient of variation, CoV (± %)**
Concrete 1	187,000	33.9%	33.9%	0.112	0.028	25.0%
Concrete 2	98,000	17.8%	51.7%	0.112	0.028	25.0%
CLT	87,800	16.0%	67.7%	1.200	0.136	11.3%

Steel 1	50,700	9.20%	76.9%	2.37	0.645	27.2%
Reinforcement	29,300	5.32%	82.2%	1.09	0.707	64.9%
All remaining items	97,900	17.8%	100%	N/A	N/A	N/A

The CoV for the construction product EC has been calculated using the extracted values from the ICE database (Hammond and Jones, 2019), Table 5. Using these values, a normal distribution of possible EC impacts for each construction product was produced. Figure 6 shows a bar chart for each construction product with CoV errors bar indicated.

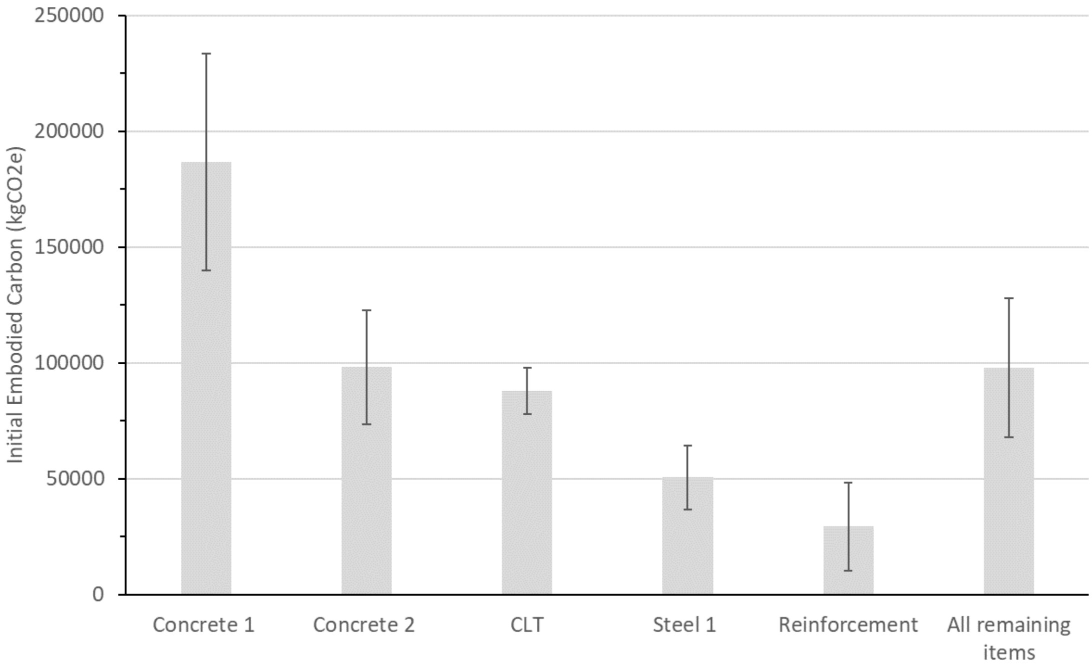

Figure 5 Scenario two (substructure and superstructure NRM 2.1 - 2.4) EC by material, with CoV error bar

Uncertainty analysis was performed on a simulation of 50,000 iterations for the substructure and superstructure (NRM 2.1-2.4). The average product stage EC was 551,000 $kgCO_2e$, with a standard deviation of 65,700 $kgCO_2e$ (± 11.9%). The results varied from 247,000 $kgCO_2e$ to 858,000 $kgCO_2e$.

3.3 Summary

The average, standard deviation, CoV, minimum and maximum for both scenarios have been summarised, Table 6.

Table 6 Uncertainty analysis results summary, embodied carbon (kgCO2e and $kgCO_2e/m^2$ GIFA)

		Average	St. Dev	CoV (%)	Minimum	Maximum
Scenario One - Full Building	Absolute EC ($kgCO_2e$)	930,000	93,000	10.0%	513,000	1,300,000

	EC ($kgCO_2e/m^2$ GIFA)	526	52.0	10.0%	290	736
Scenario Two - Substructure and Superstructure NRM 2.1-4	Absolute EC ($kgCO_2e$)	551,000	65,700	11.9%	247,000	858,000
	EC ($kgCO_2e/m^2$ GIFA)	312	37.1	11.9%	140	485

3.4 Sensitivity check

A sensitivity check was performed by varying the number of iterations in the Monte-Carlo simulation from 50,000 (used in this study) to between 1,000 and 2,000,000. The time taken for the analysis was recorded. A Dell Inspiron laptop with 16GB of memory RAM, running on an Intel(R) Core™ i7-4712HQ CPU at 2.30GHz was used for the analysis. As expected, as the number of iterations, N, increased, the running time increased. The largest analysis, with two million iterations, took 208 seconds to complete. For the purpose of a post-analysis assessment, the running time is less important. However, if the uncertainty procedure were integrated into an assessment tool this running time would not allow real-time interaction. Additionally, if fewer construction products were used in the analysis, similar to scenario two, the running time would reduce as the random value generator for each construction products at each iteration would need to run fewer times. A 50,000-iteration simulation took 6 seconds, for scenario one.

The variation between both mean EC and standard deviation decreased as the number of iterations increased. However, the mean difference for average and standard deviation was ≤1% after 10,000 and 4,000 iterations for scenario one and two, respectively.

3.4.1 Reliability check

For both scenarios, the reliability of the uncertainty analysis was checked by performing 25 identical analyses. The average and standard deviation EC varied by less than 1% across the 25 tests with the same number of iterations. However, the minimum and maximum EC values varied significantly (± 7%) and, therefore, this parameter is less reliable across multiple repetitions. This is because a normal distribution is assumed for each construction products and therefore the probability of the minimum and maximum values being selected is low.

3.5 Alternative distributions

The construction products EC average values and standard deviations from ICE database (Hammond and Jones, 2019) were used to create a normal distribution of possible values for the EC. Multiple distributions can be used to represent data variability and have been surveyed (Lloyd and Ries, 2007). Random square distribution, a normal distribution (used in this study) and a truncated normal distribution were tested to see how the total product-stage EC result could vary. The analysis has been performed for both scenarios for 50,000 iterations. Table 7 and Table 8 provide a summary of the key parameters for each scenario, respectively. The CoV is equal to the standard deviation divided by the average.

Table 7 Average, standard deviation, coefficient of variation (CoV), minimum, maximum and range values for initial EC (kgCO2e) for scenario one (full scope).

Analysis	Average	St. Dev	CoV (%)	Minimum	Maximum
Normal	930,000	93,000	10.0%	513,000	1,300,000
Square	929,000	53,600	5.77%	746,000	1,110,000
Truncated normal	929,000	92,000	9.90%	549,000	1,300,000

Table 8 Average, standard deviation, coefficient of variation (CoV), minimum, maximum and range values for initial EC (kgCO2e) for scenario two (superstructure only)

Analysis	Average	St. Dev	CoV (%)	Minimum	Maximum
Normal	551,000	65,700	11.9%	247,000	858,000
Square	550,000	38,200	6.94%	423,000	676,000
Truncated normal	551,000	64,800	11.8%	294,000	823,000

4 Discussion

This paper set out to provide a methodology to quantify uncertainty in EC assessments for product stage carbon only. This procedure was tested on two scenarios for an educational case study building. The aim of the uncertainty analysis is to provide designers with an understanding of possible CoV in construction product ECCs across the high-impact construction products and determine a confidence level in product stage EC prediction based on variance, particularly in early stage assessments. In the context of designers needing to demonstrate that assets are zero carbon, this also assists in decision making and material selection choices to ensure carbon reductions. The procedure is intended for use in supporting design decisions and not for demonstrating compliance with legal requirements

It was identified that 13 construction products in scenario one (full scope) and 5 construction products in scenario two (substructure and superstructure NRM2.1 – 2.4) represented 80% EC. The number of construction products used in the assessment directly affects the running time of the simulation, which may be a consideration for future use. Secondly, the identification of these construction products helps to prioritise the areas of focus for EC reductions. The average material CoV for the two scenarios were 35% and 31%, respectively, where reinforcement had the largest individual variability (64.9%) based on 44 data points. Other construction products, such as steel structural sections (27.2% CoV from ten data points), are based on fewer data points. The overall EC resulted in a CoV of ± 10.0% (scenario one) and ±11.9% (scenario two) representing 68.2% solutions from the Monte-Carlo simulations. Sensitivity and repeatability checks were performed and alternative distributions for material ECCs examined.

Reinforcement exhibited the highest construction products CoV of 64.9%, followed by structural steel profiles with 44.8%. Despite this high variability, these construction products represent only 6.3% of the total EC. Concrete, in contrast, has a lower variation (25.0%) but a high quantity and high contribution (30.8%) to the total EC. As a preliminary step in industry/reporting practice, the lower CoV bound, which equates to one standard deviation below the ECC average, could be used to define ECC reduction targets in order to select EPDs. For scenario one, adopting this approach would result in potential reductions for concrete and reinforcement of 71,500 and 20,000 $kgCO_2e$, respectively, and a 10.0% reduction in total EC. While it should be encouraged for designers to seek out construction products with an ECC below these thresholds, it is worth noting that construction products that fall below one standard deviation in a normal distribution inherently represent only 15.9% of possible solutions, which could represent an increasing challenge when searching for EPDs for specific projects.

In the absence of mean and standard deviation values for some construction products (four construction products in scenario one), interim CoV values have been used. This interim value was calculated from the average CoV from the other construction products. If the methodology were to be developed further, data points from other sources could be collected and used to calculate these values for the missing construction products. In addition, multiple databases could be used to generate CoVs based on larger datasets. The average construction product CoV for scenario one and two were 35% and 31%, respectively, and were used for construction products without variability data available. This is comparable to the highest possible variation from the EC3 (Labs, 2019) uncertainty methodology, used for approximating uncertainty in individual EPDs, also used in OneClickLCA (Bionova Ltd, 2020) which equates to ± 34.6%.

Alternatively, individual EPDs could be collected and compared to determine average values, standard deviation and, therefore, CoV to be used in the uncertainty analysis. Construction product data could also be divided into finer categories such as concrete strength, recycled content and geographical location etc. However, the numbers of data points available in these categories may be low with high variability. As projects progress and designs become more “fixed”, products and manufacturer will be selected. The methodology could be adjusted to use specific EPD information for “confirmed” construction products. Although, as previously discussed, EPDs inherently have a degree of uncertainty and this should be included in the assessment (Labs, 2019).

Each individual construction product type may have a different range and distribution of EPDs (i.e. with most EPDs toward the upper or lower extremes of ECC) and, therefore, be more/less accurately represented by non-normal distributions in a simulation (e.g. left- or right-skewed, log-normal etc). Depending on the number of data points and variability of data, this could include log-normal distribution or perhaps only a single data point. As such, a further development of the proposed uncertainty methodology could account for different distribution by construction product, depending on its data availability and quality. ICE material database (Hammond and Jones, 2019) materials generally indicate log-normal or normal distribution for ECC. In this study, the CoV is lower when assuming a square distribution compared to normal and is unlikely to accurately represent the data available.

The uncertainty analysis currently selects the construction products that contribute approximately 80% of the building EC. However, in different real-world scenarios, practitioners may have access to differing amounts of accurate data, which would shift reliance more or less onto assumed/interim CoV values employed in this method. In the present study, for scenarios one and two, 13 and 5 construction products were selected, respectively. Theoretically, if an alternative contribution value of 50% were adopted in scenario one then only 5 construction products (rather than 13) would be included and the other 8 construction products would be added to the remaining items. This would result in an almost identical average EC (525 vs. 526 $kgCO_2e/m^2$ GIFA) and similar CoV (± 11.3% vs. 10.0%) but increased range of results by ~18% (from ± 40 up to 47%). In contrast though, due to the lower number of construction products being assessed, the method running time would be reduced by 69% which may be of greater value than the increase in uncertainty.

In contrast, it could be argued that the methodology should address more than 80% EC. In the case study here though, 93 construction products were included in the original assessment and only 13 construction products were required to reach the 80% selection criteria for the uncertainty procedure. Of these, the lowest contributor in scenario one (Precast concrete) represented only 1.7% of the total EC in comparison to 20.1% from the largest contributor, concrete 1. In this scenario, any one of the remaining unselected construction products would represent less than 1.7% of the total EC and their additional inclusion would result in a greater duration of data collection and analysis run time. Given that one aim of the methodology was to identify and target high-impact construction products for carbon reductions while approximating uncertainty for the remaining lower-impact construction products, selecting construction products up to 80% EC appears to strike a good balance for this case study but may differ for other projects.

Figure 4 and Figure 6 present the relative construction product carbon results, including CoV errors bars. These figures can be used to identify the effect of choosing lower-carbon EPDs for different construction products relative to other products in the project. This could also apply to EC comparisons of design options or multiple projects. Depending on the construction products, the standard deviation could be large in the lower impact construction products and, therefore, the analysis could be under-predicting the "all remaining items" carbon variation. Alternative analysis could be undertaken such that construction products are investigated, and ranked, by weight as well as GWP impact.

This study has a number of limitations to consider. Product stage (cradle to gate) assessments have been shown to miss up to 40% of whole-life carbon emissions (Pomponi et al., 2018). For scenario 2, the exclusion of other LCA stages is less of a concern because the carbon associated with replacement and refurbishment is lower in structures over the 60-year life cycle compared to other building elements such as finishes, façades and services. The uncertainty procedure proposed in the paper could be extended to account for additional LCA stages. However, EPDs do not always include data for stages beyond the product stage (A1-3). Approximation of CoV for input values for other stages has been used elsewhere and has shown that the resultant CoV for the full life-cycle of a case study building was 17% (GWP, not including biogenic carbon) compared to the pre-use and maintenance stages which had a CoV of 20% (Blengini and Di Carlo, 2010). Additionally, it should be noted that the authors applied CoV to parameters additional to those used in the present study, including quantity, transport distance, waste percentages and maintenance. It has also been identified that 38% of EPDs are missing information required by ISO standards (ISO, 2006a, ISO, 2006b), partly resulting from poor harmonisation between product category rules (PCRs) across materials and EPD data (Gelowitz and McArthur, 2017) and the underlying material source information in the ICE database (Hammond and Jones, 2019) has not been reviewed as part of this study.

It is important to note that the consideration of product stage only and the 0/0 approach to biogenic carbon is conservative and assumes that the sequestered carbon is released at the end-of-life and balanced across the life cycle. If the -1/+1 approach were adopted, this would underpredict the product stage carbon and materials containing biogenic carbon could be negative. This would change the material ranking as part of the uncertainty procedure and identification of the highest contributing materials. The assessment also wouldn't consider the end-of-life impact. If biogenic carbon were included, the initial result for product stage carbon would be 45% lower. Alternative end-of-life impacts could be considered if the procedure were extended to include additional LCA stages.

Additionally, due to a lack of material and quantity information, services (other than lifts) were excluded from the study and therefore the scope of assessment isn't representative of the whole building. However, the minimum scope requirements according to RICS (2017) do not include the product stage EC of services. In addition, building elements with high replacement rates, such as services and internal elements, accumulate large amounts of EC over the building life cycle but may have a comparatively small impact at product stage. The accuracy of material quantities at different project stages may differ, particularly at early stage stages where structural calculations can be based on approximations (such as reinforcement rates). Mass parameter uncertainty is not currently considered in the uncertainty methodology. Previous studies have considered this by design stage or as a single quantity CoV (Blengini and Di Carlo, 2010).

Operational greenhouse gases emissions contribute approximately 33% whole life carbon emissions in typical office buildings but are beyond the scope of this paper (RICS, 2017). If the proposed methodology were used for optioneering exercises where alternative materials are being considered, the operational impacts could be affected by changes in performance characteristics. An example of this could be the thermal resistance of insulation and the benefits of thermal mass from exposed concrete. Passive design strategies, including natural ventilation, high fabric efficiency and thermal mass, may cause a “penalty” in EC but a whole life carbon saving when considering the operational benefits. As operational carbon is not included as part of the uncertainty procedure, these effects are unable to be quantified.

The proposed uncertainty method is intended to be able to give designers the possible range of error and, therefore, an indication of confidence/caution in their product stage assessments. This would be particularly important when tracking carbon over the course of a project relative to a baseline value. Without accounting for uncertainty, issues could arise with false reporting of carbon savings due to construction product replacements. Alternatively, designers could find that at a later project stage, where specific products or manufacturers are being selected, the carbon assessment increases due to original underestimation. Therefore, practitioners could use this approach to identify key construction products with high-impact or high-uncertainty (such as concrete and reinforcement in this case study), as hotspots for carbon, and better focus their efforts when specifying construction products. The lower-bound material CoV has been proposed as guidance for an ECC target. However, the selection of low-carbon materials should be considered alongside other performance characteristics such as durability, thermal resistance and efficiency of equipment, as these choices may increase the life cycle impacts.

5 Conclusions

As the energy supply system decarbonises and operational greenhouse gases emissions reduce, EC will soon make up most of the whole-life carbon in new buildings and the construction industry must reach net-zero by 2050. This will require designers to demonstrate that assets are achieving net-zero with accurate and detailed reporting.

Based on the literature and the results from the presented study, the possible range of results for carbon assessments is large and introduces a significant margin of error in prediction. However, this methodology for post-analysis of epistemic uncertainty in product-stage carbon assessments can support designers to estimate the uncertainty associated with the variability of material ECCs. This is particularly important in the early stages of a project where the level of detail in material and/or product selection is low. This approach can help designers to see the implications of their material choices, good or bad, in order to make informed decisions to reduce product stage carbon through prioritisation, and ensure those assumptions follow through to construction. In addition, this will help to not overpromise on carbon reductions.

If the methodology were to be developed further, data points from other sources could be collated and used to improve the interim CoV values (calculated as the average variation of all construction products used in the study). Similarly, alternative distributions could be used for representing the data variability such as uniform or log normal. The method demonstrated here considered product stage ECC uncertainty only. Future work will investigate the inclusion of additional LCA stages and other forms of parameter uncertainty, such as mass parameters. It will be also extended to be used for LCA assessment comparisons.

CRediT authorship contribution statement

Ellie Marsh: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft. John Orr: Funding acquisition, Project administration, Methodology, Resources, Supervision, Writing - review & editing. Tim Ibell: Resources, Supervision, Writing - review & editing.

Data Access Statement

The data created in this research is openly available from the University of Cambridge data repository at XXX (DOI to follow) .

Declaration of Competing Interest

None.

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