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A Method for Uncertainty Management in Life Cycle Assessment Studies – A Tiered-Hybrid Case Study of an Irish Construction Project

A thesis submitted to Technological University Dublin in fulfilment of the requirements for the degree of Doctor of Philosophy

By

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Abstract

Life Cycle Assessment (LCA) quantifies the potential environmental impact of a product system throughout its life cycle from raw material extraction, production, manufacture, use and maintenance through to final disposal. The results from LCA studies are often used to support decision-making processes and policy development. LCA is conducted in four iterative steps, being Goal and Scope definition, Life Cycle Inventory Analysis (LCI), Life Cycle Impact Assessment (LCIA), and Interpretation. The guidelines for each step are provided in the International Organization for Standardization (ISO) standards, ISO 14040:2006 and 14044:2006.

Uncertainty arises in all steps of an LCA, yet the propagation and reporting of these uncertainties is not mandatory for ISO compliance and is often not done in LCA case studies. There have been significant research efforts to improve uncertainty classification and quantification in LCA, particularly focusing on the LCI step. However, a structured uncertainty management method for all steps in an LCA is still needed. The intent of this research is to improve uncertainty reporting in LCA case studies through the development and demonstration of a structured uncertainty management method that can readily be integrated into the international standards for LCA.

The case study chosen to demonstrate the uncertainty management method was a construction project in Ireland, focusing on climate change. For this case study, the data and uncertainties for the LCI step were compiled in Excel. The uncertainties were propagated, and the potential impact was calculated using an open source software for statistical programming, RStudio. Code was also written in RStudio to identify and rank the input uncertainties that contributed the most to the total output uncertainty. These

input uncertainties indicate where measures can be applied to reduce the total uncertainty, and in turn, improve the reliability of the decisions made based on the study results.

The results of the case study found that the highest contributing uncertainties were due to the choice of the background inventory datasets, the uncertainties in the characterization factors used for climate change, and the quantified sector emissions intensities for Ireland. Additionally, the case study results indicated that the probability the deterministic result underestimates the environmental impact is approximately 93% when uncertainty is included. This outcome is particularly valuable for comparative studies. It is recommended that further work focuses on the implications of correlation, covariance, and independent sampling, particularly when extending this work to other impact categories besides climate change.

Declaration Page

I certify that this thesis which I now submit for examination for the award of PhD, is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

This thesis was prepared according to the regulations for graduate study by research of the Technological University Dublin and has not been submitted in whole or in part for another award in any other third level institution.

The work reported on in this thesis conforms to the principles and requirements of the TU Dublin's guidelines for ethics in research.

TU Dublin has permission to keep, lend or copy this thesis in whole or in part, on condition that any such use of the material of the thesis be duly acknowledged.

Signature Deidre [illegible] Date 27/10/2020

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I am incredibly grateful to have met so many amazing people throughout this journey.

Abbreviations List

ADP	Abiotic Depletion Potential
AP	Acidification Potential
APOS	Allocation point of substitution
AR5	Fifth Assessment Report from the IPCC
ARM	Agreed Rules of Measurement
ATP	Aquatic Toxicity Potential
BOQ(s)	Bill(s) of Quantities
CA-QC	Canada (Quebec)
CAS	Chemical Abstracts Service
CCF	Climate-carbon feedback
CEN	Comité Européen de Normalisation (European Committee for Standardization)
CF	Characterization Factor
CF_4	Tetrafluoromethane
CFC	Chlorofluorocarbon
CH	Switzerland
CH_4	Methane
CML	Centrum voor Milieuwetenschappen Leiden (Leiden Institute of Environmental Sciences)
CO	Carbon monoxide
CO_2	Carbon dioxide
CO_2-eq.	Carbon dioxide equivalents
CSEI	Corrected SEI
CSO	Central Statistics Office
CTU_e	Comparative Toxic Units, ecosystem damage potential
CTU_h	Comparative Toxic Units, human toxicity potential
Cu	Copper
DE	Germany
DQI	Data Quality Indicator
DQR	Data Quality Rating
EC	European Commission
EE	Embodied Energy
EEIO	Environmentally Extended Input-Output
EF	Emission Factor

EIA	Environmental Impact Assessment
EP	Eutrophication Potential
EPD	Environmental Product Declaration
GHG	Greenhouse Gas
GWP	Global Warming Potential
GLO	Global
GlobalABC	Global Alliance for Buildings and Construction
H^+	Proton
HCC	Hydrochlorocarbon
HCFC	Hydrochlorofluorocarbon
HCl	Hydrogen chloride
HFC	Hydrofluorocarbon
HTP	Human Toxicity Potential
I-O	Input-Output
IC	Impact Category
ICE	Inventory of Carbon and Energy
IEA	International Energy Agency
IEC	International Electrotechnical Commission
IES	Institute for Environment and Sustainability
ILCD	International Reference Life Cycle Data System
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
JRC	Joint Research Centre
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory Analysis
LCIA	Life Cycle Impact Assessment
Li	Lithium
MR-IO	Multi-Region Input-Output
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne (Statistical Classification of Economic Activities in the European Community)
N_2O	Dinitrogen monoxide
NH_3	Ammonia
NMVOC	Non-methane volatile organic compound
NO_x	Nitrogen oxides
PCR	Product Category Rules

PED	Primary Energy Demand
PEF	Product Environmental Footprint
PEFCR	Product Environmental Footprint Category Rules
PFC	Perfluorocarbon
PO_4	Phosphate
RER	Europe
RoW	Rest-of-World
Sb	Antimony
SD	Standard Deviation
SEI	Sectoral Emissions Intensity
SF_6	Sulfur hexafluoride
SO_2	Sulfur dioxide
SR-IO	Single Region Input-Output
TC	Technical Committee
TRL	Technology Readiness Level
UK	United Kingdom
UNEP	United Nations Environment Programme
UPR	Unit Process
US	United States

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CHAPTER 1. INTRODUCTION

1.1 Overview

Life Cycle Assessment (LCA) quantifies the potential environmental impact of a product system throughout its life cycle from raw material extraction (cradle) through to final disposal (grave). Guidelines for conducting an LCA are provided in the International Organization for Standardization (ISO) standards for LCA. However, compliance with these standards does not guarantee consistency in the methods that have been applied for LCAs of similar case studies (Heijungs, 2014; Henriksson *et al.*, 2014; Weidema, 2014). This limits the comparability of LCA study results, as comparisons cannot be directly made between studies that have used different methods (Ingwersen and Stevenson, 2012; Subramanian *et al.*, 2012; Hunsager, Bach and Breuer, 2014; Minkov *et al.*, 2015; Heijungs *et al.*, 2019). Other limitations of LCA include the use of unrepresentative data, the presence of data gaps, and the use of value-choices and assumptions (Huijbregts, 1998a; Huijbregts *et al.*, 2001; Ross, Evans and Webber, 2002; Heijungs and Huijbregts, 2004; Lloyd and Ries, 2007; Heijungs and Lenzen, 2014). These limitations are discussed in more detail in Chapter 2 (Sections 2.1 and 2.2.6).

To address the limitations of LCA, previous research has focused on developing more specific methods based on the international standards for categorized groups of product systems and on including uncertainty analysis in LCA studies (Heijungs and Huijbregts, 2004; EPD International, 2019; Heijungs *et al.*, 2019; Zampori and Pant, 2019). The former aims to harmonize the methodology applied and allow for LCA studies of the same product to be compared (Hunsager, Bach and Breuer, 2014; European Commission, 2019). The latter has been researched for over 20 years, being initially considered during the development of environmental LCA itself (Heijungs *et al.*, 2019). However, uncertainty is still ignored or only theoretically addressed in the majority of LCA case studies to date (Lloyd and Ries, 2007; Igos *et al.*, 2019).

1.2 Motivation

It is well recognized by many researchers that uncertainty analysis needs to be incorporated into LCA studies to improve the reliability of the results (Huijbregts, 1998b, 1998a; Ciroth, Fleischer and Steinbach, 2004; Heijungs and Huijbregts, 2004; Guo and Murphy, 2012; Rosenbaum, Georgiadis and Fantke, 2018; Heijungs *et al.*, 2019). Uncertainty analysis is defined by ISO as "a systematic procedure to quantify the uncertainty introduced in the results of a Life Cycle Inventory Analysis (LCI) due to the cumulative effects of model imprecision, input uncertainty and data variability" (ISO 14044, 2006). This definition focuses only on uncertainty in the LCI step, however uncertainty arises in all steps of an LCA study (Huijbregts, 1998a).

Uncertainty analysis is not mandatory for compliance with the international standards for LCA (it is only recommended), which has resulted in uncertainty often not being assessed in LCA case studies (Ross, Evans and Webber, 2002; Lloyd and Ries, 2007; Igos *et al.*, 2019). Other reasons for ignoring uncertainty in LCA case studies are time and budget constraints, a lack of knowledge or expertise, and a lack of a method or framework to follow (Ross, Evans and Webber, 2002; Ciroth, Fleischer and Steinbach, 2004; Rosenbaum, Georgiadis and Fantke, 2018). The implications of ignoring uncertainty can be significant since the conclusions of LCA studies are often used to support decision-making processes and policy development (Williams, Weber and Hawkins, 2009; Owsianiak *et al.*, 2018). It is argued that all decisions are made with some unidentified uncertainty; however, by including a measure of uncertainty, more effective decisions can be made (Morgan and Henrion, 1990; Coulon *et al.*, 1997; Booker and Ross, 2011; Clavreul *et al.*, 2013; Rosenbaum, Georgiadis and Fantke, 2018).

The intent of this research is to improve uncertainty management and reporting in LCA case studies.

1.3 Aim and Objectives

The overall aim of this research is to develop a methodology for uncertainty management in LCA that provides a transparent and consistent way to report uncertainty to the decision maker. Uncertainty management involves identifying, classifying, quantifying, qualifying, reducing, and reporting the uncertainty.

The objectives are to:

1. review the methods used to construct the Life Cycle Inventory Analysis (LCI) model and clearly define the best practice;
2. clearly define the weaknesses in the current practice for assessing uncertainty in LCA;
3. develop a practical method for assessing uncertainty in LCA which addresses these weaknesses;
4. propose a potential integration of this method into the international standard for LCA studies (ISO 14044:2006), or other product-specific standards; and
5. demonstrate the usability and effectiveness of the developed method by applying it in an LCA case study that uses the best practice approach for constructing the LCI model.

1.4 Methodological Overview

Uncertainty classification and uncertainty management methodologies were developed that build on previous research for uncertainty in LCA and in other areas of science and risk assessment. The developed methods were demonstrated in an LCA case study. To assess the usability and effectiveness of these methods, criteria were defined to describe the ideal method. The five criteria defined in Chapter 4 are: unambiguous, clear framework, easy to use in practice, (minimal) additional resource requirement, and clear reporting to decision makers. These criteria were chosen based on literature review of reasons stated for not commonly conducting uncertainty analyses in LCA case studies.

The product system chosen for the case study was the construction of an apartment development in Ireland. This product system was selected to demonstrate the usability of the uncertainty management method in a case study consisting of multiple different components. Each component requires the collection of inventory data and uncertainty information. The functional unit defined for the case study is the constructed apartment development, as specified by all the items included in the bill of quantities for the construction project. The system boundary for the LCA is from cradle to constructed building, and therefore does not include the use and maintenance or disposal parts of the life cycle. The approach used to construct the LCI model is Tiered-hybrid analysis (see Chapter 2, Section 2.3.3).

The data sources used for the case study include the bill of quantities for the construction project, Ecoinvent datasets (Wernet *et al.*, 2016), Intergovernmental Panel for Climate Change (IPCC) Global Warming Potentials (Myhre *et al.*, 2013), Irish Input-Output tables (Central Statistics Office, 2009), and the Irish Environmental Accounts data (Tol, Lyons and Mayor, 2008). The inventory data were compiled in Excel, along with the uncertainties in the data. The uncertainties were propagated and the potential impact calculated in RStudio, an open source software for statistical programming (RStudio Team, 2016). The case study conducted follows the International Standard for LCA, ISO 14044:2006, and applies the developed uncertainty management method for LCA (see Chapter 4).

1.5 Thesis Layout

Chapter 1 describes the motivation, aims and objectives behind this work.

Chapter 2 provides a critical review of LCA. It introduces each step in an LCA study, including the Goal and Scope definition, LCI, LCIA and Interpretation. It further discusses the strengths and weaknesses of each approach used to construct the LCI model. This chapter identifies the best practice for LCI.

Chapter 3 defines uncertainty and uncertainty management. It further discusses uncertainty identification, classification, quantification, qualification, and reduction methods. This chapter identifies what is needed to improve uncertainty management in practical LCA case studies.

Chapter 4 introduces the developed uncertainty classification for LCA that builds on previous work and addresses the barriers identified for classification in LCA. It further introduces the developed method for uncertainty management in LCA studies and proposes a potential integration for this method into the steps of an LCA as defined in ISO 14044:2006.

Chapter 5 presents the methodology for the LCA case study. This case study is used to demonstrate the usability and effectiveness of the developed uncertainty management methodology presented in Chapter 4.

Chapter 6 presents the results of the LCI, LCIA and Interpretation of the LCA case study and discusses the experience of using the uncertainty management methodology.

Chapter 7 concludes by summarizing the main findings and presenting recommendations for future research.

1.6 Contributions to knowledge

The contributions to knowledge of this research are presented and discussed below.

(1) A practical application of a three-dimensional uncertainty classification for LCA in a Tiered-hybrid case study that defines and separates aggregated uncertainties and connects to the identification and quantification steps in uncertainty management.

The current methods for uncertainty classification in LCA are ambiguous. Many different classifications exist that differ in the amount of detail provided regarding the uncertainty, and classes overlap due to vague and inconsistent definitions. By classifying uncertainty in multiple dimensions, a detailed and coherent way to distinguish between uncertainties is developed that can be applied consistently across LCA studies. The new classification is presented in Chapter 4, Section 4.2.

(2) A structured uncertainty management method for LCA that provides a detailed way to report uncertainties to the decision maker and is integrated into the steps of an LCA as defined by ISO 14044:2006.

The ISO standards do not provide a guideline on how to manage uncertainties in LCA case studies. Uncertainties have been ignored due to resource limitations as well as limitations in guidance and expertise in how to manage uncertainty. A method is therefore developed to fill this gap. The method is presented in Chapter 4, Section 4.3.

(3) The first application of a detailed and structured uncertainty management method in a Tiered-hybrid case study that identifies and classifies uncertainties in all steps of an LCA and demonstrates an iterative approach to uncertainty reduction.

LCA studies that have included an assessment of uncertainty have focused mainly on parameter uncertainties in Process analysis (Rosenbaum, Georgiadis and Fantke, 2018). The structured uncertainty management method developed here is applied to identify, classify, quantify, qualify, and propagate numerous uncertainties within a Tiered-hybrid case study. The case study methodology is presented in Chapter 5 and the results in Chapter 6.

CHAPTER 2. LIFE CYCLE ASSESSMENT

This chapter defines Life Cycle Assessment (LCA) and introduces the four steps used to conduct an LCA study, being Goal and Scope definition, Life Cycle Inventory Analysis (LCI), Life Cycle Impact Assessment (LCIA), and Interpretation. It summarizes the methodological choices that must be defined in each step and identifies the missing links in LCA studies that should be addressed to generate results that are robust, reliable, and repeatable. Since the case study chosen for this thesis is a construction project for an apartment development in Ireland, this chapter also refers to examples from LCA case studies of buildings.

2.1 Introduction to Life Cycle Assessment

Life Cycle Assessment (LCA) is defined as, “the compilation and evaluation of the inputs, outputs, and potential environmental impacts of a product system throughout its life cycle” (ISO 14040, 2006; ISO 14044, 2006). LCA can be used to make comparisons between product systems with similar functions, or to identify ‘hot spots’ within a product system’s life cycle. ‘Hot spots’ are defined as the parts of the life cycle that are contributing the most to the overall potential impact of the product system being assessed.

The results from LCA studies are used to support decision-making processes, including those made by governments, industries, corporations and consumers (Williams, Weber and Hawkins, 2009; Owsianiak *et al.*, 2018). LCA results have been used to inform policy development, implementation, and evaluation (Sala *et al.*, 2016). For example, the design of waste management systems, introduction of new technologies, and assessment of recycling strategies (Owsianiak *et al.*, 2018). Industries and corporations use LCA results to improve manufacturing processes or market products in terms of their environmental performance. Consumers make purchasing decisions based on product labels that communicate life-cycle based results, such as Type I (ISO 14024, 2018) environmental labels.

LCA studies often follow the guidelines provided by the international standards, ISO 14040:2006 and ISO 14044:2006. International standards are developed and agreed upon by technical committees with the aim of providing transparent and consistent procedures or guidelines regarding products, processes or services (ISO/IEC GUIDE 2, 2004). For LCA, these standards are reviewed by the International Organization for Standardization (ISO) every 5 years. The latest review was conducted in 2016 with no updates to the 2006 standards (ISO 14040, 2006; ISO 14044, 2006).

LCA studies that comply with the ISO standards should apply consistent methods for similar product systems to allow for comparisons, however this is often not the case (Heijungs, 2014; Henriksson *et al.*, 2014; Weidema, 2014). Due to the ambiguity of the ISO standards for LCA, various methods can be selected for assessing the impacts of the same product system yielding results that can vary by an order of magnitude (Henriksson *et al.*, 2014; Weidema, 2014). Furthermore, complying with the ISO standards has been argued to not always be possible due to time, budget, and resource constraints, and is therefore considered difficult to achieve (Heijungs, 2014). This has led to clarifications of the standards being published, such as the International Reference Life Cycle Data System (ILCD) handbook (EC-JRC-IES, 2010), and to product-specific guidelines being developed (ISO 14025, 2006; Zampori and Pant, 2019).

The International Reference Life Cycle Data System (ILCD) handbook was published by the European Commission's Joint Research Centre to aid LCA practitioners in complying with the ISO standards. This handbook provides a detailed technical guideline for the methodological choices given in the ISO standards, and addresses in more detail issues and common errors made in LCA studies (EC-JRC-IES, 2010). The ILCD aims to provide a common basis for consistent and quality-assured life cycle data, methods, and assessments for robust studies.

Product-specific guidelines have been developed to address the inconsistencies in methods applied in LCA studies of the same product system or within the same product category (Zampori and Pant, 2019). A product category consists of products that fulfil equivalent functions (ISO 14025, 2006). These guidelines are based on and claim to comply with the ISO standards for LCA but reduce the methodological choices that are left to the LCA practitioner. The aim is to harmonize the methods used within a product category to allow for comparison of the LCA results.

One such product-specific guideline is ISO 14025:2006 for developing Type III environmental labels, also known as Environmental Product Declarations (EPDs). EPDs have been produced for various products using more specific methods as indicated in Product Category Rules (PCR) (Frydendal, Hansen and Bonou, 2018). The development of PCR for unique product categories is mandatory according to ISO 14025:2006. PCR are specific to a product category and provide the requirements and guidelines for conducting an LCA of a product within that category (Hunsager, Bach and Breuer, 2014; EPD International, 2019). However, multiple verified PCR exist for the same product category that differ in the methods used for data modelling and calculation rules that can influence the results (Subramanian *et al.*, 2012; Minkov *et al.*, 2015; Frydendal, Hansen and Bonou, 2018). This means that comparisons across EPDs can only be made if they have applied the same set of PCR (Ingwersen and Stevenson, 2012; Subramanian *et al.*, 2012; Hunsager, Bach and Breuer, 2014; Minkov *et al.*, 2015).

In the buildings and construction sector, the use of EPDs has increased globally, in part due to the EU regulation, EC No. 305/2011 (Frydendal, Hansen and Bonou, 2018). This regulation states that EPDs should be used when available to assess the sustainability of resource consumption and the impact of construction works on the environment (EC, 2011). This further led to the development of the harmonized European standard that provides the core PCR for EPDs for any construction product or service, EN 15804:2012+A2:2019 (CEN, 2019). In fact, there are a series of European standards (CEN/TC 350) and international standards (ISO/TC 59/SC 17) that provide harmonized approaches for assessing life cycle impacts of buildings and construction works. However, even with the harmonized approaches within this sector, direct comparison of the potential environmental impact of one building to another is still a challenge. The services provided by each building are unique and should be considered in the comparisons (Ortiz, Castells and Sonnemann, 2009; Goldstein and Rasmussen, 2018). These services are dependent on the building type (for example, commercial or residential), architectural style, and other technical and user-specific requirements.

To improve the transparency and comparability of environmental declarations based on LCA, the Product Environmental Footprint (PEF) method was developed by the European Commission's Joint Research Centre (Zampori and Pant, 2019). The PEF method aims to harmonize the methods used across a defined product category through the development of a new set of Product Environmental Footprint Category Rules (PEFCR) that allow for comparability. The PEF method also aims to improve business-to-business and business-to-consumer communication of the LCA results (Bach *et al.*, 2018; Minkov, Lehmann and Finkbeiner, 2019). At the time of writing this thesis, the PEF method was at the beginning of the transition phase, having completed the pilot phase in 2018 (European Commission, 2019). At the end of the transition phase, the PEF method aims to be used in policy development. However, there have been shortcomings identified for the PEF method, including the definition of the product categories within which comparisons can be made (Bach *et al.*, 2018). It is suggested that these shortcomings will be addressed in the PEF transition phase.

The four steps for conducting an LCA study are shown in Figure 1, and will be discussed in detail in the following sections. The arrows in Figure 1 indicate the iterative nature of LCA. As more information is collected throughout each step, it may be necessary to go back to previous steps to adjust the scope or methods (EC-JRC-IES, 2010).

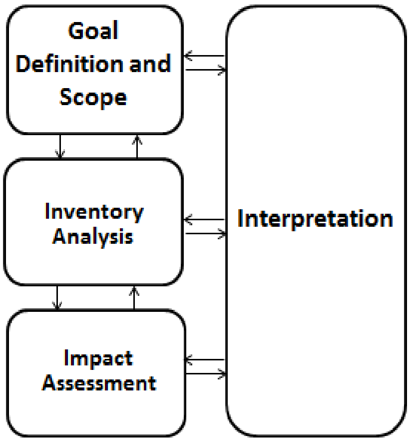


Figure 1: Life Cycle Assessment Steps (adapted from ISO 14044:2006)

2.2 Goal and Scope Definition

The Goal and Scope definition states the purpose, motivation and objectives behind the study and sets the methodology to be used throughout each step of the LCA (Finnveden *et al.*, 2009). According to ISO, the goal of an LCA study should state: (i) the intended application; (ii) the reasons for carrying out the study; (iii) the intended audience; (iv) if the results are to be used in a comparative study; and (v) if the results are intended to be disclosed to the public, in order for the study to be considered compliant (ISO 14044: *Section 4.2.2*, 2006).

The scope definition describes the methodology to be used, as well as any limitations of the study. The scope should include descriptions of the 14 requirements listed in Table 1, including the functional unit, reference flow, system boundary, data quality requirements, methodological choices and limitations (ISO 14044: *Section 4.2.3*, 2006). Table 1 further categorizes these requirements into the step that they are likely to appear in the LCA model. Although, the procedures for these requirements are described in the Goal and Scope definition, the problems associated with them occur in other steps of the LCA study (Reap *et al.*, 2008a, 2008b).

Table 1: Requirements for Scope definitions of LCA Studies

	ISO Scope Definition Requirement	Step 1	Step 2	Step 3	Step 4
1)	Product system to be studied	✓	✓		
2)	Functions of the product system(s)	✓	✓		
3)	Functional unit	✓	✓		
4)	System boundary	✓	✓		
5)	Allocation rules		✓		
6)	Characterization method and type of impacts			✓	
7)	Interpretation method				✓
8)	Data requirement		✓	✓	
9)	Assumptions	✓	✓	✓	✓
10)	Value choices and optional elements	✓	✓	✓	✓
11)	Limitations	✓	✓	✓	✓
12)	Data quality requirement		✓	✓	
13)	Type of critical review, if any	✓			
14)	Type and format of the report required	✓			

*Step 1- Goal and Scope definition; Step 2- LCI; Step 3- LCIA; Step 4- Interpretation

2.2.1 Functional Unit and Reference Flow

The functional unit is a unit of measure that describes the function of the product system (ISO 14044: *Section 4.2.3.2*, 2006). Finnveden *et al.* (2009) define the functional unit as a "quantitative measure of the functions that goods (or services) provide". The choice of the functional unit is dependent on the goal of the study. Its purpose is to provide a reference to which the inputs and outputs of the model are collected. For example, for buildings, the functional unit might be 1 m^2 of floor area or even more specifically 1 m^2 of heated floor space per year.

The reference flow is defined as the "measure of the outputs from processes in a given product system required to fulfil the function expressed by the functional unit" (ISO 14044: *Section 4.2.3.2,* 2006). Considering the example for the functional unit of 1 m^2 heated floor space per year, a suitable reference flow might be the total heated floor space of the building, such as 20,000 m^2 heated floor space over a lifetime of 50 years.

2.2.2 Scaling Factors and Scaling

Scaling Factors are commonly applied in LCA. They are used to convert the inventory data collected for each process within the system boundary (see Section 2.2.3) to the quantity required by the defined reference flow (Bjørn *et al.*, 2018). Scaling is also used when upscaling data from processes on a laboratory or pilot scale for use in an LCA study of that process on a commercial or industrial scale. This type of scaling adds uncertainty to the LCA study, particularly for emerging technologies that are in an early stage of development (Caduff *et al.*, 2014; Olsen, Borup and Andersen, 2018).

In a review article by Buyle *et al.* (2019), methods for applying scaling in LCA studies of emerging technologies are discussed and associated with the Technology Readiness Level (TRL) of the product system being assessed. The TRL gives a number from 1-9 for technologies under development, where higher numbers indicate more mature technologies. At low TRLs, which indicate an immature technology with little market penetration, it may be better to apply theoretical potentials using theoretical yields and efficiencies. As the TRL increases, linear scaling and extrapolation can be used, and once the TRL is above 9, learning and experience curves can be applied.

2.2.3 System Boundary

The system boundary defines the processes that are to be included in the LCA study. A system boundary can be defined as cradle-to-grave, cradle-to-gate, gate-to-gate, or gate-to-grave. 'Cradle' is the beginning of the life cycle from extraction of raw materials (primary or secondary materials) that are used to produce the product being assessed (ISO 14044: *Section 4.2.3.3*, 2006). 'Gate' refers to the beginning or end of a process within the system boundary and 'grave' is the final disposal of the product and its components. A cradle-to-grave system boundary should include all processes in the life cycle, whereas the latter three system boundaries are partial life cycles that include all processes along the defined supply chain.

The international standard states that omitting life cycle stages, processes, inputs, and/or outputs is only permitted if it does not significantly change the overall conclusions of the study (ISO 14044: *Section 4.2.3.3,* 2006). However, it is often impossible to include all information within the defined system boundary due to a lack of data or a lack of knowledge of the supply chain (Suh *et al.*, 2004). Furthermore, it is difficult to prove that an excluded process is negligible, particularly if the data is not available to conduct a comparative study of the different system boundaries. Therefore, the system boundary needs to be clearly defined for LCA studies, including any cut-offs in the boundary that are applied. The cut-off criteria should be defined in the scope definition (EC-JRC-IES, 2010).

2.2.3.1 Buildings and Construction

For buildings, the life cycle system boundary is divided into three stages, being pre-occupancy, occupancy and post-occupancy (Van Ooteghem and Xu, 2012). The pre-occupancy stage includes the extraction of raw materials, production, manufacture, transportation, and construction. The pre-occupancy stage is a cradle-to-gate system boundary, where the 'gate' is defined as the fully constructed building ready to be occupied. The occupancy stage includes the use and maintenance of the building and the post-occupancy stage includes the demolition of the building and disposal of its components. The occupancy stage for buildings ranges from 50 to 100 years, a 50-year life span being the most commonly applied in LCA studies as it allows for a reasonable cycle of repair, maintenance and replacement of building components (Haapio and Viitaniemi, 2008; Goldstein and Rasmussen, 2018).

Because of this life span, the occupancy stage has contributed the highest to the overall impact compared to the other two stages (Gustavsson, Joelsson and Sathre, 2010; Nemry *et al.*, 2010; Verbeeck and Hens, 2010; Goldstein and Rasmussen, 2018). A study conducted on over 73 buildings across 13 countries found that the operational energy contributes 80-90% to the overall energy consumption, with the embodied energy of a building contributing 10-20% and the demolition having little contribution (Ramesh, Prakash and Shukla, 2010). Another study found that the occupancy stage after 50 years of use contributes to greater than 90% to both the total energy consumption and greenhouse gas emissions (Van Ooteghem and Xu, 2012).

Yet, it should be noted that the operational energy demand of a building can change with improvements in energy efficiency and changes in the building material used (Gustavsson and Joelsson, 2010; Goldstein and Rasmussen, 2018). The former shifts the contribution of the occupancy stage to the pre-occupancy stage in terms of their relative contributions to the total impact of the building (Ramesh, Prakash and Shukla, 2010; Goldstein and Rasmussen, 2018). An example of the latter is the use of wood as a construction material, which has been reported to increase operational energy demand but decrease the environmental impact overall depending on the disposal scenario (Heeren *et al.*, 2015).

2.2.4 Data Quality Requirement

Data quality is defined as “characteristics of data that relate to their ability to satisfy stated requirements” (ISO 14044: *Section 4.3.2.6*, 2006). The ISO standards for LCA state that data quality requirements should be described by precision, completeness, representativeness, consistency, and reproducibility. The following data quality requirements should be stated in the scope definition:

1) Age of data and minimum length of time over which data should be collected
2) Geographical area from which data for unit processes should be collected to satisfy the goal of the study
3) Technological coverage (use of a technology mix or specific technology)
4) Precision (measure of variability)
5) Completeness (percent of the flows that are measured or estimated)
6) Representativeness (qualitative assessment of the degree to which the dataset reflects the true population of interest)
7) Consistency (qualitative assessment of whether the study methodology is applied uniformly)
8) Reproducibility (qualitative assessment of the extent to which the methodology and data information can be reproduced)
9) Sources of data
10) Uncertainty of all information (data, models, assumptions)

The LCA report must include all the above information as well as how the missing data was treated to be compliant with ISO 14044:2006. However, the missing uncertainty data for all information (Item 10) is often not addressed (Ross, Evans and Webber, 2002; Igos *et al.*, 2019). Furthermore, the ISO standards do not specify how to fulfil the data quality requirements.

Methods have been developed to assess data quality in LCA studies. For example, the PEF method uses a semi-quantitative method referred to as the data quality rating (DQR) to measure the quality of the inventory datasets and the final result (Zampori and Pant, 2019). The DQR rates the quality based on precision, technological representativeness, geographical representativeness, and time-related representativeness. This method, along with other methods for assessing data quality in LCA are discussed in more detail in Chapter 3 (Section 3.4.2).

2.2.5 Methodological Choices

Methodological choices for the LCI, LCIA and Interpretation steps of an LCA study are made during the Goal and Scope definition. This includes defining the system boundary and the data quality requirements (as previously discussed in Sections 2.2.3 and 2.2.4). It also involves selecting the LCIA impact categories and characterization models (discussed in Section 2.4), and specifying the allocation rules, value-choices and expert opinions to be applied (ISO 14044: *Section 4.2.3*, 2006). Value-choices are often used during the LCIA step and are discussed in Section 2.4. Allocation is outlined in the following section.

2.2.5.1 Allocation

Allocation is defined as “partitioning the input and output flows of a process or product system between the product system under study and one or more product systems” (ISO 14044: *Section 4.3.4*, 2006). The use of allocation may be considered when a process or product system produces more than one output. Allocation rules are reported in the Goal and Scope definition; however, they are applied in the LCI step. The international standards for LCA recommend that allocation is avoided wherever possible. Allocation can be avoided by either:

1) dividing the process to be allocated into subprocesses, and then collecting more specific data for the subprocess to be assessed, or
2) expanding the product system being studied to include the additional functions of the co-products through extension of the system boundary.

Where it is not possible to avoid allocation, the international standard recommends that allocation is conducted in one of two ways and in the following order:

1) partitioning of the inputs and outputs of a system according to quantitative physical properties between its different products or functions. For example, according to the mass of different co-products.
2) partitioning of the inputs and outputs of a system according to other relationships between its different products or functions. This is applied where physical properties alone cannot be used as the basis for allocation. For example, inputs and outputs from mining ore consisting of multiple metals (such as Copper, Lead and Zinc) could be partitioned according to the market value of each metal.

The choice of allocation rule applied changes the results of the study. The international standard recommends using sensitivity analysis to quantify the differences in the results generated by this choice. Sensitivity analysis is discussed in more detail in Chapter 3 (Section 3.1).

2.2.6 Limitations

All limitations of the study are required by ISO to be listed in the scope definition. These limitations are related to the methodological choices from Section 2.2.5 and can include:

- lack of consistency or transparency,
- lack of available data,

- use of unrepresentative data,
- use of value-choices and expert opinions,
- presence of data gaps, and
- an incomplete system boundary.

Other unforeseen limitations may arise during an LCA study. Since LCA is an iterative process, as seen in Figure 1, unforeseen limitations may lead to adjustments in the Goal and Scope definition and are required to be documented (ISO 14044: *Section 4.2.3*, 2006). Transparency of the limitations is key to ensure that the study can be repeated by another LCA practitioner.

2.2.6.1 Buildings and Construction

For buildings, reported limitations have included variation in data for building materials, a lack of transparency in the methods used, and a lack of an industry standard that allows for comparisons across regions and countries (Menzies, Banfill and Turan, 2007; Haapio and Viitaniemi, 2008; Ortiz, Castells and Sonnemann, 2009; Aktas and Bilec, 2012; Van Ooteghem and Xu, 2012; Goldstein and Rasmussen, 2018). The variation in inventory data has resulted from the lack of an agreed methodology, such as for the defined scope, system boundary, assumptions (for example, building life span), and LCI model. Harmonization of the methods used aims to address these limitations and improve the comparability of the results from one study to another (see Section 2.1 for a more detailed discussion).

2.3 Life Cycle Inventory Analysis

Life Cycle Inventory Analysis (LCI) is defined as the compilation and quantification of inputs and outputs for a given product system throughout its life cycle (Suh and Huppes, 2005). The inputs may include energy, water and natural resources, whereas the outputs may include emissions to air, water and soil (Crawford, 2011). During the LCI step, the inputs and outputs for each process within the system boundary are collected and scaled to the functional unit or reference flow. Where possible, these inventory data are validated using either mass or energy balances, or through comparisons to data from similar processes (ISO 14044: *Section 4.3.3.2*, 2006). The data must also meet the data quality requirements specified in the scope definition (see Section 2.2.4).

During collection of the inventory data, the processes within the system boundary are divided into the foreground system and the background system. Generally, the foreground system consists of processes that are specific to the product system being assessed (EC-JRC-IES, 2010; Bjørn *et al.*, 2018). Product-specific data is collected for these processes. This data comes from measurements or a combination of literature values and estimations. The data compiled for the foreground system is referred to as the foreground data or activity data (SAIC, 2006).

The background system consists of the remaining processes that are either upstream or downstream of the foreground system. Background data is obtained from generic datasets provided in databases, and is less specific to the product system being assessed (EC-JRC-IES, 2010). Databases can also be used to fill in data gaps in the foreground system if more specific data is not available (Bjørn *et al.*, 2018). Many databases exist for use in LCA that contain peer-reviewed datasets, including Ecoinvent (Wernet *et al.*, 2016) and GaBi Databases (Sphera, 2020).

The LCI result is calculated by summing the common flows for each process within the system boundary (Bjørn *et al.*, 2018). The result produced is in the form of a list of unique entries (often referred to as flows) that can contain over 1000 items (Hauschild, 2015).

This list includes the name of each flow (for example, Carbon dioxide, Zinc or Mercury) and the compartment it is emitted to or extracted from (such as, to freshwater, to the upper troposphere/lower stratosphere or from natural resources in the ground) (Heijungs and Suh, 2002; Wernet *et al.*, 2016). In this form, the LCI result is ready for use in the LCIA step (discussed in detail in Section 2.4).

Since LCA studies involve large amounts of data, LCA software has been developed and commercialized to manage the inventory data and calculate the LCI result. This includes software such as GaBi LCA Software (Sphera, 2020) and SimaPro (PRé, 2020). Other LCA software has also been developed that allows the LCA practitioner to write code using programming languages (such as, C++ or Python) in the background. This option is available in both OpenLCA (GreenDelta, 2020) and Brightway2 (Mutel, 2017). Statistical programming software, such as RStudio (RStudio Team, 2016), can also be used to manage large amounts of data without LCA software.

There are three main approaches to construct the LCI model and calculate the result. These include Process analysis, Environmentally Extended Input-Output analysis, and Hybrid Techniques. Each approach will be discussed in the following sections.

2.3.1 Process Analysis

Process analysis uses a bottom-up approach to compile inventory data (EC-JRC-IES, 2010; Bjørn *et al.*, 2018). This approach requires extensive knowledge and data on the processes within the system boundary and the physical flows that connect them (Bullard, Penner and Pilati, 1978; Bjørn *et al.*, 2018).

Process analysis can be categorized as attributional or consequential. An attributional model uses average data for all processes included in the system boundary (Plevin, Delucchi and Creutzig, 2013). For example, an attributional model for electricity production assumes that electricity is produced simultaneously by all suppliers on the market. The inventory data are estimated based on the market share of each supplier, generating data for an average production mix (Bjørn *et al.*, 2018). However, the production mix changes with demand. In a consequential model, data are only obtained from suppliers where a change in production is observed. The aim of consequential LCI is to determine how the inputs and outputs within a system change according to a decision (Finnveden *et al.*, 2009; EC-JRC-IES, 2010; Plevin, Delucchi and Creutzig, 2013). The inventory data, therefore, are not collected for all processes within the system boundary, only those that change.

With Process analysis, two modelling structures can be used to represent the flows from one process to the next and calculate the LCI result (Heijungs and Suh, 2002; Suh and Huppes, 2005). These include Process Flow Diagram and Matrix Expression, which are discussed in the following sections.

2.3.1.1 Process Flow Diagram

Process Flow Diagrams use a flow chart to show how the processes of a product system are connected through commodity flows throughout its entire life cycle (Suh *et al.*, 2004; Suh and Huppes, 2005). The flow charts use boxes to indicate processes and arrows to represent flows. To calculate the LCI result (M_{PFD}), the quantity of a commodity (a_i) scaled to the reference flow (for example, 10 kg Steel) is multiplied by the environmental intervention (b_i) being assessed (for example, 1 kg CO_2 per kg Steel) for each process, i (see Equation 1). The common interventions are then summed to give the total environmental intervention per functional unit for all processes included in the system boundary (for example, 1000 kg CO_2 per functional unit). Ignoring recycling loops and allocation (see Section 2.2.5.1), the mathematical relationship can be expressed with Equation 1. This equation becomes more complex when accounting for loops within the flow diagram (Suh and Huppes, 2005).

$$M_{PFD} = \sum_{i=1}^{n} b_i a_i \qquad (1)$$

2.3.1.2 Matrix Expression

Matrix Expression uses a matrix equation to express the flow diagram, hence the LCI result is calculated with the use of a system of linear equations (Suh and Huppes, 2005). When setting up the matrix, the columns represent the processes and the rows the inputs and outputs for each process. The values within the matrix are zero if negligible, negative if consumed by the process and positive if produced by the process. The total overall environmental intervention, $\widetilde{M}_{ME}$, can be calculated using Equation 2:

$$\widetilde{M}_{ME} = \tilde{B}\tilde{A}^{-1}\tilde{k} \qquad (2)$$

where $\tilde{k}$ is a vector that incorporates the functional unit of the system, $\tilde{A}$ is the technology matrix, and $\tilde{B}$ is the environmental intervention matrix (Suh *et al.,* 2004). Matrix $\tilde{A}$ includes the inputs and outputs of each process for a defined operational period. Matrix $\tilde{B}$ includes the amount of pollutants or natural resources emitted or consumed by each process during the same operation time.

2.3.1.3 Strengths and Weaknesses of Process Analysis

The use of Process analysis is considered a strength since it can enhance the accuracy of the study if the data used are specific to the product being assessed (Suh and Huppes, 2005; Crawford, 2011). The data should also meet the stated data quality requirements (see Sections 2.2.4 and 3.4.2).

The main weakness reported by many researchers is truncation error (Bullard, Penner and Pilati, 1978; Crawford, 2008; Goggins, Keane and Kelly, 2010). Truncation error is limiting the number of digits to the right of the decimal point by discarding the least significant figures. This cut-off can lead to errors of around 50% to 87% depending on the complexity of the product system (Lenzen and Dey, 2000; Lenzen, 2001; Suh *et al.*, 2004; Crawford, 2008). Truncation error is unavoidable since all processes in an economy are directly and indirectly connected with each other and a cut-off is necessary (Suh *et al.*, 2004).

Another weakness is data availability and the time and resources required for data collection (Suh and Huppes, 2005; Crawford, 2011). It is not always possible to collect product-specific data for all upstream processes in a supply chain. To overcome this, LCA databases are used. However, the datasets in databases are often based on average data obtained from different production technologies from various manufacturers in multiple countries and may not be representative of the specific product being studied (Lenzen and Dey, 2000; EC-JRC-IES, 2010; Goggins, Keane and Kelly, 2010; Crawford, 2011; Wernet *et al.*, 2016; Bjørn *et al.*, 2018). Therefore, a qualitative assessment of these datasets is necessary (see Section 3.4.2).

2.3.2 Environmentally Extended Input-Output Analysis

Input-Output (I-O) analysis is used in economics to describe the interdependencies of sectors within an economy (Heijungs and Suh, 2002; Suh *et al.*, 2004). Two assumptions are made in Input-Output analysis, being proportionality and homogeneity (Treloar, 1998). Proportionality assumes that the amount of goods and services consumed by a sector are directly proportional to the cost of each product output from that sector. Homogeneity assumes that each product output from a sector requires the same mix of inputs. The relationship between sectors is assumed to occur in fixed ratios. This means that a change in the production of an output from one industry will cause a change in the production of an output from an interrelated industry by the same ratio (Suh and Huppes, 2005). The structure of economic I-O analysis is similar to that of attributional LCI (defined in Section 2.3.1) in that linear relationships are assumed (Mattila, 2018). I-O analysis has been applied in LCI and is referred to as Environmentally Extended Input-Output (EEIO) analysis.

Like economic I-O analysis, EEIO analysis uses a top-down approach for compiling inventory data that starts from economy-wide statistics and focuses in on industries and product systems. It combines monetary data from input-output tables with national environmental accounts data for aggregated sectors of an economy (Bullard, Penner and Pilati, 1978). The total environmental intervention (M_{IO}) for each sector is calculated using Equation 3, where Q is the environmental intervention vector, L is the Leontief inverse matrix, and k is the vector incorporating the functional unit.

$$M_{IO} = QLk \qquad (3)$$

Vector Q is obtained by dividing the sectoral environmental accounts data by the total production in Euro for the same sector (Suh and Huppes, 2005). The number of sectors and how they are aggregated varies between countries. For Ireland, the environmental accounts data are published for 19 aggregated sectors and contain data on, for example, greenhouse gas emissions, pesticide use, and landfilled hazardous waste (Tol, Lyons and Mayor, 2008).

The Leontief inverse (L) is calculated using Equation 4, where I is the identity matrix and A is the direct requirements matrix (Heijungs and Suh, 2002).

$$L = (I - A)^{-1} \qquad (4)$$

The identity matrix (I) is an *n x n* matrix with the number 1 along the diagonal and the number 0 in all other locations. The direct requirements matrix (A) is computed from the input-output tables by dividing each value (€) in the table by the total value output (€) from the associated sector. Subtracting the two matrices $(I - A)$ gives a similar matrix to the technology matrix, $\tilde{A}$, from Equation 2 (Suh and Huppes, 2005). Taking the inverse of this matrix, $(I - A)^{-1}$, produces the Leontief inverse matrix (L). The values within matrix L represent the total Euro input from a sector in a row to directly and indirectly produce each Euro output from a sector in a column (Treloar, 1998).

2.3.2.1 Single-Region versus Multi-Region Models

There are two forms of I-O models: single-region and multi-region. In single-region input-output (SR-IO) models, it is assumed that imported goods and services are being produced with the same technology as the domestic technology in the same sector (Wiedmann, 2009). The SR-IO approach does not differentiate between domestic and foreign production technologies.

In multi-region input-output (MR-IO) models, goods and services produced using domestic technology and those using foreign technology can be separated (Tukker and Dietzenbacher, 2013). Therefore, the impact of imported goods is differentiated from domestic goods and is quantifiable. Although MR-IO models can improve I-O analysis, particularly for product systems that rely on imports and new technologies, little is known about the error in the model (Wiedmann, 2009; Moran and Wood, 2014).

Multiple MR-IO tables exist that include I-O data for over 40 countries, such as Exiobase (Stadler *et al.*, 2018) and World Input-Output Database (Timmer *et al.*, 2015). Exiobase is an open source multi-regional environmentally extended I-O table containing data for 44 countries (28 EU members and 16 other major economies) and 5 rest of the world (RoW) regions for the years 1995-2011 (Stadler *et al.*, 2018). The World Input-Output Database (WIOD) is also publicly available. The latest version released in 2016 contains economic data for 53 sectors, covering 43 countries (28 EU members and 15 other countries) and a model for a RoW region for the years 2000-2014 (Timmer *et al.*, 2015). Environmental accounts data has been published by the European Commission's Joint Research Centre, which includes energy use and Carbon dioxide emissions data for 28 EU countries and 13 other major countries (Corsatea *et al.*, 2019). This data can be combined with the WIOD to produce a multi-regional environmentally extended I-O table.

2.3.2.2 Strengths and Weaknesses of EEIO Analysis

The main advantages of I-O analysis are that it is a relatively quick and cheap method to apply and has a systematically complete system boundary (Suh and Huppes, 2005; Crawford, 2008). I-O tables also provide very relevant information on a product system if that product system accounts for a significant proportion of the outputs from a sector (Goggins, Keane and Kelly, 2010). If there are multiple significant outputs from a sector, or where sectors are highly aggregated, however, the use of average data over the entire sector (or aggregation of sectors) produces very general results. One disadvantage of I-O analysis is therefore sector aggregation (Suh and Huppes, 2005). This leads to less relevant information on a specific product system and larger error in the results, if sectors are not first disaggregated.

The estimated error due to economic I-O data is highly dependent on its source and the sector, but is in the region of ±20% (Lenzen and Dey, 2000). Quantification of this error is difficult, however, as typically only a single data source for national input-output tables exists that does not include information on data uncertainty (Moran and Wood, 2014; Chen, Griffin and Matthews, 2018). Other studies have indicated that the majority of the error in EEIO analysis is introduced with the vector Q (refer to Equation 3), which contains the environmental intervention data per sector (Yamakawa and Peters, 2009; Lenzen, Wood and Wiedmann, 2010; Moran and Wood, 2014; Karstensen, Peters and Andrew, 2015; Chen, Griffin and Matthews, 2018). Comparatively, the uncertainty of matrix A (which is associated with the input-output tables) and the Leontief inverse (L) are considered small.

Chen *et al.* (2018) found that the environmental intervention data per sector for direct energy consumption can vary on average by ±50%. The error was found to be dependent on the sector and the source of the data (in this case data from the US Census and Use Tables). The overall EEIO analysis uncertainty for each sector considering the direct and indirect impacts was reported to be in the range of ±40%. This uncertainty is smaller than that of the environmental intervention data due to the cancellation effect of stochastic errors (Jaynes, 1957; Chen, Griffin and Matthews, 2018). When applying SR-IO models and ignoring imports, even higher uncertainties are expected (Suh and Huppes, 2005). This is due to the introduction of truncation errors that can be larger than those seen in Process analysis (50-87%; see Section 2.3.1.3).

2.3.3 Hybrid Techniques

Hybrid Techniques have been developed that combine Process and Input-Output analysis in a way that minimises their limitations (Crawford, 2008; Goggins, Keane and Kelly, 2010). The use of input-output data helps to improve the completeness of the system boundary (removing truncation errors), and the use of process data allows for a more detailed and accurate analysis (removing aggregation errors) (Suh and Huppes, 2005).

The Hybrid Techniques include Process-based hybrid analysis, Input-Output-based hybrid analysis, Tiered-hybrid analysis, and Integrated hybrid analysis, each of which uses a different combination of process and input-output data. In general, each Hybrid Technique involves examining the input materials to determine whether process data or input-output data will be used to assess their impact (Bullard, Penner and Pilati, 1978). The techniques are discussed in the following sections.

2.3.3.1 Process-based Hybrid Analysis

Process-based hybrid analysis uses input-output data upstream of process data in order to achieve a more complete system boundary (Crawford, 2011). It is based mainly on process data, using input-output data to fill in gaps or replace data that is highly uncertain (Bilec *et al.*, 2006). One disadvantage of this method is that horizontal and downstream truncation error can occur (Crawford, 2008; Goggins, Keane and Kelly, 2010).

2.3.3.2 Input-Output-based Hybrid Analysis

Input-Output-based hybrid analysis aims to combine process data and input-output data in a different way to Process-based hybrid analysis in order to remove downstream and horizontal truncation (Crawford, 2008). This is carried out by disaggregating the industry sectors of the input-output table, for example, industry j and its product i can be disaggregated into two in the input-output table (Suh and Huppes, 2005):

$$\begin{matrix} \boldsymbol{a_{11}} & \cdots & a_{1j_a} & a_{1j_b} & \cdots & \boldsymbol{a_{1n}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{i_a1} & \cdots & a_{i_aj_a} & a_{i_aj_b} & \cdots & a_{i_an} \\ a_{i_b1} & \cdots & a_{i_bj_a} & a_{i_bj_b} & \cdots & a_{i_bn} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{a_{n1}} & \cdots & a_{nj_a} & a_{nj_b} & \cdots & \boldsymbol{a_{nn}} \end{matrix}$$

The data for the new columns and rows are estimated using process-based data. The environmental intervention matrix is also disaggregated in the same way using detailed emissions data (Suh and Huppes, 2005). To calculate the LCI result, the disaggregated system must be added manually to the remaining stages of the life cycle, for example the use and disposal stages. The matrix representation for this technique is:

$$M_{IOH} = \begin{bmatrix} \tilde{B} & 0 \\ 0 & B' \end{bmatrix} \begin{bmatrix} \tilde{A} & 0 \\ 0 & 1 - A' \end{bmatrix}^{-1} \begin{bmatrix} \tilde{k} \\ k' \end{bmatrix} \qquad (5)$$

where $\tilde{B}$ is the environmental matrix for the process-based part, $\tilde{A}$ is the technology matrix for the process-based part, and $\tilde{k}$ is the arbitrary final demand vector for the process-based part. B', A', and k' are the same but for the disaggregated input-output-based part.

Three models have been defined for Input-Output-based hybrid analysis based on how the sectors of the input-output table are disaggregated, being Model II, Model III, and Model IV (Joshi, 2000). Model II is used when the product being analysed is not typical of an existing economic sector or when a new product is being introduced into the economy. Model III involves the disaggregation of a sector, along with the creation of an extended technology matrix allowing for detailed process data to be added without double counting errors (Bilec *et al.*, 2006). Model IV involves iteratively disaggregating the sectors and replacing the I-O data with process data when available (Joshi, 2000; Bilec *et al.*, 2006). Model IV is similar to Process-based hybrid analysis since it is based mainly on a detailed process framework (Bilec *et al.*, 2006).

2.3.3.3 Tiered-hybrid Analysis

Tiered-hybrid analysis uses process data for the use and disposal stages, as well as for several significant upstream processes (Suh and Huppes, 2005). Input-output data is used for the remaining input requirements, and is simply added to account for the missing inputs (Strømman, Peters and Hertwich, 2009). One advantage of the Tiered-hybrid is that it is reasonably complete and fast compared to the other techniques (Suh and Huppes, 2005). A disadvantage is that the border between the input-output data and process data must be well defined to prevent double counting errors (Suh and Huppes, 2005). The matrix representation for this technique is given in Equation 6, where $\tilde{B}$, $\tilde{A}$, and $\tilde{k}$ are the same as Equation 5 for the process-based part and B, A, and k represent the input-output-based part.

$$M_{TH} = \begin{bmatrix} \tilde{B} & 0 \\ 0 & B \end{bmatrix} \begin{bmatrix} \tilde{A} & 0 \\ 0 & 1 - A \end{bmatrix}^{-1} \begin{bmatrix} \tilde{k} \\ k \end{bmatrix} \qquad (6)$$

Several methods to address double counting errors in Tiered-hybrid analysis have been developed. One such method is by-product correction which subtracts the price of the input that is already accounted for with process data from the I-O data (Williams, 2004; Strømman, Peters and Hertwich, 2009; Acquaye, Duffy and Basu, 2011). However, this method can result in negative inputs. Therefore, tier-wise purchase correction can be used to avoid negative values. This is done by subtracting the price of the input first by the sector producing it and then by the top contributing upstream sectors identified using structural path analysis (Strømman, Peters and Hertwich, 2009; Agez *et al.*, 2020).

Other methods to avoid double counting introduce a matrix into Equation 6 that maps the I-O flows to 0 or 1 depending on whether they are already accounted for with process data. These methods range from ad hoc methods to more complex equations or algorithms

(Agez *et al.*, 2020). Ad hoc methods allow the LCA practitioner to set double counted inputs to zero, whereas algorithms systematically identify flows, group them, and remove those that are double counted. The use of complex equations or algorithms is potentially more efficient than ad hoc methods, particularly when dealing with large datasets or databases.

2.3.3.4 Integrated Hybrid Analysis

Integrated hybrid analysis differs from the previous Hybrid Techniques in that it connects the input-output table with the process data in a matrix model at both upstream and downstream cut-offs where better data are unavailable (Suh and Huppes, 2005). The matrix representation for this technique is:

$$M_{IH} = \begin{bmatrix} \tilde{B} & 0 \\ 0 & B \end{bmatrix} \begin{bmatrix} \tilde{A} & Y \\ X & 1 - A \end{bmatrix}^{-1} \begin{bmatrix} \tilde{k} \\ 0 \end{bmatrix} \qquad (7)$$

where matrix X represents the upstream cut-off flows of the process data, linked with the relevant industry sector in the input-output table. Matrix Y represents the downstream cut-off flows of the input-output data from the process data (Suh and Huppes, 2005). Each element of X is in units of monetary value/operational time, and each element of Y is in units of physical unit/monetary value. Matrices X and Y allow for the interactions between individual processes and industries to be modelled in a consistent framework. This eliminates double counting errors since the addition of input-output data to process data does not need to be completed in a separate step (Suh and Huppes, 2005). The disadvantage of this technique is that it requires a large amount of data and complexity compared to the other Hybrid Techniques (Suh *et al.*, 2004; Strømman, Peters and Hertwich, 2009).

2.3.4 Best Practice for LCI

In theory, Process analysis and Input-Output analysis should yield similar results if the data used in both analyses are specific to the product system being assessed. However, the data required for this are generally not available at the necessary level of detail (Suh *et al.*, 2004; Suh and Huppes, 2005; Crawford, 2008; Goggins, Keane and Kelly, 2010). Therefore, the Hybrid Techniques were developed.

Since the Hybrid Techniques combine the strengths of both Process and Input-Output analyses, they are assumed to produce more accurate results (Williams, Weber and Hawkins, 2009). However, methods to quantify the accuracy of one method compared to another are lacking. Yang *et al.* (2017) used a hypothetical example to show that hybrid analysis is not necessarily more accurate than Process analysis if highly aggregated input-output data is used in place of highly truncated process data. However, Pomponi *et al.* (2018) argue that the example provided combines process data with relatively low truncation errors and input-output data with relatively high aggregation errors. Therefore, the data used is not representative of the data that is available for practical case studies.

Integrated hybrid analysis is considered the state-of-the-art approach to construct the LCI model (Strømman, Peters and Hertwich, 2009; Goggins, Keane and Kelly, 2010). However, in practice, the decision to use one Hybrid Technique over another is based on the amount of resources available. Integrated hybrid analysis is both time and cost intensive. Tiered-hybrid analysis, on the other hand, is not as resource intensive, being considered one of the easiest techniques to apply (Nakamura and Nansai, 2016). It is also the most widely applied Hybrid Technique (Nakamura and Nansai, 2016; Yang, Heijungs and Brandão, 2017). Because of this, and due to the advantages of Tiered-hybrid analysis over the other Hybrid Techniques (completeness, analysis time, ease of use, available methods to account for double counting errors), it is considered here as best practice. However, this is also dependent on the resources available to an LCA case study. Changes in available time, budget, and product-specific process data will lead to changes in the best approach to construct the LCI model that achieves the defined Goal and Scope (see Section 2.2).

2.3.4.1 Buildings and Construction

Goldstein *et al.* (2018) reviewed the methods used in LCA case studies of individual buildings versus the built environment. For buildings, they concluded that studies generally strive for accuracy, using site specific data, such as masses and lifetimes of specific building components. Building LCAs have therefore applied Process analysis to construct the LCI model. For the built environment, on the other hand, the data required are not specific to one building but often collected from surveys or reports. In their review, Goldstein *et al.* (2018) found that both Process analysis and Input-Output analysis have been used in LCA case studies of the built environment. These studies strive to capture trends, focusing on the assessment of multiple buildings in a neighbourhood or city.

For accounting for the construction process of a building, however, process data are difficult to obtain. One reason for this is that onsite construction emissions data are not consistently reported or tracked (Bilec *et al.*, 2006). Process analysis and Hybrid Techniques have both been used to account for construction emissions depending on the availability of data (Bilec *et al.*, 2006; Li, Zhu and Zhang, 2010; Crawford, 2011). Li *et al.* (2010) applied Process analysis to assess the impact of onsite construction, accounting for the construction equipment and ancillary materials (not including the building materials). Bilec *et al.* (2006), on the other hand, applied Process-based hybrid analysis due to the lack of process data available for construction emissions.

2.4 Life Cycle Impact Assessment

Life Cycle Impact Assessment (LCIA) converts the LCI results into their potential impact on the environment (Rosenbaum *et al.*, 2018). This step is divided into four steps: classification, characterization, normalisation, and weighting. The former two steps are mandatory for ISO compliance, whereas the latter two are optional *(ISO 14044: Section 4.4.1*, 2006). The methods used in these steps are selected during the Goal and Scope definition (see Section 2.2.5). Each step is discussed in more detail in the following sections.

2.4.1 Classification

Classification assigns the LCI results to impact categories (ISO 14044: *Section 4.4.2.3*, 2006; Guinée, 2015; Rosenbaum *et al.*, 2018). For example, studies that include the climate change impact category assign the emissions of greenhouse gases (GHGs), such as the emission of methane (CH_4) into air, to that impact category. Impact categories describe environmental concerns that occur through a defined impact pathway. The impact pathway is defined as the cause-effect chain, including the physical, chemical and biological processes, that leads to damage to human health, the natural environment, or natural resources (EC-JRC-IES, 2010). The assessment of an impact category occurs at either a midpoint or endpoint along the cause-effect chain using a specified category indicator. The category indicator is defined as a quantifiable representation of an impact category (ISO 14044: *Section 3*, 2006).

A midpoint indicator is an impact category indicator located somewhere along the impact pathway between emission and category endpoint (Rosenbaum *et al.*, 2018). The exact location on the cause-effect chain depends on the impact category, but occurs where the pathway to damage beyond that point arises through a similar mechanism (Hauschild *et* *al.*, 2013). For example, radiative forcing is the category indicator for climate change. Radiative forcing occurs when GHGs in the atmosphere absorb radiation reflected from the Earth's surface and emit it in all directions (Myhre *et al.*, 2013). When the emission occurs towards the Earth's surface, this is referred to as positive radiative forcing and may lead to temperature increases in the Earth's surface. For each GHG emitted into the atmosphere, the impact pathway may differ up to the point of radiative forcing. After this point, the mechanism is similar for all GHGs, but differs in intensity depending on the GHG released. Depending on the impact category, the midpoint indicator may not actually occur mid-way through the impact pathway but closer to the endpoint (EC-JRC-IES, 2010). This is seen for the human toxicity impact category, for example.

Endpoint indicators are defined more specifically according to the damage caused to the three areas of protection: human health, natural environment, and natural resources (EC-JRC-IES, 2010; Rosenbaum *et al.*, 2018). The endpoint indictors, therefore, represent impacts further down the impact pathway, or cause-effect chain, than midpoint indictors. Endpoint impact results combine multiple impact categories into a single score and require weighting and normalisation (discussed in Sections 2.4.3 and 2.4.4). There are various LCIA endpoint models that are used in LCA Software, such as Eco-Indicator (Goedkoop and Spriensma, 2001) and ReCiPe (Huijbregts *et al.*, 2017).

Endpoint results have been assumed to be more uncertain than midpoint results due to the complexity of the impact pathway (Reap *et al.*, 2008b; Hauschild, 2015). However, Rosenbaum *et al.* (2018) argue that from a decision-support perspective this may not always be the case. They state that the overall uncertainty of decisions made based on the midpoint results may be similar to those made based on endpoint results. This is because midpoint results have higher precision and lower accuracy than endpoint results and are less representative of the potential damage that occurs at the endpoint.

2.4.2 Characterization

Characterization is the calculation of category indicator results (Hauschild, 2015; Rosenbaum *et al.*, 2018). Characterization factors indicate the environmental impact per unit of emission released or resource extracted (Huijbregts *et al.*, 2017). They convert the LCI results into the same unit for each impact category, such as kg CO_2-equivalents for climate change. To calculate the LCIA result for each impact category (IC), the sum of the LCI result multiplied by its associated CF for each item i is taken (Equation 8).

$$IC\ Result = \sum_i LCI_i \cdot CF_i \qquad (8)$$

Characterization Factors are derived from characterization models. These models quantify the effect of a specific emission or extracted resource on the environmental concern being assessed (Rosenbaum *et al.*, 2018). There are multiple characterization models that can be used to derive the CFs. Some of these models are considered to be mature, while others require significant development to ensure that their use does not lead to incorrect decisions being made (Drielsma *et al.*, 2016). LCA studies should consider multiple impact categories to ensure that the reduction of an impact in one category does not lead to an increase in another (EC-JRC-IES, 2010).

Some examples of impact categories include climate change, energy demand, resource depletion, acidification, eutrophication, aquatic toxicity, and human toxicity. These are described further in Table 2.

Table 2: Examples of LCIA midpoint impact categories with selected characterization models and characterization factors

Midpoint Impact Category	LCI Results (per functional unit)	Characterization Model	Category Indicator	Characterization Factor	Unit	Environmental Relevance (Acero, Rodríguez and Ciroth, 2015)
Climate Change	Quantity of greenhouse gas (CO_2, CH_4, etc.) emitted	IPCC AR5 GWP 100 years	Infrared Radiative Forcing	Global Warming Potential (GWP)	kg CO_2-equivalent per functional unit	Infrared radiative forcing represents the potential effect of greenhouse gases on global temperature, climate, and biodiversity.
Energy Demand	Quantity of energy extracted in MJ	Primary Energy Demand from renewables and non-renewables	Energy demand	Primary Energy Demand (PED)	MJ per functional unit	Energy demand represents the potential effect of energy consumption on availability of primary energy from renewable and non-renewable sources.
Resource Depletion	Quantity of elements/minerals (Li, Cu, etc.) extracted	CML 2001- Jan. 2016, Abiotic Depletion Potential Elements	Decrease of resources	Abiotic Depletion Potential Elements (ADP Elements)	kg Sb-equivalent per functional unit	A decrease of resources represents the potential effect of unsustainable use on abiotic resource abundance and ecosystem collapse.
	Quantity of natural resources (crude oil, etc.) extracted	CML 2001- Jan. 2016, Abiotic Depletion Potential Fossil	Decrease of resources	Abiotic Depletion Potential Fossil (ADP Fossil)	MJ per functional unit	A decrease of resources represents the potential effect of unsustainable use on abiotic resource abundance and ecosystem collapse.
Acidification	Quantity of emission (SO_2, NO_x, etc.)	CML 2001- Jan. 2016, Acidification Potential	Proton release to water and soil (H^+ aqueous)	Acidification Potential (AP)	kg SO_2-equivalent per functional unit	Proton release from anthropogenic emissions represents the potential effect of increased acidity on ecosystem quality and biodiversity.
Eutrophication	Quantity of emission (PO_4^{3-}, etc.)	CML 2001- Jan. 2016, Eutrophication Potential	Nutrient release (nitrogen and phosphate)	Eutrophication Potential (EP)	kg PO_4^{3-}-equivalent per functional unit	Release of nutrients represents the potential effect of biomass formation on ecosystem quality.
Ecotoxicity	Quantity of toxic chemical released	USEtox™ 2.1, Aquatic Toxicity Potential	Toxic chemical release (based on fate, effect and exposure factors)	Aquatic Toxicity Potential (ATP)	CTUe (Comparative Toxic Units, ecosystem damage potential)	Toxic chemical release represents the potential effect of biodiversity loss on ecosystem quality and species extinction.
Human Toxicity	Quantity of carcinogenic chemical released	USEtox™ 2.1, Human Toxicity Potential, cancer	Carcinogenic chemical release (based on fate, effect and exposure factors)	Human Toxicity Potential (HTP), cancer	CTUh (Comparative Toxic Units, human toxicity potential)	Carcinogenic chemical release represents the potential effect of cancer on human health.

2.4.3 Normalisation

Normalisation expresses the results of each impact category (calculated with Equation 8) on a common scale (ISO 14044: *Section 4.4.3.2*, 2006; Rosenbaum *et al.*, 2018). In order to do this, a reference system is selected, such as a geographical zone (global, local, or regional), an inhabitant of a geographical zone, or an industrial sector of a geographical zone (Rosenbaum *et al.*, 2018). To quantify the NFs for each impact category, LCI and LCIA are conducted on the reference system up to the characterization step (Section 2.4.2). The results are often divided by the population of the reference region, depending on the Equation 8 are multiplied by the corresponding NF to calculate the normalised LCIA results.

Normalisation can help with communication of the results from the characterization step to decision makers (Benini and Sala, 2016; Pizzol *et al.*, 2017). However, care needs to be taken when interpreting these results, as the choice of a reference system is ambiguous and can change the results of a study (Rosenbaum *et al.*, 2018). Furthermore, there are several methodological choices and assumptions required to derive NFs, and therefore, the uncertainty of the results can be high. Benini *et al.* (2016) found that this uncertainty is dependent on the impact category being assessed. For some impact categories, high methodological uncertainties in the NFs arise from the inventory data and characterization models. Global NFs have been recommended for use and have been developed for multiple impact categories in compliance with the ILCD Handbook (Pizzol *et al.*, 2017; Crenna *et al.*, 2019). However, even for the global NFs, work is still needed to reduce the uncertainties (Crenna *et al.*, 2019). Uncertainty is discussed in more detail in Chapter 3.

2.4.4 Weighting

Weighting is another optional step of LCIA that can be applied after normalisation. This step applies numerical weighting factors to impact category results to prioritize one impact over another (Rosenbaum *et al.*, 2018). Weighting is useful for aggregating the LCIA results into a single score, comparing across impact categories, and communicating prioritized results. Weighting factors can be based on political targets, environmental control and damage costs, or preferences from a panel of experts (Huijbregts, 1998a). They are not science-based and always involve value-choices (Finnveden, 1997; Huijbregts, 1998a; ISO 14044:*Section 4.4.3.4*, 2006; EC-JRC-IES, 2010; Freidberg, 2018; Rosenbaum *et al.*, 2018).

Value-choices (also known as value judgement) are decisions made based on implicit or recognized opinions, beliefs, or bias. Value-choices can lead to different LCA results, and are therefore required to be explicitly stated in the scope definition (EC-JRC-IES, 2010; De Schryver *et al.*, 2011). For example, different individuals, organizations, and societies may have different preferences, and therefore reach different conclusions based on the same initial data (Rosenbaum *et al.*, 2018). Justifying the reasoning behind a value-choice is very controversial and can be argued differently according to one's ethical values, including views on society and nature (Finnveden, 1997; Finnveden *et al.*, 2009).

Weighting factors can also be applied to approaches that support the precautionary principle (Finnveden *et al.*, 2009). The precautionary principle states that where there are threats of serious or irreversible damage, lack of a full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation. Hence when there is insufficient knowledge, a conservative approach should be taken. Weighting factors can help identify this approach.

Like normalisation factors, the use of weighting factors may lead to an increase in the overall uncertainty of the results (refer to Chapter 3 for a discussion on uncertainty). More research is also needed to improve the robustness and transparency of weighting in LCA (Pizzol *et al.*, 2017).

2.5 Interpretation

The interpretation step of LCA is used to assess the overall quality and reliability of the results. This is an iterative process, as seen in Figure 1. The interpretation step is usually conducted in three steps (ISO 14044: *Section 4.5.1,* 2006):

1. identification of significant issues,
2. evaluation of the significant issues, and
3. presentation of the final conclusions, limitations, and recommendations.

Significant issues are defined as key processes, data, or methodological choices and assumptions (for example, allocation rules, value-choices, and expert opinion) that influence the overall result (ISO 14044: *Section 4.5.2.1*, 2006; EC-JRC-IES, 2010; Hauschild, Bonou and Olsen, 2018). The extent to which they influence the result is assessed in the evaluation.

The evaluation includes completeness, consistency, and sensitivity checks, which are discussed in the following sections. The basis from which the final conclusions, limitations, and recommendations are formulated is also determined during the evaluation (Hauschild, Bonou and Olsen, 2018).

2.5.1 Completeness Check

The completeness check determines the extent of which the inventory and impact assessment data are complete for significant processes and impacts (those identified as significant issues) (ISO 14044: *Section 4.5.3.2*, 2006; Hauschild, Bonou and Olsen, 2018). Datasets that are found to be incomplete should either be improved by filling in the data gaps or justified and reported with the final conclusions. This check aims to iteratively improve the completeness of the significant processes and impacts. It also ensures that the cut-off criteria (refer to Section 2.2.3) and the data quality requirements (refer to Section 2.2.4) stated in the Goal and Scope definition have been met (EC-JRC-IES, 2010).

2.5.2 Consistency Check

The consistency check determines whether the assumptions, methods and data used in the study are consistent with the Goal and Scope definition (ISO 14044: *Section 4.5.3.4,* 2006; Hauschild, Bonou and Olsen, 2018). For example, it checks that the weighting factors and normalisation factors (if used) have been applied consistently, as well as the system boundary and allocation rules (ISO 14044: *Section 4.5.3.4,* 2006; EC-JRC-IES, 2010). It also evaluates the influence of any inconsistencies found on the overall results. These inconsistencies are considered in the final conclusions, limitations, and recommendations of the study.

2.5.3 Sensitivity Check

The purpose of the sensitivity check is to assess the reliability of the final results, conclusions and recommendations of the LCA study (ISO 14044: *Section 4.5.3.3,* 2006; EC-JRC-IES, 2010). The sensitivity check is conducted by scenario analysis or by qualitative assessment based on expert opinion of the significant issues (EC-JRC-IES, 2010). Scenario analysis calculates and compares the results of different scenarios, such as the use of different approaches to construct the inventory data or different weighting factors. The output of the sensitivity check indicates the influence of the scenarios on the overall results (ISO 14044: *Section 4.5.3.3*, 2006).

This check is done iteratively to ensure that the data quality requirements and other methodological choices stated in the Goal and Scope definition have been met (Hauschild, Bonou and Olsen, 2018). In the case where further collection or refining of the data is needed, the Goal and Scope definition should be adjusted accordingly and/or the limitations documented with the final conclusions. As an iterative step, the sensitivity check can also use the results of previous sensitivity and uncertainty analyses if they have been conducted. For ISO compliance, it is only mandatory to include these in the interpretation if they have been conducted previously in the LCI and LCIA steps (ISO 14044: *Section 4.5.3.3*, 2006). However, little guidance on how or when to conduct these analyses is provided in the standards (Reap *et al.*, 2008b).

Sensitivity analysis and uncertainty analysis in LCA will be defined and discussed in detail in Chapter 3. The challenges identified in literature for conducting these analyses include: modelling and propagation of the uncertainties, completeness of the analysis, communication of the results, and availability of resources (Björklund, 2002; Ross, Evans and Webber, 2002; Lloyd and Ries, 2007; Reap *et al.*, 2008b). Inconsistent management of the uncertainties in an LCA study, such as partial quantification of some uncertain aspects, can lead to false confidence in the reliability of the results (Reap *et al.*, 2008b). A recent review article found that most studies still only address uncertainty theoretically (Igos *et al.*, 2019).

2.6 Conclusion

The first objective of this research (see Chapter 1) was to identify the best practice approach for constructing an LCI model. It was found that Tiered-hybrid analysis along with methods to account for double counting errors is considered best practice. This is due to the advantages reported for this method over the other Hybrid Techniques, including the completeness, analysis time, and ease of use. However, this is dependent on the resources (time, budget, and product-specific data) that are available for a particular case study. A review study of methods used for buildings and the built environment concluded that process data has mainly been used for case studies of single buildings (Goldstein and Rasmussen, 2018). For the construction process itself, however, process data and input-output data have been used depending on data availability (Bilec *et al.*, 2006; Li, Zhu and Zhang, 2010; Crawford, 2011).

The main limitations for LCA that need to be addressed to improve the robustness, reliability and repeatability of the results include:

- inconsistency of the methods applied across case studies that lead to incomparability of the results
- lack of guidance from the international standards on how to fulfil data quality requirements
- lack of guidance from the international standards on how to conduct sensitivity and uncertainty analyses

The first point is being addressed through the development of harmonized, product-specific methodologies, such as PEF. The latter two points will be discussed in more detail in Chapter 3, which presents a critical review of uncertainty in LCA.

CHAPTER 3. UNCERTAINTY IN LCA

Uncertainty management provides a means to assess the confidence and minimise the error in the results obtained from complex systems and models. This is particularly valuable to the end-user of the results. LCA results are increasingly being used to inform decisions related to environmental technologies and policies, such as carbon footprints and labelling (Williams, Weber and Hawkins, 2009). Therefore, the reliability and certainty of these results should be assessed. Furthermore, it has been acknowledged that decisions are often being made based on LCA results without properly understanding the specific methods, assumptions, and data used in the analysis (Plevin, Delucchi and Creutzig, 2013). Disregarding uncertainties may lead to further implications, such as policies being implemented that have little impact and large costs (Johnson *et al.*, 2011). Including uncertainty information along with the results can help decision makers make better informed decisions based on the precision required and implement transparent, robust and reliable decision-support models (Morgan and Henrion, 1990; Coulon *et al.*, 1997; Booker and Ross, 2011; Clavreul *et al.*, 2013).

Quantifying uncertainty in LCA studies is not a requirement as per the ISO standards, and is generally still not well reported in LCA case studies despite over 20 years of research. ISO 14044:2006 states that uncertainty arises in LCA studies from input uncertainties and data variability associated with data in the LCI step. In order to deal with this uncertainty, the standard recommends the use of ranges and probability distributions to support the LCI conclusions, but this is not mandatory for compliance (ISO 14044, 2006). LCA studies require large amounts of data and assumptions throughout each step of the assessment, and therefore assessing and propagating the uncertainty is not straight forward.

It has been argued that the extra time and cost involved in quantifying data uncertainty is a deterrent to conducting the analysis (Ross, Evans and Webber, 2002; Rosenbaum, Georgiadis and Fantke, 2018). Furthermore, including uncertainty analysis may lead to overly complicated and confusing results that would inhibit as opposed to inform decision making (Björklund, 2002). In 2002, a survey of LCA studies concluded that none of the studies stated how the poor data quality affected the reliability of the results, such as through assessing the uncertainties (Ross, Evans and Webber, 2002). Later in 2007, another study investigated the methods used in LCA studies that considered uncertainties and concluded that most of the 24 studies surveyed used stochastic modelling to address uncertainty in the input parameters (Lloyd and Ries, 2007). The review concluded that better methods to reliably characterize, propagate and analyse uncertainty in LCA studies were still needed. A more recent review in 2019 has shown that there has been an increase in the use of uncertainty analysis in LCA studies, however, most of the studies address uncertainty theoretically with little discussion on its practical implementation (Igos *et al.*, 2019).

This chapter defines uncertainty and uncertainty management in LCA studies. It reviews the methods that have been applied to identify, classify, quantify, and qualify uncertainty, and determines where improvements can be made to increase the use of uncertainty management in LCA.

3.1 Definition of Uncertainty in LCA

The definition for uncertainty in the ISO standard does not consider all aspects of the analysis and is based mainly on uncertainty in the LCI data. However, uncertainty can arise and propagate through all steps of an LCA study, not just in the LCI (Huijbregts, 1998a; Björklund, 2002; Lloyd and Ries, 2007; Rosenbaum, Georgiadis and Fantke, 2018). There are multiple definitions for uncertainty in LCA, including:

- “originating from inaccurate measurements, lack of data, and model assumptions” (Huijbregts, 1998a);
- a probabilistic difference between the measured value and the true value (Ciroth, Fleischer and Steinbach, 2004);
- “any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system” (Walker *et al.*, 2003; Igos *et al.*, 2019); and
- “the problem of using information that is unavailable, wrong, unreliable, or that shows a certain degree of variability” (Heijungs and Huijbregts, 2004).

3.1.1 Uncertainty and Variability

Variability is defined as the fluctuation in value of a parameter due to real world scenarios (Huijbregts, 1998a), and is usually irreducible. Some researchers have argued that uncertainty and variability should be separated in LCA studies (Huijbregts, 1998a; Steinmann *et al.*, 2014), whereas others state that separation is unnecessary due to the overlap between them (Finnveden, 2000; Lloyd and Ries, 2007). Uncertainty and variability are often used interchangeably amongst LCA researchers since the definitions are not standardized and the methodologies to evaluate them are essentially the same (Heijungs and Huijbregts, 2004; Finnveden *et al.*, 2009).

An attempt was made to quantify variability and uncertainty separately in a study conducted by Steinmann *et al.* (2014). They found that variability was far larger than uncertainty to the point where reductions in uncertainty would not improve study results. However, they also conclude that this is a case-by-case finding, as not all variability and uncertainty factors were considered, and correlation error was ignored. Furthermore, they could not separate uncertainty and variability entirely, stating that "disentangling uncertainty and variability is not always feasible" (Steinmann *et al.*, 2014). Therefore, while separation of uncertainty and variability may help to focus resources on reducing uncertainties, it may not be completely possible in practice. Furthermore, both uncertainty and variability lead to probable ranges in the output result which can be quantified through propagation of quantified input ranges. These input ranges can be inclusive of all types of errors arising due to both variability and uncertainty. In fact, variability can be classified as a type of uncertainty, which will be discussed further in Section 3.3.

3.1.2 Uncertainty analysis and Sensitivity analysis

Uncertainty analysis focuses on propagating all errors due to measurements, instrumentation, assumptions, estimations, models, and scenarios throughout the entire data collection and LCI and LCIA calculation process. Uncertainties propagate through a system and will show in the calculated results, as well as any intermediate results, and are difficult to predict as large uncertainties may result from small input uncertainties, while uncertainties from small input values may diminish each other (Ciroth, Fleischer and Steinbach, 2004).

Sensitivity analysis is often used in place of uncertainty analysis (Rosenbaum, Georgiadis and Fantke, 2018). Sensitivity is defined as, "the influence that one parameter (the independent variable) has on the value of another (the dependent variable), both of which may be either continuous or discrete" (Björklund, 2002). Sensitivity analysis answers the question of how sensitive the overall result is to a change in a parameter, often being reported as the relative percent change. There are two types of sensitivity analyses that can be used, local and global. The local assessment changes one parameter at a time to see the change in the overall result, whereas the global assessment looks at changing multiple parameters at the same time (Mastrucci *et al.*, 2017). It is generally easier to conduct a local sensitivity analysis as opposed to a full uncertainty analysis due to the amount of data required for the latter. Rosenbaum, Georgiadis and Fantke (2018) found that LCA studies that conduct sensitivity analysis usually apply local sensitivity analysis and do not consider uncertainty.

3.1.3 Uncertainty Management

The uncertainties that arise throughout all steps in an LCA must be well managed to allow for reduction of the total uncertainty of the study (Booker and Ross, 2011). Total uncertainty is the combination and aggregation of all relevant uncertainties within a study, including both stochastic uncertainty (distributions) and data uncertainty (deterministic values) (Coulon *et al.*, 1997). Uncertainty management generally involves four steps: identification, classification, quantification/qualification, and reduction. It further reports the contribution of each identified uncertainty to the total aggregated uncertainty (Ross, Booker and Montoya, 2013). The steps of uncertainty management will be discussed in more detail in the following sections.

3.2 Uncertainty Identification

The first step in uncertainty management is identification. This step involves determining where in a model uncertainty arises. A model is an abstraction of reality, that is, it is a representation of how a defined system or process functions in real life. The discrepancy between a model output and what is observed in reality is considered uncertainty (Warmink *et al.*, 2010). In environmental modelling, uncertainty analysis methods exist, however, there are many different methods available and, as previously discussed for LCA studies, the results of studies applying different methods are not comparable

(Warmink *et al.*, 2010). The challenge of incomparability and ambiguity is not only seen in LCA but also in risk assessment, environmental science, and engineering.

A standard method for uncertainty identification in LCA studies does not currently exist. Therefore, uncertainty identification in environmental modelling was reviewed for its applicability to LCA. For this, LCA is considered as a model used to quantify potential environmental impacts. The inputs for the model are the inputs in each step of an LCA (see Chapter 2) and the outputs are the final LCIA results.

3.2.1 Uncertainty Identification in Environmental Modelling

Dee (1995) categorized the process of environmental modelling into four levels, being the natural system, conceptual model, algorithmic implementation, and software implementation. The natural system includes the real-world phenomena or processes for which data are collected. The conceptual model describes the natural system through defined model variables, assumptions, and behaviours, which are then converted into a set of equations, rules, and procedures during algorithmic implementation. Software implementation involves converting the algorithm into code.

Building on this research, Kolkman *et al.* (2005) used the four defined modelling levels to describe the process of knowledge generation from the perspective of the model builder (Figure 2). They described the modelling levels as transformative steps in the modelling process, where at steps further away from the natural system, the model, along with the inputs and outputs, correspond less with reality. This idea was then used in the context of uncertainty identification by Warmink *et al.* (2010), where each modelling level or transformational step was used to identify uncertainty in the model.

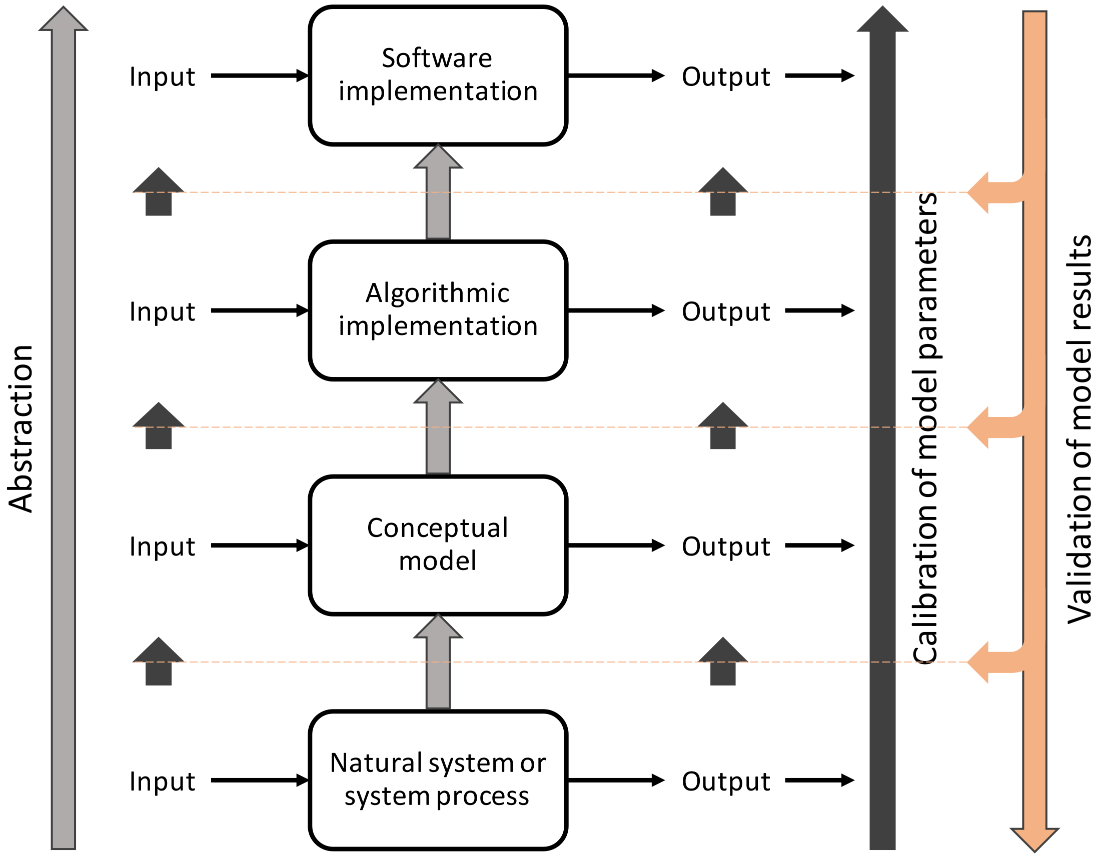


Figure 2: Knowledge abstraction throughout the modelling cycle (adapted from Dee (1995) and Kolkman, Kok and van der Veen (2005))

3.2.1.1 Validation and Verification

Validation is considered part of the modelling process in Figure 2. This may be useful in some environmental models, however in LCA it might not always be possible (see Section 2.3). It should be further noted that validation and verification are two different approaches. Verification can be used to ensure that the equations within the model are being solved correctly, but it cannot determine if the equations and the outputs agree with what occurs in reality (Dee, 1995). Validation ensures that the predictions from the model agree with what is observed. With this definition, validation is not possible for LCA studies, as well as for complex natural systems (Oreskes, Shrader-Frechette and Belitz, 1994). For the latter reason, an alternative definition for validation of models was proposed by Dee (1995):

"Validation of a computational model is the process of formulating and substantiating explicit claims about the applicability and accuracy of computational results, with reference to the intended purposes of the model as well as to the natural system it represents".

This type of validation could be addressed with uncertainty analysis. The uncertainty information gathered at each step of the modelling cycle (Figure 2) can be used to assess the reliability and accuracy of the results and of the model itself. This gives an indication of the confidence the model builder has in the results.

3.2.1.2 An Approach for Global Identification of Unique Uncertainties

The identification step in uncertainty management involves gathering a list of unique uncertainties that do not overlap, which can help simplify the other steps in an uncertainty assessment (Warmink et al., 2010). Identified uncertainties should be classified to avoid double counting the same uncertainty. To do this, the identified uncertainties need to be disaggregated to the point that they can only be defined by a single classification and cannot exist as part of multiple classifications.

A procedure was developed for environmental models that contains two identification steps: global identification and refined identification (Figure 3). The global identification lists all the possible uncertainties in the model. These uncertainties are then classified, as depicted in Figure 3. If the uncertainty can be classified into multiple classes, another identification step is conducted (refined identification). This step disaggregates the uncertainty further until it can only be part of one uncertainty class (Warmink *et al.*, 2010). Uncertainty Classification will be discussed in Section 3.3.

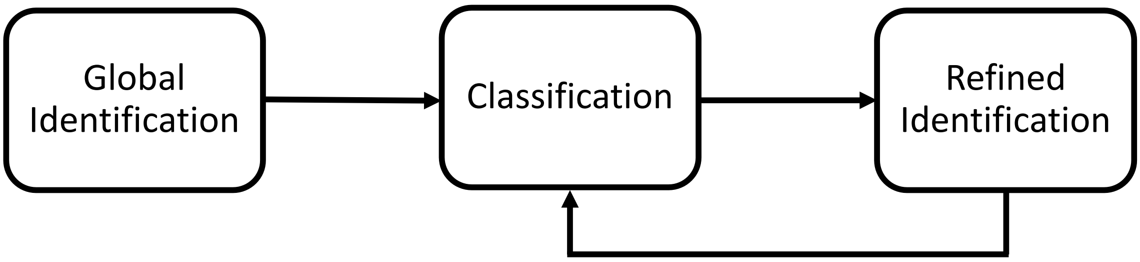


Figure 3: Uncertainty Identification process (adapted from Warmink et al., 2010)

3.2.2 Uncertainty Identification in LCA

Uncertainty arises in all steps of an environmental model (including in LCA) due to the data, decisions and models used, where some uncertainties are very detailed and others consist of many aggregated uncertainties (Warmink *et al.*, 2010). Some identified uncertainties for LCA studies include:

- uncertainty in the input data, calculations and output data (Ciroth, Fleischer and Steinbach, 2004);
- uncertainties due to decisions, ethical beliefs and value judgments (Finnveden, 1997);
- uncertainties resulting from the use of different methods (Coulon *et al.*, 1997);
- uncertainties due to aggregation of emissions into impact categories and the use of relationships that ignore spatial and temporal characteristics (Huijbregts, 1998a); and
- uncertainty in the environmental relevance, accuracy or representativeness of an indicator for an impact category or area of protection (Rosenbaum, Georgiadis and Fantke, 2018).

Table 3 gives examples of identified uncertainties that may arise within the Goal and Scope definition, LCI and LCIA steps of an LCA study. The uncertainties that arise during the Goal and Scope are mainly due to choices, such as for the system boundary, functional unit, and cut-off criteria (see Section 2.2). The uncertainties in the LCI vary from those introduced in the models, choices made, and data used (see Section 2.3). In the LCIA step, uncertainties are generally aggregated from models and data used in deriving the characterization factors (see Section 2.4).

Table 3: Identification of Uncertainty in LCA

LCA Step	Examples[1,2]
Goal and Scope	System boundary definition Choice of functional unit and reference flow Choice of LCI and allocation rules Definition of cut-off criteria Representativeness of the environmental impacts Choice of LCIA impact categories and characterization factors Consistency of methodological choices with the goal and scope Technological, geographical and temporal representativeness
LCI	Representativeness of background processes Representativeness of foreground data collected Technological, geographical and temporal variability Approximation or estimation models for missing data Measurement error Misinterpretation of qualitative descriptions Disagreements in model behaviour Simplification of real-world systems Error in scaling and forecasting models Inaccurate or unrepresentative data
LCIA	Error in characterization factors Representativeness of the modelling structure Technological, geographical and temporal variability Variability in the characterization factors Representativeness of the weighting models and normalisation

[1](Lloyd and Ries, 2007), [2](Igos *et al.*, 2019)

3.3 Uncertainty Classification

Classification is the second step in uncertainty management that divides uncertainties into different categories or classes based on their source. There is no standard classification for LCA studies, or in other areas of science and engineering. It is often left up to the modeller to decide how to categorize the uncertainties, which can be a daunting task. However, implementation of a standard uncertainty classification can provide clarity on how to conduct an uncertainty analysis in LCA studies and potentially lead to more studies quantifying and reporting uncertainties. This research aims to address this with the development of a standard uncertainty classification for LCA (see Section 4.2).

3.3.1 Uncertainty Classification in Physical Science and Engineering

For physical science and engineering applications, five uncertainty classes have been identified (Ross, Booker and Montoya, 2013):

- aleatoric – uncertainty arising from natural variability,
- epistemic – uncertainty arising from lack of knowledge,
- irreducible – uncertainty that cannot be reduced by obtaining more information,
- reducible – uncertainty that can be reduced by obtaining more information, and
- inference uncertainties – uncertainty introduced through the use of measurements and observations from other applications to estimate the result of an unmeasurable application.

It should be noted that there is no available method to distinguish between epistemic and aleatoric uncertainty, and therefore it is often difficult to determine whether an uncertainty belongs to one class or another (Kiureghian and Ditlevsen, 2009).

3.3.2 Uncertainty Classification in Risk Assessment and Policy Analysis

In risk assessment and policy analysis, uncertainties have been classified into seven classes (Morgan and Henrion, 1990):

- statistical variation – random error that occurs in measurements,
- subjective judgement – error introduced through use of suspected or unknown bias or assumptions,

- linguistic imprecision – reflects the error introduced due to the use of vague words (for example, fast or tall) to describe a quantity or event,
- variability – describes the error due to change in a quantity over time or space,
- inherent randomness – error introduced that is unpredictable and therefore irreducible even with further research,
- disagreement – addresses error due to differences in opinions and interpretations between experts, and
- approximation – error introduced due to the use of simplistic models to represent real-world events.

Walker *et al.* (2003) developed a classification matrix for model-based decision support activities that defined uncertainty in three dimensions from the point of view of the modeller. The three dimensions are location, level, and nature (Figure 4). Location identifies where the uncertainty arises in the model, level describes the amount of information known spanning from deterministic knowledge to total ignorance, and nature describes whether the uncertainty is epistemic or aleatoric (see Table 4). The classification matrix ensures that the uncertainties identified are unique and provides a structured way to communicate the uncertainties to the decision maker.

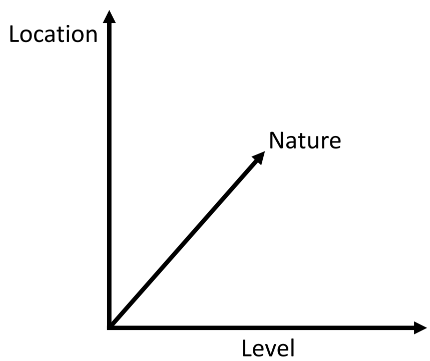


Figure 4: The three dimensions of uncertainty classification (adapted from Walker *et al.* (2003))

3.3.3 Uncertainty Classification in Environmental Modelling

In 2010, the classification matrix developed by Walker *et al.* (2003) (see Section 3.3.2) was applied in environmental modelling. The definitions of the location, level, and nature dimensions were updated to include qualitative uncertainty and ambiguity, to remove total ignorance and model outcome uncertainty, and to distinguish between model structure and model technical uncertainties (Warmink *et al.*, 2010).

Qualitative uncertainty refers to uncertainties that cannot be expressed in numerical values and can generally be measured using the qualitative methods in Chapter 3. Ambiguity arises from having multiple equally valid options that cannot necessarily be reduced through further research. Warmink *et al.* (2010) also extended the definition of aleatoric uncertainty to include that due to irreducible random variability that cannot be explained within the resources available to the study.

Table 4 shows the definitions of the original uncertainties for each dimension from 2003 and the updates made in 2010. Efforts were also made to link the classification matrix to the uncertainty identification in Figure 2, stating that by having a structured method to identify and classify unique uncertainties, the comparability of the uncertainty results between studies improves. However, this method was not found to reduce the time and effort required to conduct an uncertainty assessment in practice in environmental modelling.

Table 4: Definitions of uncertainty classification for each dimension

Dimension / Class	Walker *et al.*, 2003	Warmink *et al.*, 2010
Location:		
Context	Model context is defined as anything outside the model boundary. The uncertainties arise from the assumptions and choices used to define the model.	
Input	Input is associated with the data used to describe the system that may depend on geographical and temporal information. The uncertainties arise from uncertainties in measurements, uncertainties from results of other models used as inputs and uncertainties due to scaling.	
Model Structure	Combine model structure and model technical as once class - Model Uncertainty. Model structure uncertainty is uncertainty in the form of the model itself.	Model structure is defined as the mathematical relations between the variables or model components which are chosen to describe the system located within the model boundaries.
Model Technical	Combine model structure and model technical as once class - Model Uncertainty. Model technical uncertainty is uncertainty arising from the computer implementation of the model.	Model technical refers to the technical and numerical aspects related to the software implementation of the model and the numerical implementation of the algorithms.
Parameters	Parameter uncertainty is associated with the data and the methods used to calibrate the model parameters and does not directly depend on the geographical or temporal information.	
Model outcome uncertainty	Model outcome uncertainty is the accumulated uncertainty associated with the model outcomes of interest to the decision maker.	N/A – omitted because it results from uncertainties in the other locations
Level:		
Statistical	Statistical uncertainty is any uncertainty which can be represented with probabilities or numbers, such as measurement uncertainty in data.	
Scenario	Uncertainties in the use of one scenario over another where the probability of a particular scenario occurring is not known.	
Qualitative	N/A – not included	Qualitative uncertainty is uncertainty that cannot be expressed in terms of measurable values, such as expert opinions and linguistic probabilities.
Recognized Ignorance	Uncertainty exists about the relations and mechanisms being studied. It can be divided into reducible ignorance and irreducible ignorance, the former achieved through further research.	
Total Ignorance	Opposite of determinism. We do not know what we do not know.	N/A – omitted because in practice we cannot identify what we do not know.
Nature:		
Epistemic uncertainty	The uncertainty due to imperfection of our knowledge, which may be reduced by more research.	
Natural variability (aleatoric uncertainty)	Inherent uncertainty or random system behaviour that cannot be reduced.	Random system behaviour that cannot be reduced with the resources available.
Ambiguity	N/A – included in epistemic uncertainty	Ambiguity occurs when multiple valid methods exist.

3.3.4 Uncertainty Classification in LCA

The most common classification identified and mentioned in LCA studies is parameter, scenario, and model (Rosenbaum, Georgiadis and Fantke, 2018), as defined in Table 5. However, other uncertainty classifications have been used in LCA that are based on models in physical science, engineering, and risk assessment. These vary in level of detail from very broad to more specifically defined.

Table 5: Definitions of Parameter, Scenario and Model uncertainties

Class	Definition
Parameter	Uncertainty in the data used, arising from imprecise, incomplete or outdated measurements, unrepresentative data or lack of data (Huijbregts, 1998a; Huijbregts *et al.*, 2003).
Scenario	Uncertainty due to normative choices made, including choice of functional unit, allocation rules, characterization model and weighting method applied (Huijbregts, 1998a; Huijbregts *et al.*, 2003). It can be reduced or eliminated in principle by gathering more data, refining the model, or otherwise making more effort (Johnson *et al.*, 2011).
Model	Uncertainty due to the mathematical models (Huijbregts *et al.*, 2003) or model structure applied. It arises when there are a variety of model options available for a problem without a consensus on which model to use (Laskey, 1996).

Huijbregts (1998a) identified six classes of uncertainty in LCA: model uncertainty, parameter uncertainty, uncertainty due to choices, spatial variability, temporal variability, and variability between objects and sources. An additional five classes were added to this by Björklund (2002), being: epistemic uncertainty, data inaccuracy, data gaps, unrepresentative data, mistakes, and estimation of uncertainty. In 2003, Huijbregts *et al.* (2003) presented a broader classification focusing on model, scenario and parameter uncertainties, and Sonnemann, Schuhmacher and Castells (2003) renamed the classification as technical, methodological and epistemological.

In 2009, Williams, Weber and Hawkins (2009) aggregated the classification into two classes: measurement and complex systems modelling. A more detailed classification was addressed again in 2011 based on the classification developed by Morgan and Henrion (1990) for risk assessment and policy analysis. This classification added an additional three classes to the seven classes identified (see Section 3.3.2), being model uncertainty, scenario uncertainty and epistemic uncertainty (Johnson *et al.*, 2011). In 2014, uncertainty classification was again organized into three classes: parameter uncertainty, model uncertainty, and decision support uncertainty (Steinmann *et al.*, 2014).

Building on work done by Walker *et al.* (2003), Igos *et al.* (2019) theoretically applied the classification matrix (see Section 3.3.2) to LCA. They defined the location dimension for LCA studies as parameter, scenario, and model, but changed the naming of these to quantity, context, and model structure uncertainty, respectively. This was done to avoid confusion with the definitions of the classes in the location dimension (see Table 4). However, this again renames the classification for LCA studies.

Igos *et al.* (2019) further state that the level dimension can be included in LCA studies through qualitative evaluations, and the nature dimension by distinguishing between epistemic and aleatoric uncertainties. However, this is difficult to do in practice. For this reason, Warmink *et al.* (2010) previously added additional classes to the matrix (see Section 3.3.3).

Uncertainty classification in LCA has still not been standardized, nor has it been linked to uncertainty management and communication. The classification and uncertainty management method developed in Chapter 4 aim to achieve this.

3.4 Uncertainty Quantification and Qualification

The third step in uncertainty management is uncertainty quantification or qualification, which includes the propagation of uncertainty throughout the modelling cycle.

Qualification methods are used where uncertainties cannot be quantified. This section presents some of the methods that have been used in LCA to quantify and qualify uncertainties.

3.4.1 Uncertainty Quantification Methods in LCA

Managing and propagating uncertainties throughout an LCA study is complex due to the large amount of data and methodological choices within the study that make it easy to over- or under- estimate the total uncertainty of the final result (Lloyd and Ries, 2007). A full quantitative uncertainty assessment is very time consuming in practice, however some methods are more efficient than others (Maurice *et al.*, 2000; Sonnemann, Schuhmacher and Castells, 2003). For example, some methods will only quantify and propagate the uncertainty of inputs that have been identified as significant issues through sensitivity analysis (see Sections 2.5 and 3.1.2). This assumes that the highest contributing input data is also the most contributing to the total uncertainty of the result. The ideal quantification method balances the computational time and effort with the quality of information provided by the assessment and the accuracy that is required.

The mathematical framework for handling and propagating uncertain quantities is well-known since it has been widely applied in areas such as engineering and risk assessment (Coulon *et al.*, 1997). Some methods for quantifying uncertainty in LCA studies include Monte Carlo analysis, Latin hypercube sampling, Taylor series expansion, Zadeh fuzzy sets and logic theory, and Bayesian model averaging. Each is discussed in further detail in the following sections.

3.4.1.1 Monte Carlo Analysis

Monte Carlo analysis is the most common method of quantifying parameter uncertainty in LCA studies (Huijbregts *et al.*, 2003; Imbeault-Tétreault *et al.*, 2013; Rosenbaum, Georgiadis and Fantke, 2018). In this method, inputs are first specified as uncertainty distributions. A value is then selected at random from these distributions and the output calculated. This procedure is repeated many times (usually 1,000 - 10,000 times), producing a distribution of the output values that reflects the combined uncertainty. The benefit of Monte Carlo analysis is that multiple parameter distributions can be sampled at the same time over their entire domain, allowing for interactions between parameters to also be captured.

The limitations of Monte Carlo analysis, however, include that it is computationally expensive in terms of time and memory, it requires coding skills, and it requires the distributions of each input parameter to be defined (Ross, Evans and Webber, 2002; Ciroth, 2004; Williams, Weber and Hawkins, 2009; Imbeault-Tétreault *et al.*, 2013). It has further been suggested that Monte Carlo analysis can only be used to assess uncertainty due to calculations in LCA and cannot say anything about choices, variability and missing data (Ciroth, 2004).

To reduce the time for the analysis, a selection of parameters by expert judgement has been used and the uncertainty simulated only for those input uncertainties. However this leads to an estimation of the uncertainty based on the assumption that the selected parameters are the most relevant to the total uncertainty (Ciroth, 2004). Monte Carlo analysis is included in some software packages, such as GaBi and Simapro, for quantifying parameter uncertainty (as defined in Table 5) or performing sensitivity analysis of the inventory data. In this sense, the requirement for coding is not necessary, however, the analysis itself should be well understood by LCA practitioners to prevent ill-specified input distributions or uncertainty ranges from being used.

3.4.1.2 Latin Hypercube Sampling

Latin hypercube sampling is done in the same way as Monte Carlo analysis, however it samples the input distributions from defined segments of non-overlapping intervals that are each considered to have an equal probability (Morgan and Henrion, 1990; Rosenbaum, Georgiadis and Fantke, 2018). This is done by selecting a value at random from each interval according to the probability distribution within the interval, leading to generally more precise random samples than Monte Carlo that are more uniformly spread out (Morgan and Henrion, 1990; Igos *et al.*, 2019). An advantage of this method over Monte Carlo sampling of the entire distribution is that it can be less time consuming. However, this type of sampling can also introduce bias in the results due to the choice of intervals (Morgan and Henrion, 1990).

3.4.1.3 Taylor Series Expansion

Taylor series expansion is an analytical approximation technique that uses moments of probability distributions, such as the mean and variance, to propagate uncertainty (Morgan and Henrion, 1990). This method is used in the CMLCA software, which is a software for LCA developed by the Leiden Institute of Environmental Sciences (Rosenbaum, Georgiadis and Fantke, 2018; Heijungs, 2020).

The approximations are made based on a nominal scenario, which is defined as the mean scenario or the expected value. The deviation of the expected value of the output ($y - y^0$) is approximated in terms of the deviations in the expected values of the inputs, as given by Equation 9 (Morgan and Henrion, 1990). Equation 9 shows the first three terms of the approximation (each term shown on a different line), where x_i^0 and y^0 are the expected input and output values of the nominal scenario and x_i and y are the observed input and output values.

$$y - y^0 = \sum_{i=1}^{n}(x_i - x_i^0)\left[\frac{\partial y}{\partial x_i}\right]_{x^0} +$$

$$\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - x_i^0)(x_j - x_j^0)\left[\frac{\partial^2 y}{\partial x_i \partial x_j}\right]_{x^0} +$$

$$\frac{1}{3!}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}(x_i - x_i^0)(x_j - x_j^0)(x_k - x_k^0)\left[\frac{\partial^3 y}{\partial x_i \partial x_j \partial x_k}\right]_{x^0} + \cdots \qquad (9)$$

In Equation 9, the third term and subsequent terms reduce to zero when the deviations of the inputs from the nominal value $(x_i - x_i^0)$ are assumed to be very small. The second term will also reduce to zero when the inputs are independent. The simplest form of the Taylor series expansion is the Gaussian or first order approximation, which is represented by only the first term in Equation 9.

The variance in y ($Var[y]$) is equal to the square of the deviation in y ($Var[y] = (y - y^0)^2$), therefore the first order approximation can also be used to calculate $Var[y]$. By separating out $Var[x_i]$, the variance of the output can be approximated with Equation 10 (Morgan and Henrion, 1990).

$$Var[y] \approx \sum_{i=1}^{n} Var[x_i]\left[\frac{\partial y}{\partial x_i}\right]_{x^0}^2 \qquad (10)$$

First order approximations work well for small uncertainties; however, it may not be suitable for the larger uncertainties that occur in LCA. An advantage of using Taylor series expansion is that the uncertainty can be computed instantly, unlike Monte Carlo analysis (Imbeault-Tétreault *et al.*, 2013; Rosenbaum, Georgiadis and Fantke, 2018). A limitation is that the result obtained is in the form of moments of the distribution, such as the variance, which does not provide details regarding the tails of the distribution (Heijungs and Lenzen, 2014).

3.4.1.4 Zadeh Fuzzy Sets and Logic Theory

This method was developed in 1973 by Lotfi A. Zadeh for complex systems and decision processes. It uses linguistic and numeric variables for the characterization of simple and complex reactions into fuzzy conditional statements and fuzzy algorithms, respectively (Zadeh, 1973). Fuzzy conditional statements are "if-then" statements using linguistic or numeric variables. For example, a linguistic variable for colour may be red. The possible choices for a linguistic variable make up a fuzzy set, for example, red, blue, green, and yellow. Fuzzy algorithms are an ordered list of instructions based on fuzzy conditional statements.

The approach was developed in order to describe the behaviour of systems that are too complex or not enough detail is known to be defined by precise mathematical models (Zadeh, 1973; Tan, 2008; Clavreul *et al.*, 2013). These systems include human-centred systems involving individuals or groups of people where the behaviour cannot be defined by mechanical systems. As the complexity of these systems increase, the ability to predict their real-world behaviour with precise quantitative analysis diminishes (Zadeh, 1973).

Fuzzy sets and logic have been applied to quantify uncertainty in LCA studies and used in hybrid quantification methods combining them with Monte Carlo sampling (Tan, 2008; Heijungs and Tan, 2010; Clavreul, Guyonnet and Christensen, 2012). A disadvantage of this method is that defining fuzzy sets and weighting methods is subjective (Igos *et al.*, 2019).

3.4.1.5 *Bayesian Model Averaging*

In LCA studies, the Bayesian framework has been used to combine process and input-output data to generate output distributions for embodied CO_2-equivalents of construction materials (Shipworth, 2002). It has also been used as an updating method to convert the estimated prior distributions into more accurate posterior distributions for a case study of buildings (Acquaye, 2010).

The Bayesian framework is based on Bayes' theorem. This can be used to determine the probability of an event occurring given that another event has already occurred and is defined by Equation 11.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad (11)$$

Where $P(A|B)$ is the probability of A occurring given that B has occurred, $P(B|A)$ is the probability of B occurring given that A has occurred, and $P(A)$ and $P(B)$ are the probabilities of A and B, respectively.

Bayesian model averaging has been used to quantify model uncertainty in environmental models and risk assessment (Neuman, 2003; Ye *et al.*, 2010). This technique extends from Bayes' theorem and combines the predictions of multiple valid models to determine the joint uncertainty (Morales-Casique, Neuman and Vesselinov, 2010). The prior distributions of the models are conditional of the selected model's accuracy and not of the parameters within the model. Bayes' theorem can be used to derive the posterior distribution of the model uncertainty based on the prior distributions (Fragoso, Bertoli and Louzada, 2018).

This method could also be used to quantify model uncertainty (see Table 5) in LCA. Quantifying model uncertainty can demonstrate how policy decisions and environmental outcomes are influenced by the defined model scope (Johnson *et al.*, 2011). However, the inability of LCA results to be measured or fully validated could be a limiting factor for quantification through Bayesian model averaging (Clavreul *et al.*, 2013).

3.4.2 Uncertainty Qualification Methods in LCA

The quality of the data used in an LCA study is one factor used to assess the reliability of the results and must be defined in the Goal and Scope definition (see Section 2.2.4) (Coulon *et al.*, 1997; ISO 14044, 2006). Data can be defined as any piece of information used in the LCI, and data quality as information about the representativeness of the data, such as its age, geography and technology (Weidema and Wesnaes, 1996).

Uncertainty qualification can be used to support uncertainty quantification, where data for quantification is not available or where the quantification does not address the fact that the data used is unrepresentative (Coulon *et al.*, 1997; Xiaocun Zhang and Wang, 2017). Qualitative methods can also be used to reduce the effort of uncertainty analysis by identifying and selecting the most significant uncertainties to be used in quantitative methods to estimate the total uncertainty (Wang and Shen, 2013).

Data quality can be assessed through expert opinion, however, a more consistent framework to apply qualitative analysis is through the use of pedigree matrices (Weidema and Wesnaes, 1996; Coulon *et al.*, 1997). Pedigree matrices can be used to assign qualitative judgments in replacement of quantitative uncertainty parameters. One example is the Numerical Unit Spread Assessment Pedigree (NUSAP) (Henriksson *et al.*, 2014). This pedigree matrix has been used to compliment quantitative uncertainty assessments, providing a framework to address uncertainties that cannot be quantified (van der Sluijs *et al.*, 2005). For example, some technical, methodological, and epistemic dimensions of uncertainties are unquantifiable. The qualitative assessment involves a pedigree matrix where linguistic descriptions are used to describe qualitative criteria on a numerical scale from 0 (weak) to 4 (strong). The NUSAP pedigree matrix has been applied in LCA to qualify the LCI data, the first being the data quality indicator method (Weidema and Wesnaes, 1996).

Two methods are discussed in further detail in this section, the data quality indicator (DQI) method and the data quality rating (DQR). The DQI has been used to qualify uncertainty in LCA and is applied in the Ecoinvent database. The DQR is used in the Product Environmental Footprint (PEF) methodology to assess data quality.

3.4.2.1 Data Quality Indicators

The data quality indicator (DQI) method scores the LCI data from 1 (most certain) to 5 (least certain) for five independent indicators, being reliability, completeness, temporal correlation, geographical correlation, and further technological correlation. The first two indicators are independent of the study to which the data are applied, whereas the latter three indicators are dependent on the data quality goals specified in the study (Weidema, 1998). The scores can range from (1,1,1,1,1) to (5,5,5,5,5) from the most certain to the least certain.

The pedigree matrix with the detailed linguistic descriptions is given in Table 6. This matrix was tested for replicability of the indicator scores by comparing the scoring of different people given the same information. It was found that the scores selected were generally in agreement, and when deviations occurred, the scores were within one value (Weidema, 1998). The highest variation was found for the reliability indicator and the lowest in the selection of the temporal and geographical correlation indicator scores.

Although only seven experts were involved in the test of the DQI pedigree matrix, it was concluded that the agreement in the scores was enough to suggest the method could be used for communication of qualitative assessments of large amounts of data.

Table 6: Data Quality Indicator Pedigree Matrix (Weidema, 1998)

Indicator Scores	1	2	3	4	5
Reliability	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on assumption	Qualified estimate (ex. with use of an expert)	Non-qualified estimate or unknown origin
Completeness	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for adequate periods	Representative data from an adequate number of sites but for shorter periods	Representative data but from a smaller number of sites and shorter periods or incomplete data from an adequate number of sites and periods	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods
Temporal correlation	Less than 3 years of difference to year of study	Less than 6 years of difference	Less than 10 years of difference	Less than 25 years of difference	Age of data unknown or more than 15 years of difference
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area or area with very different production conditions
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials but from same technology	Unknown technology or data on related processes or materials, but from different technology

This DQI method has been further applied as a tool for quantifying the uncertainty in Ecoinvent datasets using expert judgement to convert the quality indicators into quantities that can be combined with other quantitative uncertainties (Henriksson *et al.*, 2014). The methodology is described in more detail in Section 3.4.3.

3.4.2.2 Data Quality Rating

The Data quality rating (DQR) is a semi-quantitative method for assessing data quality that is used in the PEF method for measuring the data quality of each dataset used as well as the overall quality of the final result (EC-JRC-IES, 2010; Zampori and Pant, 2019). It differs from the DQI method as it only considers four quality criteria, being technological representativeness (TeR), geographical representativeness (GeR), precision (P) and time-related representativeness (TiR). A score of 1 to 5 is assigned to each criterion based on defined pedigree matrices for activity data and elementary flows, where 1 is excellent quality and 5 is poor quality. These scores can be combined into a total DQR by Equation 12.

$$DQR = \frac{TeR + GeR + TiR + P}{4} \qquad (12)$$

The TeR, GeR and TiR assess the degree to which the modelled processes and products represent the system being analysed and the P is related to the level of uncertainty in the derived data (Zampori and Pant, 2019). For a DQR of ≤ 1.5, the overall data quality level is "excellent quality"; of $1.5 < DQR \leq 2.0$, "very good quality"; $2.0 < DQR \leq 3.0$, "good quality", $3.0 < DQR \leq 4.0$, "fair quality"; and of >4.0, "poor quality".

When calculating the DQR of a newly generated dataset or for an overall PEF impact category result, it is recommended to take the weighted average of each criterion from the most significant (the most contributing to the final result) activity data and direct elementary flows as the value to input into Equation 12 (Zampori and Pant, 2019).

3.4.3 Uncertainty Qualification and Quantification in Ecoinvent

As stated briefly in Section 3.4.2.1, the DQI method has been incorporated into the Ecoinvent database to consider the quality of the data used in the datasets and add this to the quantified uncertainty of the data itself. In order to do this, the qualitative indicator scores from 1 to 5 for each indicator (reliability, completeness, temporal correlation, geographical correlation, and further technological correlation) are converted into quantities and then added to the quantified uncertainty of the data. This converted qualitative uncertainty is referred to as additional uncertainty and the quantified uncertainty of the data as basic uncertainty. The additional uncertainty is assumed to be normally distributed with a mean value of zero and a variance that is based on expert judgement and associated to each indicator score as shown in Table 7.

Table 7: Ecoinvent uncertainty factors for converting DQI to additional uncertainties (Weidema *et al.*, 2013)

	relative variance (σ^2)				
Indicator Score	1	2	3	4	5
Reliability	0.000	0.0006	0.002	0.008	0.04
Completeness	0.000	0.0001	0.0006	0.002	0.008
Temporal correlation	0.000	0.0002	0.002	0.008	0.04
Geographical correlation	0.000	0.000025	0.0001	0.0006	0.002
Further technological correlation	0.000	0.0006	0.008	0.04	0.12

The basic uncertainty can either be quantified by the analyst of the data provided to Ecoinvent and reported in the dataset or estimated with uncertainty factors based on expert judgement assuming the distribution for the basic uncertainty is lognormal (Weidema *et al.*, 2013; Qin and Suh, 2017). The estimation for the variance of the underlying normal distribution for the basic uncertainties for pollutants emitted to air are given in Table 8.

Table 8: Ecoinvent default basic uncertainty values for pollutants emitted to air (Weidema *et al.*, 2013)

Input/output group	relative variance of the underlying normal distribution (σ^2)		
	Combustion emissions	Process emissions	Agricultural emissions
CO_2	0.0006	0.0006	
SO_2	0.0006		
NO_x, N_2O	0.04		0.03
CH_4, NH_3	0.04		0.008
Individual hydrocarbons	0.04	0.12	
Polycyclic aromatic hydrocarbons	0.3		
CO, heavy metals	0.65		
Inorganic emissions, others		0.04	

The additional uncertainty can be added to the basic uncertainty through the addition of the variances as defined in Equation 13.

$$\sigma^2 = \sum_{n=1}^{6} \sigma_n^2 \qquad (13)$$

Where σ_1^2 is the basic uncertainty and σ_2^2 to σ_6^2 are the variances for reliability, completeness, temporal correlation, geographical correlation and further technological correlation, respectively. The distributions for both the additional uncertainties and basic uncertainty are independent.

3.4.4 Correlation and Covariance

Another consideration when combining uncertainties is the correlation of the data. Correlation occurs when two or more random variables are not completely independent, meaning that one variable changes with changes in another variable. This is also referred to as covariance. Correlation is a scaled version of covariance that indicates the relative strength of the covariance as well as the direction. Covariance describes the direction of the relationship with values between -∞ and +∞, whereas correlation scales the covariance between -1 and +1. A value very close to -1 means that the two variables have a strong negative linear correlation and very close to +1 indicates that they have a strong positive linear correlation. Covariance and correlation can be calculated with Equations 14 and 15, respectively, where x' and y' denote the mean of a sample of possible values for an input and the mean of the corresponding output values, x_i and y_i denote the observed input and corresponding output value, and n is the total number of observations.

$$Cov\ (x, y) = \frac{\sum_{i=1}^{n}(x_i - x')(y_i - y')}{n - 1} \tag{14}$$

$$Corr(x, y) = \frac{\sum_{i=1}^{n}(x_i - x')(y_i - y')}{\sqrt{\sum_{i=1}^{n}(x_i - x')^2 \sum_{i=1}^{n}(y_i - y')^2}} \tag{15}$$

Correlation occurs in LCA studies when the same upstream processes are used for functionally equivalent products, and consequently the uncertainty is counted multiple times (Wang and Work, 2014). In comparative studies, correlation will cause the difference between two products to be overestimated (Coulon *et al.*, 1997).

3.5 Uncertainty Reduction and Contribution

The last step in uncertainty management is reduction and reporting of the uncertainty. In this step, the uncertainty contributions of the input data can also be calculated. This measures the degree to which each input contributes to the overall uncertainty of the output.

3.5.1 Uncertainty Reduction and Contribution in LCA

The iterative approach of LCA, as seen in Figure 1, should be considered when managing uncertainties (Rosenbaum, Georgiadis and Fantke, 2018). Since the aim of uncertainty management is to improve the reliability, robustness and repeatability of study results, uncertainties should not only be reported but also reduced where possible. In theory, the reduction of uncertainty can be done by first identifying the input data with high uncertainties that influence the overall result and focusing reduction efforts on these inputs.

Clavreul *et al.* (2012) used Taylor series first order approximation (see Section 3.4.1.3) to estimate the uncertainty contributions of the inputs in an LCA case study of waste management. The contribution could be used to prioritise efforts for further data collection to reduce uncertainties. Lo *et al.* (2005) also quantified the reduction of uncertainty in an LCA case study comparing alternative waste treatment options. They used a combined Bayesian method (see Section 3.4.1.5) with Monte Carlo analysis (see Section 3.4.1.2) to quantify the uncertainty. The posterior distribution was updated with site-specific data to reduce uncertainties. The uncertainties were ranked using the correlation equation (Equation 15).

In practice, the majority of LCA studies still report results without uncertainty due to a lack of resources (time and budget), lack of a framework or method (such as accessibility in LCA software), and a lack of knowledge or expertise (Ross, Evans and Webber, 2002; Rosenbaum, Georgiadis and Fantke, 2018; Igos *et al.*, 2019). However, it is argued that reporting results with uncertainties should become common practice to improve their robustness and lead to better informed decisions (Booker and Ross, 2011; Clavreul *et al.*, 2013; Heijungs *et al.*, 2019).

A method for uncertainty management, including reduction, has been developed in this research and is presented in Chapter 4.

3.5.2 Uncertainty Contribution in Risk Assessment and Policy Analysis

Quantifying the contributions of the input uncertainties to the total output uncertainty has been applied in other areas outside of LCA, such as in risk assessment and policy analysis. As has been applied in Lo *et al.* (2005), the contributions can be calculated using the correlation equation (Equation 15). This averages the effect of each input over the joint probability distribution for all other inputs (Morgan and Henrion, 1990). With this, the contribution of the input uncertainties to the total output are calculated and ranked from most significant to least significant. Reduction strategies can then be focused on these significant input uncertainties in order to reduce the overall uncertainty of the output.

3.6 Conclusion

There is a lack of guidance from the international standards for LCA on how to assess data quality and how to apply sensitivity analysis and uncertainty analysis in LCA case studies (see Chapter 2). This chapter therefore reviewed methods that have been developed to address these limitations.

For assessing data quality, data quality indicators (DQI) and the data quality rating (DQR) have been developed. These have been applied in LCA databases and product-specific methodologies (see Section 3.4.2), including the Ecoinvent database and the PEF method.

In terms of sensitivity analysis, both local and global sensitivity analyses have been used in LCA (see Section 3.1.2). Local sensitivity analysis has been applied more often than global sensitivity analysis due to its ease of use (Mastrucci *et al.*, 2017; Rosenbaum, Georgiadis and Fantke, 2018). Global sensitivity analysis has a higher computational requirement but is useful for assessing the interactions between inputs. These interactions cannot be captured with local sensitivity analysis.

For uncertainty analysis, the ISO standards also do not provide guidance for managing (identifying, classifying, quantifying and reducing) uncertainties (Muller *et al.*, 2018). Although methods for quantification and qualification have been applied in LCA (see Sections 3.4 and 3.5), reporting uncertainty is still not common practice in case studies (Rosenbaum, Georgiadis and Fantke, 2018; Igos *et al.*, 2019).

The following aspects need to be addressed to improve the quantification and reporting of uncertainties in practical case studies:

- development of standardised uncertainty identification and uncertainty classification methods for LCA that remove the current ambiguities;
- connection of the uncertainty classification to standardised quantification and qualification methods;
- application of an iterative uncertainty reduction method that identifies significant uncertainties where resources for reduction can be applied;
- development of a standardised uncertainty management method that considers the above three points; and
- integration of the standardized method into the international standards for LCA or other product-specific standards with the aim of improving uncertainty reporting.

A method has been developed for uncertainty management in LCA considering the above points. This method is presented in Chapter 4.

CHAPTER 4. UNCERTAINTY MANAGEMENT METHODOLOGY

In this chapter, an uncertainty classification and an uncertainty management methodology are both proposed that build on previous research for dealing with uncertainties in LCA (refer to Chapter 3). The proposed classification is the second step of the uncertainty management methodology, which includes four steps: identification, classification, quantification or qualification, and reduction. The uncertainty management methodology is integrated into the steps of an LCA study as defined by ISO 14044:2006 (see Chapter 2).

Section 4.1 of this chapter first defines the criteria used to qualitatively assess the existing uncertainty classifications that were discussed in Chapter 3 (see Section 3.3). The proposed classification is then introduced in Section 4.2, and the proposed uncertainty management methodology for LCA case studies in Section 4.3. Worked examples for classifying uncertainties with the proposed classification are presented in Section 4.4. The final conclusions for the chapter are summarized in Section 4.5.

4.1 Defining Uncertainty Classification Criteria for LCA

Five criteria for assessing and comparing uncertainty classifications for use in practical LCA case studies were defined for the purposes of this study. These criteria were selected based on the reasons that uncertainty is not commonly applied in LCA case studies (see Chapter 3) and considering the ambiguity and inconsistency in uncertainty classification (see Section 3.3.4). The five criteria are defined below:

1. Unambiguous – the degree to which the uncertainties are easily categorized into a unique class by the LCA practitioner, without potentially overlapping with other classes.
2. Clear framework – the degree to which the classification is clearly connected to the uncertainty management methodology for LCA.
3. Easy to use in practice – the degree to which the classification is easy to follow and apply in LCA case studies.
4. Additional resource requirement – the degree to which use of the classification requires additional resources, including time/budget and expertise of the LCA practitioner.
5. Clear reporting to decision makers – the degree to which the classification provides a clear explanation of the uncertainties in the LCA that is easily communicated to and understood by the decision maker.

These criteria were used to qualitatively compare the three uncertainty classifications (Walker *et al.*, 2003; Warmink *et al.*, 2010; Igos *et al.*, 2019) to that of the model-scenario-parameter classification (defined in Table 5). Table 9 summarizes the result of the qualitative comparison.

As can be seen in Table 9, the model-scenario-parameter classification fails in providing a user-friendly method that is easy to understand. The main barriers identified include: ambiguity in differentiating between uncertainty classes; the lack of a coherent structure for classification, uncertainty management and reporting; and the requirement of additional resources. The proposed classification in Section 4.2 focuses on addressing these barriers.

Table 9: Comparison of Uncertainty Classifications

Criteria	model-scenario-parameter[1]	Walker *et al.* (2003)	Warmink *et al.* (2010)	Igos *et al.* (2019)
1. Unambiguous	Ambiguity in differentiating between model and scenario uncertainties	Ambiguity in differentiating between epistemic and aleatoric uncertainties and in identifying total ignorance	Additional level and nature classes to address ambiguities in Walker *et al.*	Ambiguity in differentiating between epistemic and aleatoric uncertainties and in identifying total ignorance. Renamed scenario uncertainty defined by the common classification for LCA as context uncertainty.
2. Clear framework	No clear methodology (one reason uncertainty is ignored in LCA)	Clear classification framework, however, it is not clearly connected to identification and quantification	Clear identification and classification framework, however not clearly connected to quantification	Clear classification for the location dimension. No clear framework for identification or quantification that is connected to the classification, although options for quantification and qualification methods are discussed.
3. Easy to use	Difficult due to lack of a clear framework/ lack of a method, and due to ambiguity in the classes	Ambiguities in the classification potentially make it more difficult to apply in LCA	Classification and identification methods potentially easy to use in LCA	Classification potentially easy to use in LCA. Three options are identified for uncertainty assessment that are based on the expertise of the analyst.
4. Additional resource requirement	Significant (one reason uncertainty is ignored in LCA)	Potentially significant for LCA	Potentially significant for LCA	Potentially significant for LCA, depending on the method chosen by the analyst.
5. Clear reporting	No standard reporting method for all uncertainty classes that is easily understood by decision makers	Clear reporting of the uncertainty classes	Clear reporting of the uncertainty classes	Recommends a clear reporting strategy, however, as in the common classification, there is no standard reporting method for this in LCA – it is left up to the analyst.

[1]Classification as Model, Scenario or Parameter uncertainty as defined in Table 5

4.2 Proposed Uncertainty Classification for LCA

Building on the work of Walker *et al.* (2003), Warmink *et al.* (2010), and Igos *et al.* (2019), an uncertainty classification for LCA case studies is presented in this section. The classification is defined in the same three dimensions: location, nature, and level (see Sections 3.3.2 and 3.3.3). The differences introduced in each dimension for their application to LCA are discussed in Sections 4.2.1 to 4.2.3, and a flow diagram for classifying the identified uncertainty in an LCA case study is presented in Section 4.2.4.

4.2.1 Defining the location dimension for LCA

The location dimension identifies where uncertainty arises in the model. To avoid introducing yet another naming system for uncertainty classification in LCA, the classes within this dimension are named as model, scenario, and parameter (see Table 5).

One barrier identified by Igos *et al.* (2019) is that a class within the level dimension has also been named as scenario uncertainty. To distinguish between these, the name of the class in the level dimension has been renamed (see Section 4.2.3).

Uncertainty classification in LCA has been researched for over 20 years leading to the commonly identified classification of model, parameter, and scenario uncertainty (see Section 3.3.4). Therefore, the classification proposed here keeps this nomenclature. The addition of the nature and level dimensions to this classification offers a structured way to provide more details regarding the uncertainty being classified.

4.2.2 Defining the nature dimension for LCA

One barrier for classification in the nature dimension that was identified by Warmink *et al.* (2010) is the difficulty in distinguishing between epistemic and aleatoric uncertainty in practice (see Section 3.3.3). To address this, they added a third class to the nature dimension, being ambiguity. For the same reason, ambiguity is also added to the nature dimension for the developed uncertainty classification proposed for LCA.

LCA uses aggregated data as inputs into the LCI and LCIA steps, for example Ecoinvent datasets and characterization factors (see Sections 2.3 and 2.4). Aggregated data will also include aggregated uncertainties, if published by the data provider. For example, the characterization factors for climate change are published with aggregated uncertainty (Myhre *et al.*, 2013). Similarly, aggregated basic and additional uncertainties are quantified for the Ecoinvent datasets (see Section 3.4.3). Because of this, a fourth class is proposed for the nature dimension for use in LCA, being aggregated uncertainty. This uncertainty is not included in previous classifications (see Section 3.3.4).

Aggregated uncertainty is uncertainty calculated by the data provider through propagation of the uncertainties of the data, assumptions, choices, and models used to produce the data. Disaggregating these uncertainties may not always be practical since the information used to calculate them are not available to the LCA practitioner. Classifying these uncertainties as aggregated uncertainty within the nature dimension allows for the uncertainty to be treated like an independent uncertainty within the LCA case study. By highlighting the aggregated uncertainties, research can be geared towards reducing these uncertainties or updating them as data becomes available. Aggregated uncertainty in the Ecoinvent datasets will be discussed further in Chapter 5, Section 5.5.

Therefore, the nature dimension proposed for the developed uncertainty classification for LCA is divided into four classes: aggregated, practical irreducible, ambiguity, and epistemic (see Table 10). The term practical is defined by resource (time/budget) availability for the LCA case study.

Table 10: Summary of uncertainty classes for Location and Nature dimensions used in this study

	Nature			
Location[1]	Aggregated	Practical Irreducible	Ambiguity	Epistemic
Model (uncertainty due to mathematical models or model structure used)	Uncertainty for a mathematical model or model structure that was calculated and propagated by another source	Uncertainty due to natural variability in the model outcomes that are not reducible within the resources available to the study	Uncertainty due to the availability of multiple equally probable and valid models for which there is no scientific consensus for choosing one over the other	Uncertainty due to imperfect information contained in the mathematical model or model structure applied that may be reduced with further research
Scenario (uncertainty due to normative choices made)	Uncertainty in a normative choice that was calculated and propagated by another source	Uncertainty in the normative choices or assumptions that arise from natural variability that are not reducible within the resources available to the study	Uncertainty due to the availability of multiple equally probable and valid options that are not agreed upon by experts	Uncertainty due to imperfect knowledge of the scenario applied that can be reduced with further research
Parameter (uncertainty in data used)	Uncertainty in the input data that was calculated and propagated by another source	Uncertainty in the input data that arises due to natural variability that is not reducible within the resources available to the study	Uncertainty in the input data due to disagreement amongst experts	Uncertainty in the input data due to a lack of knowledge that can be reduced with further research

[1]Refer to Table 5 for more detailed definitions

4.2.3 Defining the level dimension for LCA

The level dimension identifies whether the uncertainty can be quantified or qualified based on the information available regarding the uncertainty. This information ranges from complete knowledge of the deterministic value to total ignorance regarding the value (Figure 5). The level dimension for the proposed uncertainty classification for LCA follows the structure of Warmink *et al.* (2010) (see Section 3.3.3), except that "scenario uncertainty" has been renamed to "comparative uncertainty". This was done to distinguish it from scenario uncertainty defined within the location dimension (see Section 4.2.1).

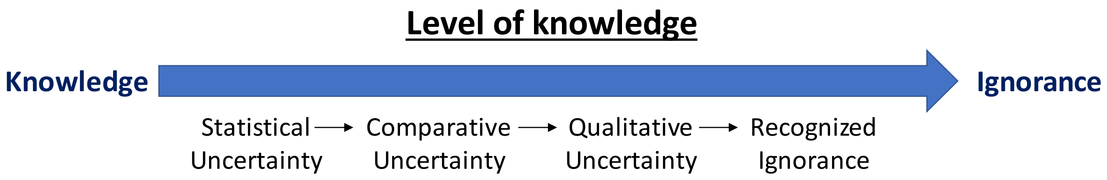


Figure 5: Level Dimension (adapted from Walker *et al.*, 2003)

Uncertainty is classified in the level dimension after the location and nature dimensions (see Table 10) to provide further information on how the uncertainty will be dealt with (quantified, qualified, and reported) in the LCA study.

4.2.4 Uncertainty Classification Flow Diagram for LCA case studies

To help classify the uncertainties into the three dimensions, a flow diagram was created (see Figure 6). As seen in the flow diagram, classification of uncertainty occurs after the uncertainty identification step. Uncertainty identification was discussed thoroughly in Chapter 3 (Section 3.2) and will be implemented into an uncertainty management method developed for LCA in the following section (Section 4.3).

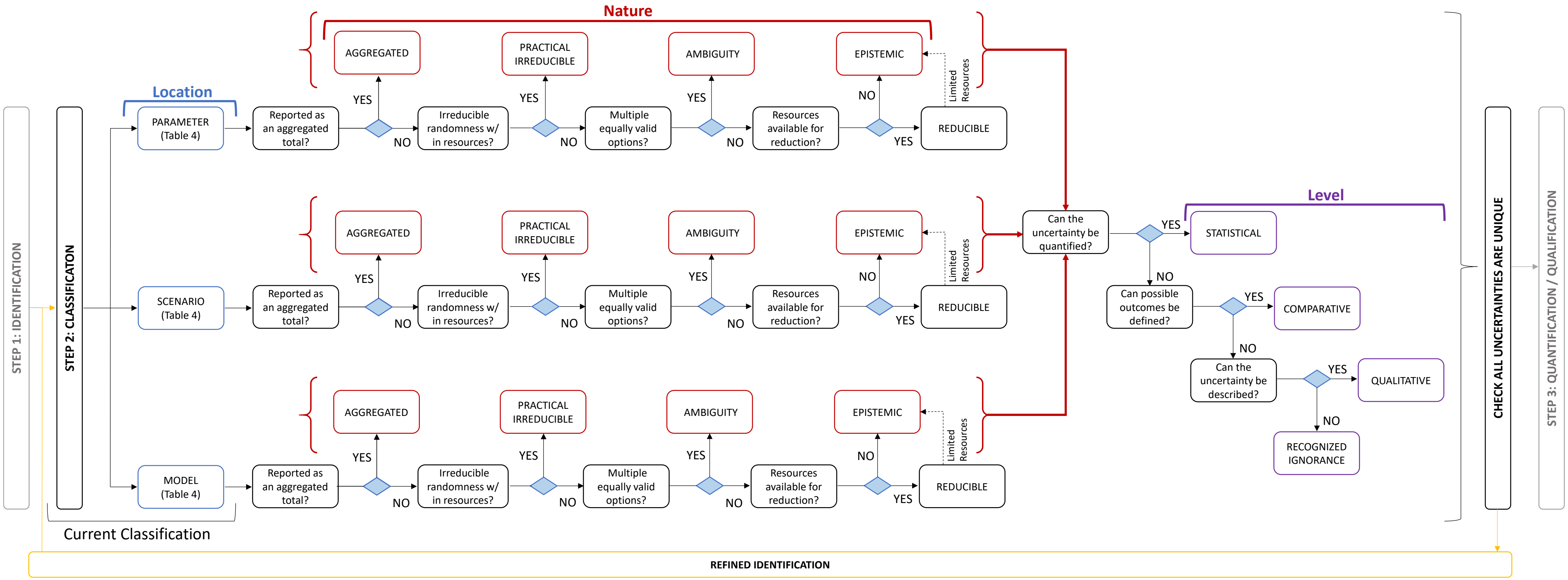


Figure 6: Flow Diagram for Uncertainty Classification in LCA Case Studies (based on Walker *et al.*, 2003; Warmink *et al.*, 2010)

Following the flow diagram, the first step in classification is to classify the uncertainty in the location dimension (see Table 5). The uncertainty is then classified in the nature dimension following the questions in diagram:

1. *"Is the uncertainty reported as an aggregated total?"* If yes, the uncertainty is classified as Aggregated. If no, move to next question.
2. *"Is the uncertainty due to irreducible randomness (or variability) that cannot be explained within resources available*?" If yes, the uncertainty is classified as Practical Irreducible. If no, move to next question.
3. *"Are there other equally valid options (data, models, expert opinions) available?"* If yes, the uncertainty is classified as Ambiguity. If no, move to next question.
4. *"Is the uncertainty reducible within the resources available to the study?"* If yes, the uncertainty should be identified as Reducible. If no, the uncertainty is Epistemic.

For the uncertainties identified as Reducible, a qualitative assessment can be done to rank the uncertainties and identify the most significant uncertainties to focus reduction efforts. This qualitative assessment can be done using the identification of key issues theory developed by Heijungs (1996), as shown in Figure 7. Key issues are the data that have a high contribution to the result and that are very uncertain or show a high degree of variability. By utilizing contribution and uncertainty to identify key issues (Figure 7), the most significant uncertainties can be addressed within the resources available, leaving the others to be reported with the results but not quantified. These reported uncertainties can be addressed when resources become available.

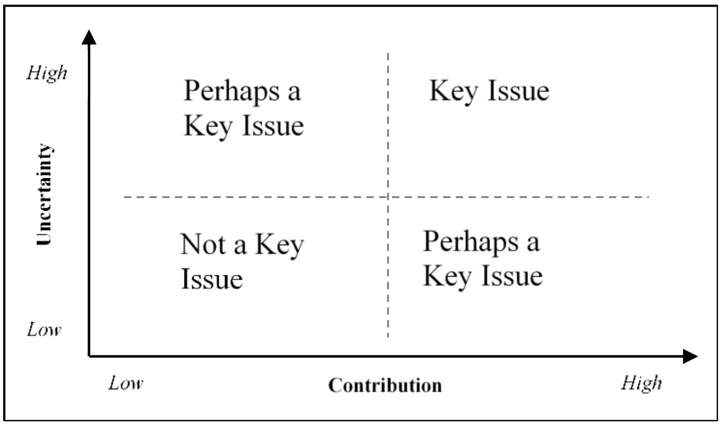


Figure 7: Contribution versus Uncertainty for identification of key issues (adapted from (Heijungs, 1996))

After classification in the nature dimension, uncertainties are classified in the level dimension following the questions in the flow diagram:

5. "*Can the uncertainty be quantified?"* If yes, then the uncertainty is further classified as Statistical. If no, move to the next question.
6. *"Can multiple possible outcomes be defined?"* If yes, the uncertainty is classified as Comparative. If no, move to next question.
7. *"Can the uncertainty be described or qualified?"* If yes, the uncertainty is classified as Qualitative. If no, it is classified as Recognized Ignorance.

Since the level dimension is based on the knowledge and information available to the analyst regarding the uncertainty, the classification can change if new information regarding the uncertainty becomes available.

Once the uncertainty is classified in all three dimensions, it is checked for uniqueness to ensure the same uncertainties are not double counted. If the uncertainties are not unique, then a second identification step is done to disaggregate and reclassify the uncertainty (as discussed in Section 3.2.1.2).

The classification presented in the flow diagram in Figure 6 is part of a structured method for uncertainty management which will be discussed in more detail in the following section.

4.3 Uncertainty Management Methodology for LCA

Key barriers to improving uncertainty management in LCA are the lack of a structured framework or guideline to follow, lack of knowledge, and lack of available resources (Ross, Evans and Webber, 2002; Rosenbaum, Georgiadis and Fantke, 2018). To address this, an uncertainty management method for LCA is developed in this section that provides the necessary guidance and knowledge of how to manage uncertainty. The structured method connects the steps of uncertainty management (see Section 3.1) to the steps of an LCA (see Section 2.1). Through this connection, the time and effort for the uncertainty assessment can be managed throughout the LCA process. Figure 8 gives an overview of the steps of uncertainty management within the steps of an LCA.

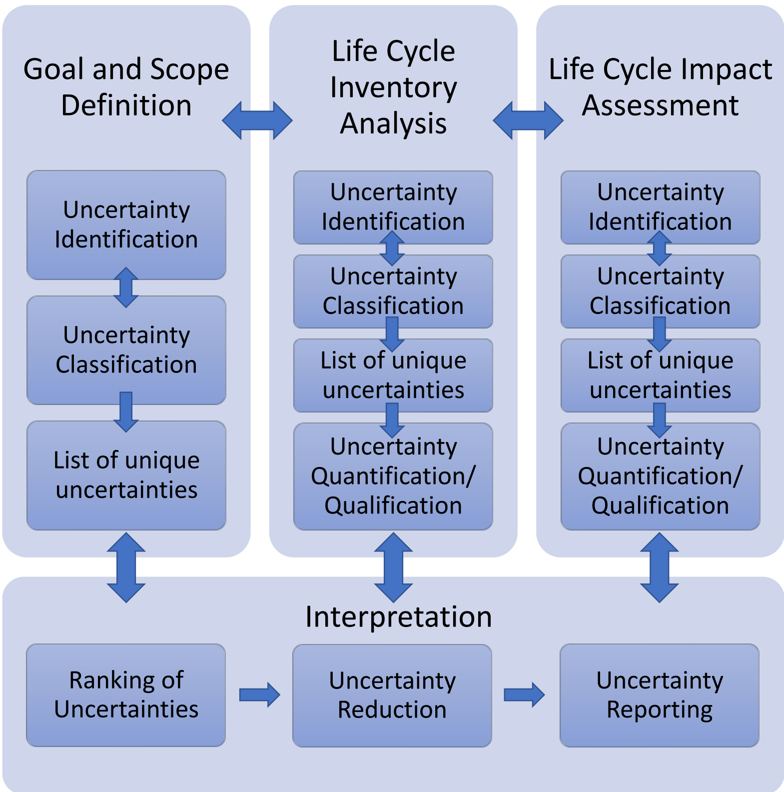


Figure 8: Uncertainty Management Method for LCA

It is further proposed that the uncertainty management method be integrated into ISO 14044:2006. The reason for this is to increase uncertainty reporting in LCA through necessary compliance, on the level of both individual case studies and developed methods that claim ISO compliance. Integration can be considered for future revisions of the standard, which are discussed and agreed by technical committees. Alternatively, the developed uncertainty management method can also be integrated into other guidance documents and product-specific standards through the same steps, which are outlined in the following sections.

4.3.1 Uncertainty Identification and Classification

Identification of uncertainty in LCA can use the same framework developed for environmental models (Figure 2), which is summarized in Figure 9. In Figure 9, the natural system is the product system being assessed and the conceptual model is the Goal and Scope definition. Algorithmic implementation includes the inventory data collection, calculation of the LCI results, the association of the LCI results with the correct characterization factor (LCIA), and the calculation of the results for each impact category being assessed. Software implementation is the coding of the algorithmic implementation in LCA software, where multiple inventory flows can be defined, and multiple impact categories calculated.

Uncertainty identification in LCA occurs at three stages where information is abstracted, as indicated in Figure 9 and discussed below. For a more detailed list of uncertainties that arise in each step of an LCA refer to Section 3.2.2.

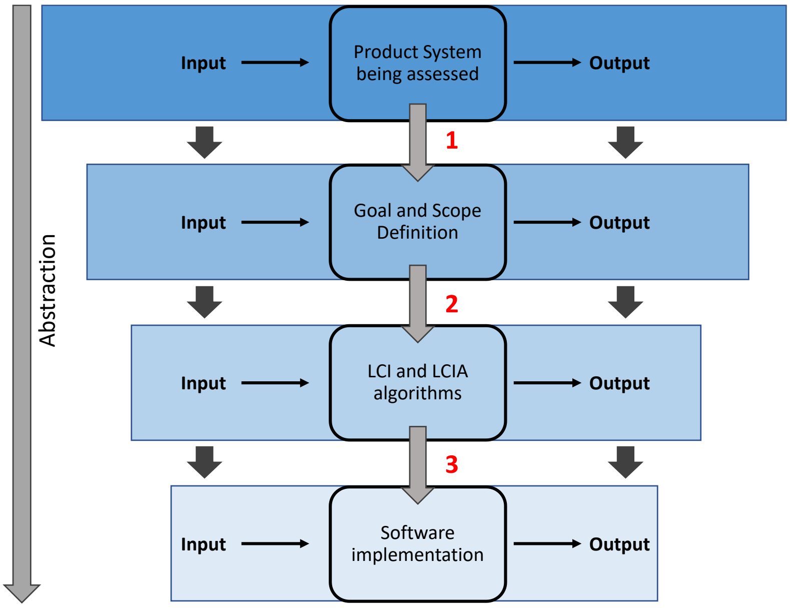


Figure 9: Uncertainty Identification in LCA

The first stage (1) is the abstraction of information regarding the product system being assessed to setup the Goal and Scope Definition. Uncertainties related to the chosen methods, cut-off criteria, functional units and system boundaries should be identified. Identification of these uncertainties are of particular interest for product-specific methods that look to set standards, such as PCR and PEFCR.

The second stage (2) is the abstraction of information from the Goal and Scope Definition for use in the LCI and LCIA steps. Data is collected and organized, and algorithmic equations are applied to yield the final LCIA result. Uncertainties related to the characterization models, inventory data, and assumptions should be identified.

The third stage (3) is the abstraction of information from the algorithms for implementation into software. Here uncertainties are introduced through coding, for example the incorrect identifier being used during classification of inputs and outputs into impact categories (see Section 2.4.1). These errors should be identified and addressed by LCA practitioners (EC-JRC-IES, 2010).

The identification step of uncertainty management should be done within the Goal and Scope definition (ISO 14044, Section 4.2, 2006), the LCI (ISO 14044, Section 4.3, 2006) and the LCIA (ISO 14044, Section 4.4, 2006) steps, with particular focus on the three stages where abstraction of information occurs (Figure 9). Identification should result in a list of uncertainties. For each uncertainty identified, the flow diagram in Figure 6 is then used to classify the uncertainty in the three dimensions and check that they are unique (refer to Section 4.2.4).

4.3.2 Uncertainty Quantification, Qualification and Reduction

At the end of the classification, the uncertainties enter step 3 of uncertainty management, being quantification and qualification. Similar to uncertainty identification and classification, uncertainty quantification and qualification should be conducted within the LCI and LCIA steps (see Figure 9). The uncertainties that have been identified and classified in the Goal and Scope definition, however, are not quantified or qualified in this step. If Epistemic or Reducible uncertainties have been classified in the Goal and Scope definition, they will be qualitatively ranked according to Figure 7 (see Section 4.2.4) and should be reported with the final result. This will be further discussed in the case study results in Chapter 6.

The final step in uncertainty management is Reduction. This step should be part of the interpretation step (ISO 14044, Section 4.5, 2006) of an LCA study (see Figure 9). Uncertainty reduction is conducted iteratively and follows the method described in Section 3.5.2. The uncertainties are quantitatively ranked according to their contribution to the overall uncertainty. This allows for resources for reducing uncertainties to be applied more effectively.

4.4 Worked Examples for Uncertainty Classification in LCA

The following examples show how to use the flow diagram (Figure 6) to classify common uncertainties that arise in LCA case studies. The flow diagram is also used in the LCA case study presented in Chapter 5. The goal of the classification is to ensure the identified uncertainties are not double counted, to improve the reporting of uncertainty in LCA case studies in a way that is useful to the decision maker, and to apply quantification and/or qualification methods uniformly across uncertainty classes.

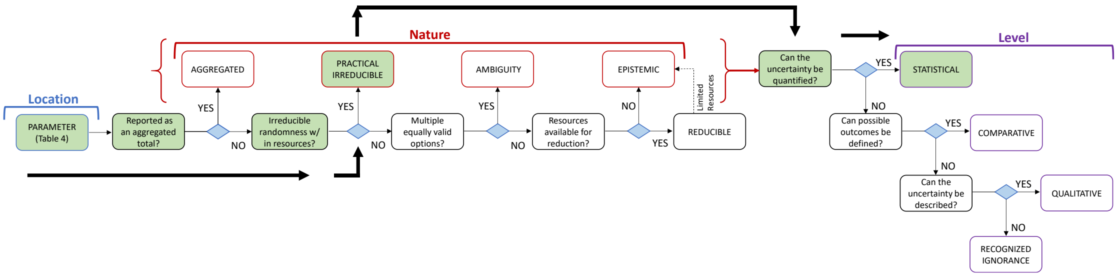
<u>Example 1:</u>

The mass of steel is required for the inventory data.

Step 1: Identification

The mass of steel is weighed on a scale with a measurement error of ±0.5g. The value obtained is used as an input for a foreground process in the life cycle inventory. A more accurate scale is not available within the resources of the study.

Step 2: Classification



Dimension	Class	Justification
Location	Parameter	The uncertainty to be classified is the instrumentation error of the analytical balance used to weigh the item.
Nature	Practical Irreducible	The uncertainty is not an aggregated uncertainty from using an output from another model as an input in the LCA model. The error is due to irreducible randomness produced by the inherent instrumentation error. It will not be measured on a more accurate scale within the study resources and therefore is classified as practical irreducible.
Level	Statistical	The uncertainty exists as a quantity; therefore, the level dimension is classified as statistical.

Step 3: Quantification/Qualification

The full classification is Parameter Practical Irreducible Statistical uncertainty. Since the class within the level dimension is statistical, quantitative methods can be used to propagate the uncertainty in the LCA study.

Step 4: Reduction

The uncertainty could be reduced with use of a scale with a lower error, for example.

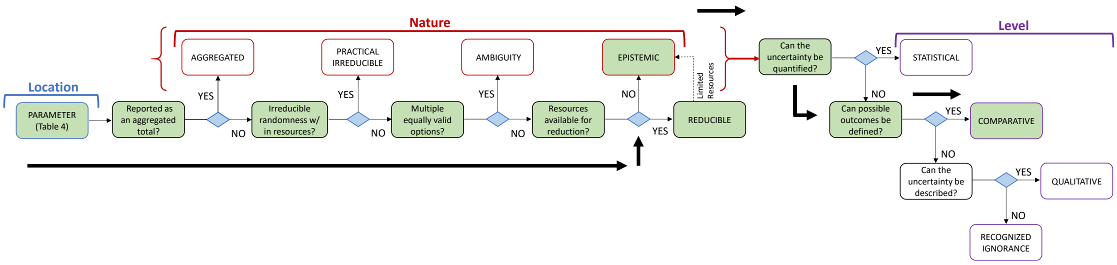
Example 2:

The width of a product is required for the inventory data.

Step 1: Identification

The width of a product is estimated as 0.5m with the help of an expert who works with the product, no other experts are consulted.

Step 2: Classification



Dimension	Class	Justification
Location	Parameter	The uncertainty to be classified is the error of the quantity provided by an expert.
Nature	Epistemic	The uncertainty is not an aggregated uncertainty from using an output from another model as an input in the LCA model. The error is due to expert opinion and not due to irreducible randomness. Since only one expert was consulted, only one estimation of the value exists and therefore the uncertainty is not due to variation in the estimates from use of multiple experts that provide different, yet equally valid options. If there are resources available to reduce this error or to collect more data to make a better estimation, then the uncertainty can be reduced. However, if resources are unavailable or limited the error is classified as epistemic.
Level	Comparative	The uncertainty in the expert opinion cannot be quantified, however possible outcomes or a range in the value could be obtained from the expert's confidence in the value. Therefore, the level dimension can be classified as comparative. It should be noted that if the expert could only provide a qualitative assessment of the confidence, then the classification would be qualitative, as opposed to comparative.

Step 3: Quantification/Qualification

The full classification is Parameter Epistemic Comparative uncertainty. Since it is comparative, quantitative methods can be used to propagate the uncertainty in the LCA study. If the level dimension was qualitative, however, qualitative methods or a combination of qualitative and quantitative methods could be used.

Step 4: Reduction

Reduction of the uncertainty could be done by taking measurements of the width of the product.

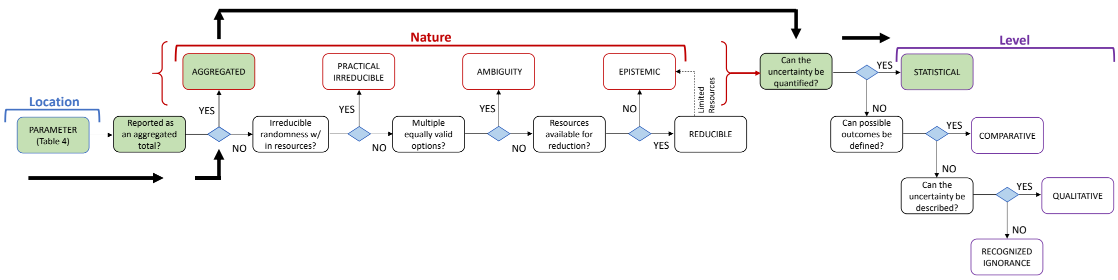
<u>Example 3:</u>

A characterization model is selected for use within the study and the derived characterization factors are applied in the LCIA step.

Step 1: Identification

The uncertainty of a characterization factor used to convert an emission to the units of the impact category is ±30%.

Step 2: Classification



Dimension	Class	Justification
Location	Parameter	The uncertainty to be classified is the aggregated error of the characterization factor.
Nature	Aggregated	The uncertainty is aggregated from calculations of the model used to derive the characterization factor, the assumptions, estimations, data and calculations of which are not available to the LCA practitioner. The characterization factor along with its aggregated uncertainty is used as an input into the LCIA step of the study.
Level	Statistical	The uncertainty exists as a quantity; therefore, the level dimension is classified as statistical.

Step 3: Quantification/Qualification

The full classification is Parameter Aggregated Statistical uncertainty. Since it is statistical, quantitative methods can be used to propagate the uncertainty in the LCA study.

Step 4: Reduction

Reduction of this uncertainty could be possible with improvements to the characterization model and data used to derive the characterization factors and propagate the uncertainty.

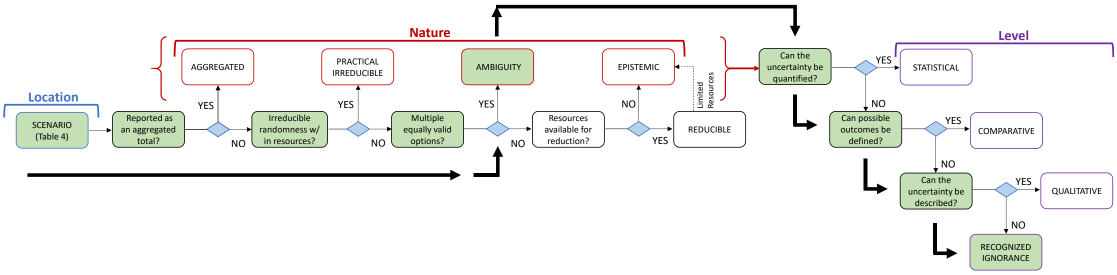
<u>Example 4:</u>

The Intergovernmental Panel on Climate Change (IPCC) characterization factors (Myhre *et al.*, 2013) are used for assessing climate change.

Step 1: Identification

The IPCC characterization factors (CFs) for climate change with a time horizon of 100 years are used for LCIA calculations. The decision to use the IPCC's CFs as opposed to those published by another source, such as the Institute of Environmental Sciences (CML) characterization factors for climate change, introduces uncertainty. Note that uncertainty arises due to the choice to use one source over another source and does not arise due to the error in the reported CF from the source. A comparison of the results from multiple characterization models for climate change is not undertaken as part of the study.

Step 2: Classification



Dimension	Class	Justification
Location	Scenario	The uncertainty to be classified is the aggregated error of the characterization factor. The uncertainty to be classified is the choice to use one method over another for the derivation of characterization factors to use as inputs in the LCIA step. This is scenario uncertainty as the method to use is defined in the Goal and Scope definition.
Nature	Ambiguity	The uncertainty for this decision is not quantified and is also not a reported aggregated uncertainty or due to irreducible randomness or variability in the value. Since there are multiple methods available to quantify the characterization factors, each of which are valid and may produce varying results, this uncertainty is classified as ambiguity.
Level	Recognized Ignorance	The goal of the LCA case study is not to compare the difference in using multiple characterization models for climate change, therefore the uncertainty is not quantifiable and possible outcomes will not be defined. Furthermore, with no further information gathered on the variations in characterization factors derived using different models, the uncertainty is also not qualifiable. Therefore, the uncertainty is classified as recognized ignorance. However, if a comparison of characterization models was in the goal of the study, then possible outcomes could be defined, and the uncertainty classified as comparative.

Step 3: Quantification/Qualification

The full classification is Scenario Ambiguity Recognized Ignorance. Although quantification or qualification of this uncertainty is not done within the study, this uncertainty can still be identified and reported to reiterate that the study results should only be compared to studies that applied the same characterization model for climate change, where a comparison is valid, since deviations could also be the result of the use of different derivation models for the CFs.

Step 4: Reduction

Reduction of this uncertainty could be possible with further research to harmonize the characterization models and data that are used to derive characterization factors.

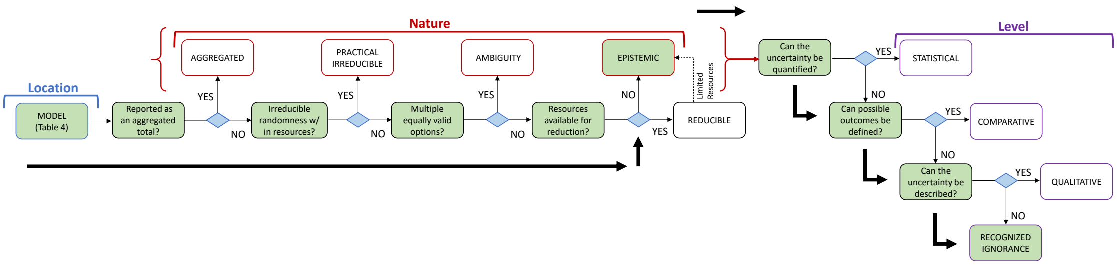
Example 5:

Data is required for the production of a product on an industrial scale that is currently produced at a laboratory scale.

Step 1: Identification

A linear relationship is used to scale the energy consumption for manufacturing a product on laboratory scale to that for manufacturing of the product on an industrial scale. No other modelling options are assessed.

Step 2: Classification



Dimension	Class	Justification
Location	Model	The uncertainty to be classified is the error in using a linear relationship to model the scale up. This is a simplification of the scale up. This occurs in LCA studies of innovative products that are not already on the market. Scaling a laboratory production process linearly is unlikely to be comparable to what the industrial process will look like once implemented, but in this example, it is the chosen model to apply.
Nature	Epistemic	The error is not reported as an aggregated uncertainty, it is not due to irreducible randomness or variability, and multiple models have not been assessed for their appropriateness. Taking the uncertainty to be irreducible within the resources available to the study, it is classified as epistemic. If resources were available to reduce the uncertainty with use of a validated model for the scale up, the model could be updated, and the uncertainty reclassified.
Level	Recognized Ignorance	Since no information is available regarding how the industrial process would be designed, the uncertainty is not quantifiable or qualifiable. Furthermore, since only one model is used, multiple outcomes will not be defined. Therefore, the uncertainty is classified as recognized ignorance.

Step 3: Quantification/Qualification

The full classification is Model Epistemic Recognized Ignorance. This uncertainty should be reported in the LCA study along with a statement that the results should be updated when the model used for the scale up is improved with better estimations.

Step 4: Reduction

Reduction could be possible with measurements taken from the industrial production, for example.

4.5 Conclusion

In this chapter, an uncertainty classification for LCA and an uncertainty management methodology were developed. The developed classification provides guidance for classifying uncertainties into the three dimensions: location, nature, and level. The classification is further connected to the identification and quantification/qualification steps in uncertainty management in a structured way.

The developed uncertainty management method for LCA provides the necessary framework for identifying, classifying, quantifying/qualifying, and reducing uncertainties within case studies. This structured method is further connected with the steps of an LCA study as defined in the international standards. It can therefore be integrated into this standard, or other product-specific standards and guides, through these steps, with the aim of improving uncertainty reporting through compliance.

However, in order to determine the ability of these methods to improve uncertainty reporting, they need to be tested across multiple LCA practitioners, researchers, and case studies. The methods are demonstrated in a case study of an Irish apartment development in Chapters 5 and 6. In Chapter 6, the experience of using the uncertainty management method is further discussed (see Section 6.7).

CHAPTER 5. CASE STUDY METHODOLOGY

In order to demonstrate the use of the uncertainty classification and uncertainty management methods developed in Chapter 4, they have been tested in an LCA case study. This chapter presents the methodology for the case study, including the Goal and Scope definition (Section 5.1), the LCI and LCIA data sources (Section 5.2), the Tiered-hybrid approach (Section 5.3), the calculation method for the LCIA results with uncertainty (Section 5.4), and the key assumptions for the study (Section 5.5).

5.1 Goal and Scope Definition

The buildings and construction sector accounts for approximately 36% of final energy use and 39% of energy- and process-related greenhouse gas (GHG) emissions (GlobalABC, IEA and UNEP, 2019). This is mainly attributed to the energy consumption during the occupancy (use) stage; however, the pre-occupancy stage becomes significant as buildings become more energy efficient (see Section 2.2.3.1). The product system chosen for the case study was an apartment development constructed in Ireland focusing on greenhouse gas emissions during the pre-occupancy stage.

This product system was selected since the buildings and construction sector accounts for a significant portion of GHG emissions, and since buildings consist of multiple components. LCA studies of buildings require the management of relatively large amounts of data and uncertainties compared to a system consisting of less components. A relatively complex system, such as a building, was therefore considered as more representative for testing the uncertainty management methodology. Climate change was selected as the impact category to assess in this case study due to the sector's GHG contribution. However, it is noted here that the uncertainty management method should also be tested with other product systems that range in their data requirement and quality (see Section 3.4.2), and across other impact categories (see Section 2.4.2) in future research. In particular, the method should be tested across product systems that vary in their Technology Readiness Level (see Section 2.2.2).

Tiered-hybrid analysis was selected to construct the LCI model (discussed further in Section 5.2). This approach was selected for the following reasons:

- it has been identified as a best practice approach (see Section 2.3.4);
- it allows for the uncertainty management method to be tested with both process data and input-output data; and
- process data for the onsite construction energy consumption and emissions were not available for this study.

The intent of this case study is to demonstrate the use of the uncertainty management method detailed in Section 4.3 in an ISO compliant LCA study with a specific focus on assessing the use of the uncertainty classification proposed in Section 4.2. The reasons for conducting this study are to: (i) use the developed uncertainty classification to aid in uncertainty management throughout the study, (ii) apply the steps of uncertainty management within the steps for LCA, (iii) present the results of the study as distributions that represent the propagated uncertainty, and (iv) compare the deterministic result (single value) and the stochastic result (distribution).

5.1.1 Functional Unit and System Boundary

The functional unit chosen for the case study is an apartment development of 27,000 meters squared that is ready for occupation. The apartment development consists of two 8-storey buildings with a gross floor area of 27,000 meters squared. The buildings surround a large publicly accessible concrete courtyard and contain ground floor retail space, a parking garage, and a total of 300 apartments that range in size from 1 to 3 bedrooms. The superstructure of the building is composed of precast concrete elements, while the basement-level substructure, ground-level transfer slab and central courtyard are composed of in-situ concrete. The envelopes of the buildings are solid concrete panels, and the floors are hollow core planks tied with a structural screed.

The system boundary to be assessed is a cradle-to-constructed building system boundary or the pre-occupancy stage of the buildings life cycle (Figure 10). As this study will focus on the pre-occupancy stage, the uncertainty management method should also be tested for the occupancy and post-occupancy stages in future research.

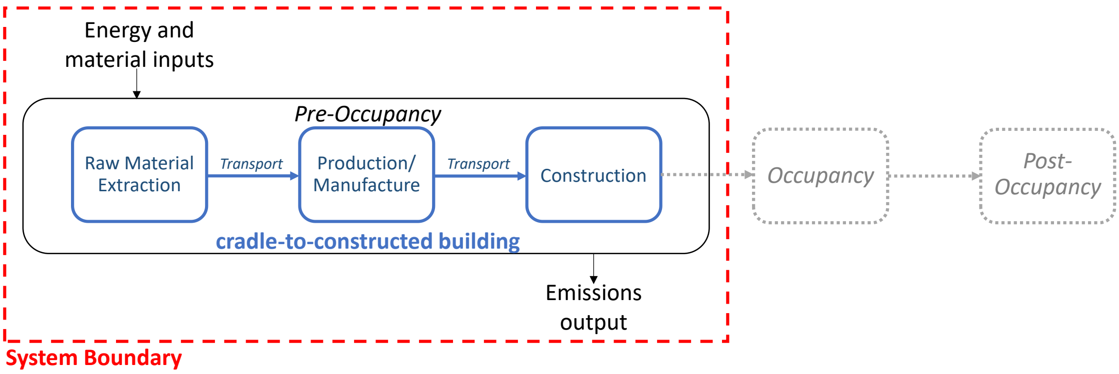


Figure 10: System boundary for case study

5.2 LCI and LCIA Data Sources

For the LCI, the data sources include the bill of quantities (BOQ) for the apartment development (foreground data), the Ecoinvent database (background process data) (Wernet *et al.*, 2016), and the Sectoral Emissions Intensities calculated using the input-output tables (Central Statistics Office, 2009) and the national accounts data (Tol, Lyons and Mayor, 2008) for Ireland (background input-output data). For the LCIA, the IPCC Global Warming Potential (GWP) characterization factors (Myhre *et al.*, 2013) for climate change were used. Each data source is discussed further in the following sections.

5.2.1 Bill of Quantities

The foreground data for the LCA case study is the bill of quantities (BOQ) of the building described in Section 5.1.1 that was constructed in Ireland in 2004. A BOQ contains the name, description, quantity, and cost for each item being billed, and is mandatory for the billing of all construction works. The items billed are further divided into those related to ground works, structural work, finishes, services and fittings. A digital representation, such as with Building Information Modelling (BIM) was not available for this building, however, it is noted here that BIM, showing a 3D representation of the building, is also very useful when compiling the foreground data and could be used in future work.

In Ireland, the Agreed Rules of Measurement (ARM) provide the guidelines that must be followed when preparing a BOQ (The Joint Committee, 2009). Therefore, ARM was used to interpret the BOQ to identify the material type and measurements of the building's components and to estimate the uncertainty of the costs and quantities. The measurements for the reported quantities in the BOQ are defined to be taken to the nearest 0.01 meters or 0.01 tonnes (The Joint Committee, 2009). However, in the BOQ for the case study building, the reported quantities have been rounded to the nearest unit (such as to the nearest meter or square meter). For example, 1.63m of timber is billed at and recorded in the BOQ as 2m and 1.42m at 1m. Therefore, the uncertainty in the measured quantities recorded in the BOQ was estimated as a uniform uncertainty of ±0.5 units and that for the costs recorded in the BOQ as ±0.5 units multiplied by the cost per unit. This was done for all items in the BOQ except for measurements given in "number", indicating the number of pieces or parts, or in "item". In the former case, the uniform uncertainty for the quantity was taken as ±1 piece or part and that for the cost as ± the cost per piece or part. In the latter case, all items were assessed through I-O analysis and the uniform uncertainty for the cost was estimated as ±5% of the total item cost.

The use of BOQs have been criticised, as the costs are usually indicative of a certain point in time and may not be updated with changes made to the design (Cunningham, 2016). This is in fact seen in the BOQ used for this study, where the cost reported for one material was used to offset the cost of a material change, but the quantity of the new material itself was not included in the bill. For these cases, input-output data was used instead of process data for modelling the production emissions of the new material as the quantity of the material could not be determined.

5.2.2 Ecoinvent Datasets

The Ecoinvent database was selected as the most suitable database to use for background process data because of the availability of uncertainty information for each dataset and the ability to download and import the datasets into Excel. The latter was essential, as all analysis was conducted using Excel and the statistical program, RStudio (RStudio Team, 2016). This was done to include all uncertainties and remove any black boxes or other limitations introduced due to use of LCA software. The uncertainty methodology used in the Ecoinvent database was described previously in Section 3.4.3.

5.2.2.1 Database Selection

Prior to the decision to use the Ecoinvent database, two other databases available to the study were also considered: GaBi version 5 and Inventory of Carbon and Energy (ICE) version 2. The Ecoinvent database available to the study was Ecoinvent version 3.1. The three databases are compared according to chosen criteria in Table 11.

GaBi version 5 did not provide uncertainty information in the datasets, however it is noted that in later versions of GaBi, uncertainty analysis can be conducted by inputting standard deviations for defined parameters, assigning either a normal or uniform distribution type and running a Monte Carlo simulation with a specified number of runs. The method is limited to only two types of distributions, and calculations for the data quality and other types of uncertainties needs to be done either outside the software or by defining additional parameters within the model. The use of Excel and RStudio (RStudio Team, 2016), along with the Ecoinvent datasets was considered more appropriate for demonstration of the uncertainty management method.

For ICE version 2, the datasets are prepared using results from literature studies that may or may not follow the ISO standards for LCA, although studies that state they are compliant are given preference. Furthermore, the probability distribution curves are not presented along with the data necessary to use them. For these reasons, the ease of use of the Ecoinvent datasets was considered more appropriate for this study.

There are two ways to use the Ecoinvent datasets, either through the database online or by using the database within a software program, such as GaBi or Simapro. In the online version of the database, each dataset can be viewed in the unlinked unit process (UPR) format, which indicates all input data sources and outputs for the gate-to-gate system boundary, along with the uncertainty and DQI scores. One criticism of the Ecoinvent database is that the online version does not include the uncertainty information in the LCI data or the LCIA data. To recreate each LCI dataset using all unit process data traced all the way back to raw material extraction in order to recalculate the LCI with uncertainty (essentially recreating the entire Ecoinvent database) would have required significant work outside the scope of this study. Therefore, the uncertainty information from the unit process level could not be used in this study and instead the basic uncertainties were estimated using Table 8 in Chapter 3. This method is also used by Ecoinvent to estimate uncertainties where measured uncertainties are not available in the unit process data.

Table 11: Comparison of three databases available for the LCA case study

Information Included	**Database**		
	Ecoinvent **v.3.1**	**GaBi 5**	**ICE v.2**
Geographical Area	Various	DE, RER, GLO, US	UK
Age of Data	Various	Various	1977-2010
Type of emissions data included	Various	Various	Total CO_2, EE, Total CO_2-eq
References for source of data reported	Yes	Yes	Yes
System Boundary Defined	Yes	Yes	Yes
Uncertainty, Probability Distribution or Standard Deviation	Standard deviation and DQI score for unit process data, but not for LCI	Not specified in datasets	Probability Distribution Curve without data
Reported Assumptions	Yes	Yes	Yes
Process or I-O data	Process, some I-O	Process	Process
Life Cycle Stages	Cradle-to-gate, cradle-to-grave, gate-to-gate	predominantly cradle-to-gate	Cradle-to-site, cradle-to-grave, cradle-to-gate
How is data collected/compiled?	Submitted by practitioners and reviewed	Submitted by practitioners and reviewed	Collected from research papers for LCA of building materials
Is the data trustworthy?	Each LCI is peer-reviewed	Data is peer-reviewed	Data comes from published sources
ISO standard Compliant	All LCI datasets are generated in compliance with the ISO standards.	All LCI datasets are generated in compliance with the ISO 14044, ISO 14064 and ISO 14025 standards.	Preference given to studies that complied with the ISO standards for LCA.

5.2.2.2 Ecoinvent System Model Selection and Database Version

When using the online version of the Ecoinvent database, there is a choice of two system models: System model with substitution (system expansion) and System model with partitioning (allocation). A system model describes how the datasets are linked to produce the product system being assessed. It further defines how the impacts of a system producing multiple products are distributed between the products, being either through allocation or system expansion (see Section 2.2.5.1).

System model with substitution (system expansion) follows a consequential approach (see Section 2.3.1), and is also known as substitution, consequential, long term. System model with partitioning uses an attributional approach.

System model with partitioning is further subdivided into two methods being: allocation, cut-off by classification and allocation at point of substitution (APOS). Cut-off by classification assumes that the waste treatment activity is cut-off from the system boundary, therefore products that use secondary materials, or recycled materials, as inputs only consider the impacts of collection and conversion of waste to secondary material in the production stage, and the burden of the waste treatment is with the production of the primary material. Whereas for APOS, the waste treatment activity is allocated to the production of the secondary material, therefore there is a burden allocated from the waste treatment process to that of using the secondary material in the production stage. Therefore, in the Cut-off system model, the primary producer takes the burden of waste management, whereas with the APOS system model, the burden of the waste management is allocated between all users of the recovered product or by-product from the waste treatment of the primary product.

For this case study, an attributional approach was selected. Since the aim of the case study was to test the uncertainty management method and not to determine the consequences of decisions within the building life cycle, an attributional approach was found to be suitable. The chosen system model for the Ecoinvent datasets was the APOS system model, therefore allocating partial impacts of waste management to the use of secondary materials in production. This system model was also the default model applied in early versions of Ecoinvent version 3, such as for version 3.1 that was used in this case study. The implications of the choice of system model have not been considered in this study, however this can be taken into consideration in future work that includes the model uncertainty of the Ecoinvent datasets.

The latest version of Ecoinvent is version 3.6, which was released in 2019. The changes to the database include updates to and additions of specific datasets to include more countries, such as South Africa, Canada, Brazil, and India, and now contains datasets for 140 countries. There were further updates to the datasets for building materials, particularly for the above-mentioned countries. Therefore, there may be small changes also for the building materials used in this case study, but it is not considered a limitation. Furthermore, although the addition of uncertainty information for the LCI data on the online database was being considered for version 3 (Weidema *et al.*, 2013), it still has not been added even in version 3.6 of the database. This information was available in the online database for version 2 and was removed in version 3. Access to the LCI uncertainties would be beneficial to this case study, as discussed earlier, but instead have been calculated through methods developed by Ecoinvent for basic and additional uncertainties.

5.2.2.3 Ecoinvent Dataset Preparation

To prepare the Ecoinvent datasets, they were converted into Excel files by rewriting the '.spold' file as a '.xml' file, following the method suggested by Ecoinvent. The resulting file could be opened in Excel, but as 245 datasets were downloaded for this case study, code was written in RStudio to extract the information from all datasets and organize the files into tables for each material (refer to Appendix V for written code).

Data for a total of 26 GHGs were extracted from each dataset using the Chemical Abstracts Service (CAS) number, as are shown in Table 15. For each dataset, a DQI score was given based on the pedigree matrix in Table 6 of Chapter 3, and the total uncertainty quantified as per Section 3.4.3. The total CO_2-equivalents for each dataset was calculated using the IPCC GWPs (Myhre *et al.*, 2013) (see Section 2.4.2). The uncertainty was propagated using the rule for multiplying uncertainties (refer to Appendix I for equations). A table including the name of each dataset from the Ecoinvent database, the DQI score, the total CO_2-euivalents and the total uncertainty is presented in Appendix IV for all 245 datasets.

To verify the code used to extract the GHG data from the Ecoinvent datasets, the calculated total CO_2-equivalents described above were compared to the LCIA datasets available in the online version of the Ecoinvent database.

5.2.3 Sectoral Emissions Intensities for Ireland

In order to calculate the Sector Emissions Intensities (SEIs) for Ireland, the Input-Output tables for Ireland in 2005 (Central Statistics Office, 2009) and the Environmental Accounts Data for Ireland from 1990-2005 (Tol, Lyons and Mayor, 2008) were obtained. The CSO publishes the input-output tables every 5 years, and therefore 2005 was chosen as it was the closest year to that of the construction of the building being assessed, which was constructed in 2004. The I-O tables for Ireland are highly aggregated (Acquaye, 2010; Acquaye and Duffy, 2010; Goggins, Keane and Kelly, 2010). EEIO is discussed in Chapter 2, Section 2.3.2.

For Ireland, the environmental accounts data contains data on the emissions of the greenhouse gases listed in Table 12 (Tol, Lyons and Mayor, 2008). The quantities of GHG in the environmental accounts data are in units of thousand tonnes of GHG for Carbon dioxide, Methane and Dinitrogen monoxide, and in tonnes of CO_2-equivalent for all other GHGs. Therefore, the quantities of Methane and Dinitrogen monoxide were converted to CO_2-equivalents before summing the quantities of all GHGs to get the total CO_2-equivalents per sector shown in Table 13. This was done using the IPCC GWPs for Methane and Dinitrogen monoxide (Table 15).

Table 12: Greenhouse Gases in Environmental Accounts Data for Ireland

Name	Formula/Abbreviation
Carbon dioxide	CO_2
Methane	CH_4
Dinitrogen monoxide	N_2O
Sulfur hexafluoride	SF_6
Tetrafluoromethane	CF_4
1,1-Difluoroethane	HFC-152a
Trifluoromethane	HFC-23
Hexafluoroethane	HFC-116
1,1,1,2-Tetrafluoroethane	HFC-134a
Difluoromethane	HFC-32
Pentafluoroethane	HFC-125
1,1,1-Trifluoroethane	HFC-143a
1,1,1,2,3,3,3-Heptafluoropropane	HFC-227ea
Perfluorocyclobutane	PFC-318

Table 13: Total carbon dioxide equivalents and production costs per sector in 2005

Sector	NACE Code (Rev1)	kt CO_2-equivalent (2005)[1]	Total Production (m€)[2]
Agriculture, fishing, forestry	1-5	22345	7,200
Coal, peat, petroleum, metal ores, quarrying	10-14	136	1,453
Food, beverage, tobacco	15-16	1127	16,840
Textiles Clothing Leather & Footwear	17-19	114	623
Wood & wood products	20	60	1,179
Pulp, paper & print production	21-22	87	13,590
Chemical production	24	703	31,625
Rubber & plastic production	25	53	1,609
Non-metallic mineral production	26	4496	2,302
Metal prod. excl. machinery & transport equip.	27-28	1677	2,813
Agriculture & industrial machinery	29	85	2,009
Office and data process machines	30	217	12,952
Electrical goods	31-33	708	11,529
Transport equipment	34-35	36	1,114
Other manufacturing	23,36-37	531	2,903
Fuel, power, water	40,41	15607	4,405
Construction	45	785	38,442
Services (excl. transport)	50-55,64-95	4356	166,551
Transport	60-63	13016	12,222
	TOTAL	**66142**	**331,360**

[1](Tol, Lyons and Mayor, 2008); [2](Central Statistics Office, 2009)

The I-O tables were aggregated into the same sectors as the environmental accounts data. The sectors are identified by the NACE codes, which is a 2-digit level sectoral classification code. The NACE Rev1 coding system was used for the 2005 I-O tables and environmental accounts data. These codes have since been redefined and updated as per NACE Rev2. Since the building used in the case study was constructed in 2004, the NACE Rev1 coding was maintained for this study. Each sector is named according to the product that accounts for the largest part of its output.

The Leontief inverse (L) matrix was calculated and multiplied by the environmental intervention vector, Q (gCO_2/€) to give the final SEIs (gCO_2/€) for each aggregated sector

(Table 14). The SEI is therefore equivalent to the "$Q(I - A)^{-1}$" part of Equation 3 (see Section 2.3.2).

Table 14: Emission Factors for Production and Sectoral Emissions Intensities

Sector	NACE Code (Rev1)	Q (gCO_2/€)	SEIs (gCO_2/€)
Agriculture, fishing, forestry	1-5	3,103	4,008
Coal, peat, petroleum, metal ores, quarrying	10-14	94	308
Food, beverage, tobacco	15-16	67	411
Textiles Clothing Leather & Footwear	17-19	182	188
Wood & wood products	20	51	81
Pulp, paper & print production	21-22	6	65
Chemical production	24	22	61
Rubber & plastic production	25	33	58
Non-metallic mineral production	26	1,953	2,209
Metal prod. excl. machinery & transport equip.	27-28	596	741
Agriculture & industrial machinery	29	43	52
Office and data process machines	30	17	18
Electrical goods	31-33	61	78
Transport equipment	34-35	32	33
Other manufacturing	23,36-37	183	471
Fuel, power, water	40,41	3,543	4,804
Construction	45	20	204
Services (excl. transport)	50-55,64-95	26	2,787
Transport	60-63	1,065	1,499

Using SR-IO analysis is a limitation for this study as multi-region input-output (MR-IO) analysis is more suitable for Ireland's open economy. Ireland imports a significant amount of construction products that may contribute to approximately 42% of the total CO_2-equivalents for the construction sector, the remaining 58% from domestic arising total embodied CO_2-equivalents for the construction sector, which can be estimated with SR-IO analysis (Acquaye and Duffy, 2010). Since SR-IO analysis was used in this case study and imports were ignored, the overall uncertainty was estimated as ±40% lognormally distributed for the analysis (see Section 2.3.2.2).

In order to assess the implications of using the SR-IO tables compared to using world I-O tables, the SEIs for the Irish construction sector were also obtained from the Exiobase I-O tables (Stadler *et al.*, 2018) (see Section 2.3.2.1). To calculate the SEI for the Irish construction sector (NACE 45), openLCA (GreenDelta, 2020), an open source LCA software, was used to run the calculations. Since Exiobase has internal flows that differ from those in openLCA for tracing the LCI impacts to LCIA (Ciroth and Bunsen, 2019), openLCA was used to calculate the LCI inputs and outputs per 1 Euro of production in the Irish construction sector (NACE 45) and the results were exported to Excel to calculate the LCIA using the IPCC GWPs (Myhre *et al.*, 2013). In Excel, the GHGs were identified and multiplied by the associated IPCC GWPs to give the gCO_2-equivalents per Euro, the sum of which could be compared to the SEI for the construction sector in Table 14.

Further research should apply a MR-IO approach that can account for upstream emissions due to imports.

5.2.4 IPCC Global Warming Potentials

The Characterization Factors chosen for assessing climate change were the Intergovernmental Panel on Climate Change (IPCC) Global Warming Potentials (GWPs) for a 100-year time period as reported in the IPCC Fifth Assessment Report (Myhre *et al.*, 2013). GWP is the ratio of the cumulative radiative forcing due to emission pulses of a substance over a defined time period to the cumulative radiative forcing over the same time period for a reference substance. The reference substance is Carbon dioxide and the defined time period for GWP_{100} is 100 years. GWP_{100} is a commonly used metric, although there is no scientific basis for the choice of this time period compared to, for example, 20 years or 500 years (Myhre *et al.*, 2013).

The GWPs are reported both with and without climate-carbon cycle feedbacks for GHGs other than CO_2 in the Fifth Assessment report (AR5) from the IPCC (Myhre *et al.*, 2013). The climate-carbon feedbacks (CCF) for CO_2 are included in both set of GWPs. CCF describes the relationship of warming on the release of carbon to the atmosphere. This feedback is reported to be positive with "high confidence", indicating that warming resulting from the release of anthropogenic GHGs into the atmosphere will lead to further release of carbon into the atmosphere (Myhre *et al.*, 2013; Friedlingstein, 2015; Sterner and Johansson, 2017). AR5 has accounted for CCF using linear feedback analysis for a time period of 100 years. However, there is still uncertainty in how the climate system responds to changes in radiative forcing and the effect of climate change on atmospheric CO_2 concentrations. The GWPs that account for CCF therefore have larger uncertainty ranges compared to those without CCF due to the large uncertainties in the CCF model (Myhre *et al.*, 2013).

For this case study, the chosen IPCC GWP_{100} factors used in the LCIA did not include the effect of climate-carbon feedbacks. Furthermore, the case study only considered the well-mixed greenhouse gas emissions, such as CO_2, N_2O, CH_4, PFCs, HFCs and SF_6 (Stocker *et al.*, 2013). It has not included the impacts due to short lived gases (such as NO_x, CO, NMVOC), aerosols and precursors (such as SO_2, NH_3, black carbon, organic carbon), and land use changes, which can have negative or positive climate feedback (Stocker *et al.*, 2013). The IPCC GWP_{100} values without CCF used in this case study and their reported uncertainties are summarized in Table 15.

Table 15: IPCC Global Warming Potentials for each Greenhouse Gas

Name of Greenhouse Gas (GHG)	**CAS Number**	**IPCC[1] GWP_{100}**	**IPCC[1] Uncertainty (%)**
Carbon dioxide	000124-38-9	1	26
Methane	000074-82-8	28	39
Dinitrogen monoxide	010024-97-2	265	29
Sulfur hexafluoride	002551-62-4	23500	33
Nitrogen fluoride	007783-54-2	16100	33
Perfluoropentane	000678-26-2	8550	33
Chloroform	000067-66-3	16	33
Tetrachloromethane (R-10)	000056-23-5	1730	33
Tetrafluoromethane (R-14)	000075-73-0	6630	33
Monochloromethane (R-40)	000074-87-3	12	33
Dichloromethane (HCC-30)	000075-09-2	9	33
Trichlorofluoromethane (CFC-11)	000075-69-4	4660	33
Dichlorodifluoromethane (CFC-12)	000075-71-8	10200	31
1,1,2-trichloro-1,2,2-trifluoroethane (CFC-113)	000076-13-1	5820	33
1,2-dichloro-1,1,2,2-tetrafluoroethane (CFC-114)	000076-14-2	8590	33
Trifluoromethane (HFC-23)	000075-46-7	12400	33
Hexafluoroethane (HFC-116)	000076-16-4	11100	33
1,1,1,2-tetrafluoroethance (HFC-134a)	000811-97-2	1120	33
1,1-Difluoroethane (HFC-152a)	000075-37-6	138	33
Dichlorofluoromethane (HCFC-21)	000075-43-4	148	33
Chlorodifluoromethane (HCFC-22)	000075-45-6	1760	33
2-chloro-1,1,1,2-tetrafluoroethane (HCFC-124)	002837-89-0	527	33
1,1,1-Trichloroethane (HCFC-140)	000071-55-6	160	33
Bromomethane (Halon 1001)	000074-83-9	2	33
Bromochlorodifluoromethane (Halon 1211)	000353-59-3	1750	33
Bromotrifluoromethane (Halon 1301)	000075-63-8	6290	33

[1]IPCC Fifth Assessment Report, excluding climate-carbon feedback (Myhre *et al.*, 2013)

The GWP_{100} values used in this study differ from the methodology applied in Ecoinvent v.3.1 for calculation of the LCIA from the LCI data. Ecoinvent uses the IPCC GWP_{100} values with CCF, which have slightly higher values for the 100-year time period. Furthermore, Ecoinvent includes in the LCIA calculation for each dataset the uptake of CO_2 by soil and the release of gases that are short-lived or are precursors, some that have negative GWP_{100} values, as summarized in Table 16 (Ecoinvent (v3.1), 2014). As stated earlier, these gases have been excluded in this study. Therefore, there are differences in the calculated LCIA for each Ecoinvent dataset using the GWP_{100} in Table 15 compared to the LCIA for each dataset published in the online Ecoinvent database. These differences were quantified and reported in Appendix IV for each dataset.

Table 16: IPCC characterization factors climate-carbon feedback

GHG	Compartment	IPCC GWP_{100} [2]
Carbon dioxide (CO_2)	to soil	-1
Sulfur dioxide (SO_2)	to air	-38.4
Nitrogen oxides (NOx)	to air	-10.8
Carbon monoxide (CO)	to air	1.9

[2]Ecoinvent version 3.1 (2014)

It is further noted that the Ecoinvent CF for SF_6 in version 3.1 is mistakenly input as 16087 as opposed to 26087, which has been acknowledged by Ecoinvent and updated in a later version (Ecoinvent (v3.1), 2014). This version was unavailable for this study; however, this mistake is unlikely to contribute significantly to the differences in the calculated LCIA due to the relatively small concentrations of SF_6 within the datasets.

5.3 Tiered-hybrid Analysis

For the LCA case study, a Tiered-hybrid approach (see Section 2.3.3.3) was used to construct the LCI. In setting up the Tiered-hybrid model, all items in the BOQ were first divided into four categories: (i) ‘Process cradle-to-site’ emissions, (ii) ‘Input-Output construction’ emissions, (iii) ‘Hybrid cradle-to-construction’ emissions, and (iv) ‘Input-Output cradle-to-construction’ emissions.

The cradle-to-site system boundary includes raw material extraction, production, and transport to the construction site, whereas cradle-to-construction also includes the onsite construction emissions. The terms process, input-output or hybrid in the category names indicate whether process, input-output or a combination of both analyses have been used. These categories are defined in Table 17.

The categorization was done manually according to the amount of detail available in the BOQ for use of Process analysis. Mathematically, this categorization could be done by mapping the process data to the I-O sector and applying either a 1 or 0 to indicate that the I-O data will be included or excluded, resulting in a matrix containing the upstream I-O cut-offs before correcting for double counting errors (Agez *et al.*, 2020). This matrix of upstream I-O cut-offs is essentially matrix X from Equation 7 in Chapter 2.

Table 17: Definitions of Tiered-hybrid analysis categories

Category	Definition	Examples	Number of Items
'Process cradle-to-site'	Includes the stages up to and including transport to the construction site as depicted in Figure 10. Process data used for all stages. Onsite construction emissions assumed to be negligible.	door hinges, handles and stops	14
'Input-Output construction'	Includes only the "construction" stage of the pre-occupancy stage depicted in Figure 10. Input-output data used for onsite construction emissions. Upstream emissions for infrastructure or machinery required are assumed negligible.	Power floating, mobilization, cutting, breaking, trowelling	87
'Hybrid cradle-to-construction'	Includes all stages in the pre-occupancy stage depicted in Figure 10. Process data is used for all stages up to and including transport to the construction site. Input-output data used for onsite construction emissions.	Structural steel and concrete	228
'Input-Output cradle-to-construction'	Includes all stages in the pre-occupancy stage depicted in Figure 10. Input-output data used for all stages. This includes all items with little detail regarding their material.	Cost offsetting for changes in material	127

Double counting errors needed to be considered for the onsite construction emissions accounted for with the I-O part of the Tiered-hybrid, as the materials were either already accounted for in the process part (for the 'Hybrid cradle-to-construction' emissions) or they were considered negligible (for the 'Input-Output construction' emissions). For the Irish economic tables, three sectors contribute to energy production, being NACE 10-14 (coal, peat, petroleum, metal ores, other mining and quarrying), NACE 23 & 36 (Petroleum and other manufacturing products) and NACE 40 (Electricity and gas)

(Wissema, 2006; Acquaye, 2010). Therefore, all upstream emissions in the I-O system were set to zero except these three aggregated sectors for inputs into the construction sector (NACE 45) to avoid double counting. In order to disaggregate these sectors further, the disaggregation constants and energy intensities in Table 18 were applied. The resulting disaggregated Leontief inverse is in Appendix III.

Table 18: Energy Sector Disaggregation Constants and Emissions Intensities

Sector	Disaggregated Sector	Disaggregation Constant[1]	Emissions Intensity[2] (t CO_2-eq./m€)
NACE 10-14	Peat	0.136	29
	Crude Oil	0.175	123
	Coal	0.116	67
NACE 23 & 36	Petroleum	0.7	67
NACE 40	Electricity	0.755	28
	Natural gas	0.205	33
	Renewable energy	0.04	0

[1](Wissema, 2006), [2](Acquaye and Duffy, 2010)

An overview of the Tiered-hybrid model is shown in Figure 11. The first step is to categorize the items in the BOQ into one of the four categories in Table 17. Each category is further divided into parts that account for cradle-to-gate emissions, transport emissions or construction emissions. The equations for each category are discussed below.

'Process cradle-to-site' emissions (E_{PCS}) are quantified using Equation 17:

$$E_{PCS} = \sum_{j=1}^{m} M_j EEI_j + \sum_{j=1}^{m} T_j D_j EEI_j \qquad (17)$$

where M_j is the quantity of material or process j (in the units of the dataset), EEI_j is the Ecoinvent emissions intensity (kg CO_2-eq/unit) quantified with Equation 18 for the Ecoinvent LCI dataset, T_j is the quantity of material j to be transported (tonnes), D_j is the distance to be transported (km), and m is the number of materials.

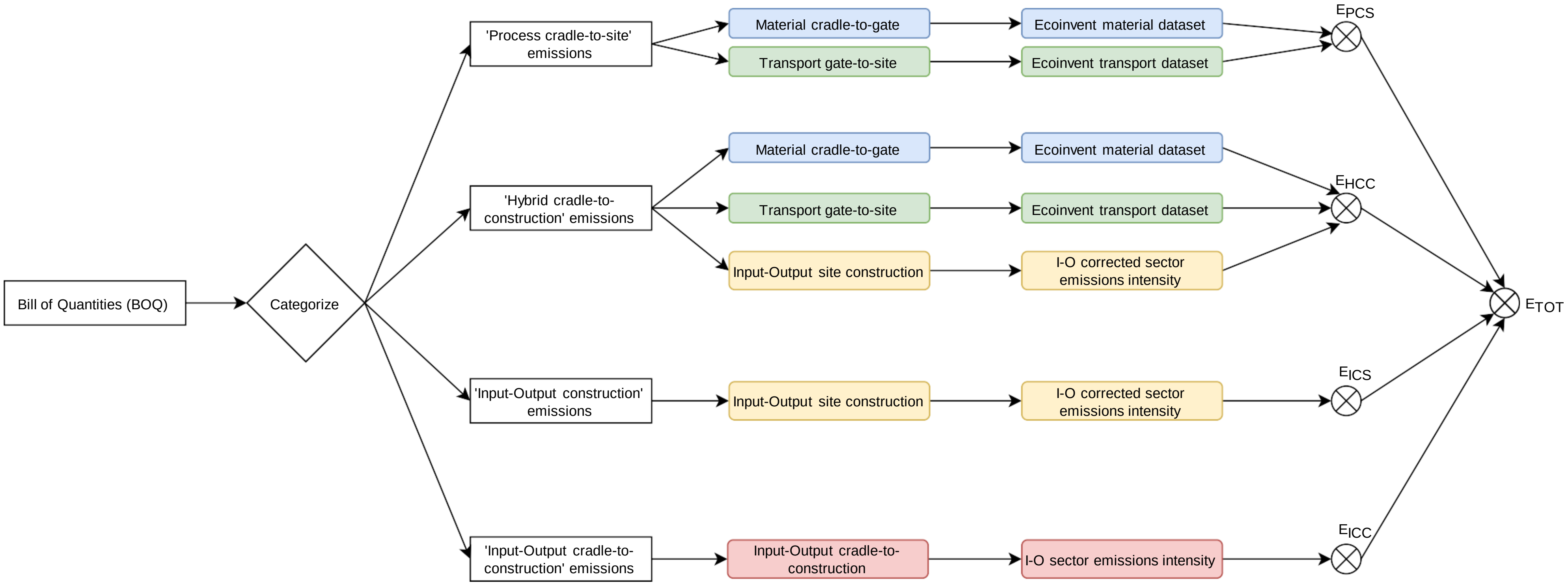


Figure 11: Tiered-hybrid analysis- Overview for the LCA Case Study of an Irish Building

$$EEI_j = \sum_{k=1}^{p} GHG_k CF_k \qquad (18)$$

where GHG_k is the quantity of greenhouse gas k produced for material or process j (kg), CF_k is the characterization factor published by the IPCC for GHG_k (kg CO_2-eq/kg GHG_k), and p is the number of greenhouse gases reported by IPCC that are included in the Ecoinvent dataset (Table 15).

'Input-Output construction' emissions (E_{ICS}) are quantified using Equation 19:

$$E_{ICS} = \sum_{j=1}^{m} P_j CSEI_j \qquad (19)$$

where P_j is the price of material or process j (€); $CSEI_j$ is the corrected sectoral emissions intensity for the Irish construction sector that accounts for double counting (kg CO_2-eq/€); and m is the number of materials.

'Hybrid cradle-to-construction' Emissions (E_{HCC}) are calculated by combining Equations 18 and 19 as shown in Equation 20 below. The I-O part also uses the corrected sectoral emissions intensity to account for double counting.

$$E_{HCC} = E_{PCS} + E_{ICS} \qquad (20)$$

'Input-Output cradle-to-construction' emissions are quantified using Equation 21 for the cradle-to-gate emissions of the BOQ item using Sectoral Emissions Intensities (SEI) quantified by Input-Output analysis.

$$E_{ICC} = \sum_{j=1}^{m} P_j SEI_j \qquad (21)$$

where P_j is the price of material or process j (€); SEI_j is the sectoral emissions intensity (uncorrected) for the Irish construction sector (kg CO_2-eq/€); and m is the number of materials.

To determine the total CO_2-equivalents for the building, the sum of the total CO_2-equivalents for each category is taken, as per Equation 22.

$$E_{TOT} = E_{PCS} + E_{ICS} + E_{HCC} + E_{ICC} \qquad (22)$$

5.4 Results Calculation and Interpretation

The uncertainty management method in Section 4.2 was used to identify and classify all uncertainties in the Tiered-hybrid analysis. From this, a list of uncertainties was obtained.

The DQI method was used for adding an additional uncertainty to the Ecoinvent datasets (see Section 3.4.3). The other quantifiable uncertainties were propagated through the LCI and LCIA calculations using Monte Carlo analysis with 10,000 simulations based on independent sampling of the input distributions (see Section 3.4.1.1). The code for the Monte Carlo simulations is provided in Appendix V. The resulting distributions are presented and discussed in Chapter 6 for the LCI and LCIA results.

Furthermore, the uncertainty contribution of the quantified input uncertainties was determined (see Section 3.5). The most significant uncertainties were identified and discussed, along with the list of uncertainties that were not quantifiable. Finally, the stochastic result obtained was compared to the deterministic result, which would be obtained if uncertainty were ignored in the case study.

It should be noted that the lognormal distribution has been used to approximate the distributions for the Ecoinvent datasets and has also been used for the Input-Output sectoral emissions intensities. This distribution is commonly used in cases where physical quantities that are non-negative, such as for pollutant concentrations (Morgan and Henrion, 1990). The moments for the distribution (refer to Appendix I for further explanation) were used to describe the final output distributions, being the mean (μ), standard deviation (σ), coefficient of variation (ν), coefficient of skewness (γ_1), and excess kurtosis (γ_2). The following equations were used to quantify the moments for each lognormal distribution, where $\mu^* = \frac{1}{n}\sum_{i=1}^{n} ln(x_i)$ and $\sigma^* = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ln(x_i) - \mu^*)^2}$ as defined in Table I of Appendix I (Morgan and Henrion, 1990):

$$\mu = \exp\,(\mu^* + \frac{\sigma^{*2}}{2}) \qquad (23)$$

$$\sigma^2 = \exp(\sigma^{*2})\,(\exp(\sigma^{*2}) - 1)\,(\exp(2\mu^*)) \qquad (24)$$

$$\nu = \frac{\sigma}{\mu} \qquad (25)$$

$$\gamma_1 = \sqrt{(\exp(\sigma^{*2}) - 1)}\,(\exp(\sigma^{*2}) + 2) \qquad (26)$$

$$\gamma_2 = \exp(4\sigma^{*2}) + 2\exp(3\sigma^{*2}) + 3\exp(2\sigma^{*2}) - 6 \qquad (27)$$

5.5 Key Assumptions

Assumptions made include that the input distributions were independent. Therefore, independent sampling of the input distributions was used to calculate the output uncertainty using Monte Carlo analysis. This was also applied for aggregated uncertainties, such as those for the LCI Ecoinvent datasets, the SEIs, and the IPCC GWPs. The use of independent sampling in this manner has recently been debated (Heijungs, Henriksson and Guinée, 2017; Qin and Suh, 2017; Suh and Qin, 2017) and proven to be significant to the underestimation of uncertainties in LCI datasets depending on the measure of correlation for the dataset and the impact category being assessed (Lesage *et al.*, 2018). Work done by Lesage *et al.* also measured the correlation of activities in the Ecoinvent version 2.2 and 3.3 databases to determine whether the use of aggregated datasets in an LCA could lead to underestimation of the uncertainties (2019). They concluded that when using independent sampling of aggregated datasets, the risk of underestimating the uncertainty increases as the correlation among the inputs increases and that this correlation varies depending on the impact category being assessed (Lesage *et al.*, 2018). It was further concluded that for climate change, low correlations are observed, but for other impact categories such as human toxicity, high correlations are observed indicating that the same few datasets are in the background of most aggregated datasets (Lesage *et al.*, 2018).

Because of the low correlation observed for climate change, it is likely that the use of independent sampling of the Ecoinvent datasets as opposed to dependent sampling will not change the results in this thesis significantly. However, in extensions of this work to other impact categories, the aggregated uncertainties as classified with Figure 6 should be examined further to determine the level of correlation and if dependent sampling should be used.

It was further assumed that the Ecoinvent process datasets had negligible upstream truncation errors and therefore the Input-Output analysis was not used for far upstream data gaps for these datasets. Input-Output analysis was only used for construction site emissions and for items in the BOQ where not enough detail was provided to use Process analysis. Onsite construction emissions are a result of direct energy consumption. Direct energy includes the energy used onsite and other direct energy purchases by construction firms (Treloar, 1997). The total energy includes both direct and indirect energy. Indirect energy being due to the upstream or embodied energy from materials and processes/services that are assumed to be covered with Process analysis.

CHAPTER 6. CASE STUDY RESULTS AND DISCUSSION

This chapter presents the results for the Tiered-hybrid attributional LCA case study of the apartment development described in Chapter 5 with a detailed uncertainty assessment following the method presented in Chapter 4 for uncertainty management. In this chapter, the uncertainties in the Goal and Scope definition (Section 6.1) and the input data (Section 6.2) are identified and classified. The uncertainties in the input data are also quantified for the BOQ data (Section 6.2.1), the Ecoinvent datasets (Section 6.2.2), and the corrected sectoral emissions intensities for the Irish construction sector (Section 6.2.3). Sections 6.3 and 6.4 present the distributions for the propagated uncertainties in the input data for the process part and the input-output part of the Tiered-hybrid model, respectively. From here forward, these are referred to as the process system and the input-output system. The total tonnes of Carbon dioxide equivalents for the apartment development from cradle-to-construction (combining the process and input-output system distributions) are reported in Section 6.5 and compared to the deterministic value that is calculated ignoring all uncertainties. Section 6.6 presents the interpretation of the LCA along with the quantified uncertainty contributions. Section 6.7 discusses the experience of using the uncertainty management methodology for this case study and Section 6.8 concludes.

6.1 Uncertainty Identification and Classification in the Goal and Scope

Uncertainty identification and classification are done during the Goal and Scope definition (see Figure 8) and are summarized in Table 19. Integrating these into the analysis as opposed to attempting the assessment after the results have been complied, allows for the opportunity to reduce uncertainties during data collection and set up of the LCA model, as well as saving time by improving the efficiency of the analysis.

Table 19: Identified and classified uncertainty in Goal and Scope definition

Identified Uncertainty	Classification as per Figure 6	Quantified in study?
Representativeness of the defined cradle-to-construction system boundary	Model practical irreducible recognized ignorance	No
Functional unit of one building as defined by the items in the BOQ	Model practical irreducible qualitative	No
Choice of APOS system model	Model ambiguity comparative	No
Choice of Ecoinvent dataset	Model ambiguity comparative	No
Choice of SR-IO tables for Ireland	Model practical irreducible comparative	No
Choice of Tiered-hybrid analysis	Model ambiguity comparative	No
Defined Process and Input-Output boundary in Tiered-hybrid model	Model practical irreducible comparative	No
Environmental impact only based on climate change	Model practical irreducible recognized ignorance	No
Lognormal distribution for Ecoinvent datasets and I-O sector emissions intensities	Model practical irreducible recognized ignorance	No
Linear scaling with emissions factors	Model practical irreducible recognized ignorance	No
Choice of Monte Carlo analysis for uncertainty propagation	Model ambiguity comparative	No
Independent sampling of input distributions	Model ambiguity recognized ignorance	No

As can be seen in Table 19, all of the uncertainties identified are model uncertainties that either arise due to natural variability that is not reducible within the resources of the study (practical irreducible) or due to ambiguity. Identification of these uncertainties can be used to inform harmonization of product-specific methods (see Section 4.3.1). Furthermore, by listing the identified and classified uncertainties for the goal and scope, the comparability of the results of the case study to other case studies becomes more apparent as the differences in methods applied are highlighted.

6.2 Input Data and Uncertainty

The input data, including the BOQ data, Ecoinvent datasets and corrected Sector Emissions Intensities, are described in this section for the Tiered-hybrid model (Figure 11). Following the methodology in Chapter 4, the uncertainties for each source of input data are identified and classified (see Section 4.3.1). The classified uncertainties that are quantified in this case study are indicated in Table 20, Table 22 and Table 24. For the identified uncertainties that were not quantified, the possible implications of ignoring the uncertainty are qualified according to Figure 7 as a ‘key issue’, ‘not a key issue’ or ‘perhaps a key issue’. The ‘key issues’ should be addressed once resources become available (see Section 4.2.4).

6.2.1 BOQ Aggregated Input Data and Uncertainty

The BOQ for the building was used to obtain the foreground data for the LCA. In order to do this, the items in the BOQ were divided into the four categories as described in Chapter 5, Section 5.3, and shown in Figure 11. The categories that included Process analysis (‘Process cradle-to-site’ emissions and ‘Hybrid cradle-to-construction’ emissions) were further categorized by material as seen in Figure 12, which shows the Tiered-hybrid model divided into the process system (blue items) and input-output system (orange items). The quantities in the BOQ represent the quantity of the materials in the process system required for the building and are multiplied by the LCI background Ecoinvent datasets for these materials (as per Equation 17). Similarly, the costs in the BOQ represent that of the materials and processes in the input-output system and are multiplied by the sector emissions intensities (as per Equations 19 and 21).

The identified and classified uncertainty for the BOQ foreground data is given in Table 20. The first two uncertainties in the table (measurement error and conversion of BOQ quantity units) have been quantified in this study, the first of which was described previously in Chapter 5, Section 5.2.1. Conversion of the BOQ quantity units was required to convert the unit to that of the functional unit of the LCI datasets obtained from the Ecoinvent database.

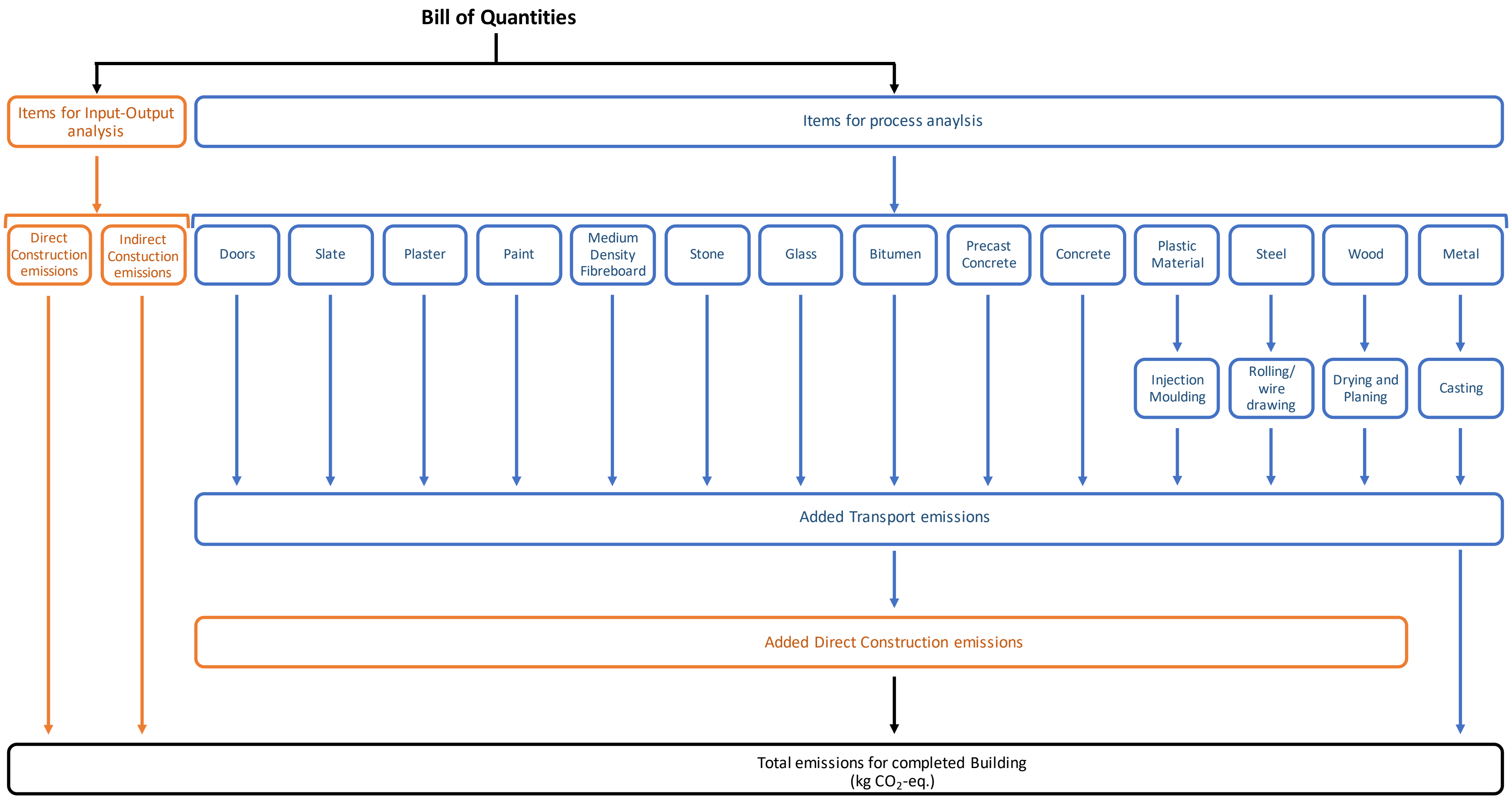


Figure 12:Tiered-hybrid model showing items of the process system (blue) and the input-output system (orange)

Table 20: Identified and classified uncertainty in foreground data

Identified Uncertainty	Classification as per Figure 6	Quantified in study?	Key Issue as per Figure 7
Measurement error in BOQ quantities and costs	Parameter practical irreducible statistical	Yes	n/a
Conversion of BOQ quantity units (unit conversion factors)	Parameter ambiguity comparative	Yes	n/a
Categorizing BOQ item into material	Scenario ambiguity comparative	No	Not a key issue
Missing direct construction emissions in BOQ	Model practical irreducible recognized ignorance	No	Not a key issue
Temporal, geographical and technological variability of unit conversion factors	Parameter practical irreducible qualitative	No	Perhaps a key issue
Inaccurate or unrepresentative BOQ data	Parameter practical irreducible comparative	No	Perhaps a key issue

For the uncertainties in Table 20 that are not quantified in this study, two are considered ‘not a key issue’ because their overall contribution and uncertainty are assumed to be insignificant. For the categorization of the BOQ item into a material, the uncertainty of this is minimal since the method of measurement for buildings and construction is standardized in Ireland with the Agreed Rules for Measurement (ARM). For similar reasons, it is unlikely that significant purchases of energy that is consumed onsite (direct construction emissions) are missing in the BOQ. The last two identified uncertainties in the table may possibly be key issues. For the temporal, geographical and technological variability of unit conversion factors, key differences could lead to changes in the contribution of the material. This was addressed by using Irish data first when available. For the presence of inaccurate or unrepresentative data in the BOQ, the contribution of the inaccuracy to the overall result could potentially be significant. For example, the BOQ used in this study includes costs for items that were not used in the final building but were replaced with other items for which the cost was subtracted. Access to better data would remove this error.

The resulting aggregated LCI data per material as seen in Figure 12 and per category as defined in Table 17 are shown in Table 21 along with the quantified uncertainty (the measurement error and the error in the unit conversion factors) as identified in Table 20.

Table 21: Aggregated Life Cycle Inventory data per category

Category / Item	Total	Uncertainty (±SD[1])	Unit
'Process cradle-to-site'			
Metal	8467	2184	kg
Transport	847	297	tonne km
'Input-Output construction'			
Direct Construction	6,473,551	13,052	Euro
'Hybrid cradle-to-construction'			
In-Situ Concrete	1.59E+04	2.45E+03	m3
Precast Concrete	1.87E+06	4.49E+05	kg
Concrete roof tiles	5.61E+06	1.86E+05	kg
Steel	3.39E+06	6.61E+05	kg
Steel pipe	2987	424	kg
Bitumen	4.7	3.2	kg
Stone	4.65E+06	1.07E+06	kg
Glazing	4691	32	m2
Float glass	866	8	m2
Medium Density Fibreboard	437	116	m3
Paint	476	120	kg
Plaster	9.67E+05	1.96E+05	kg
Slate	3.69E+04	8.63E+03	kg
Wood beam	4449	1509	m3
Wood board	1525	513	m3
Polystyrene	7.33E+04	2.66E+04	kg
Polyvinylchloride	1.67E+05	5.04E+04	kg
Polyethylene	2.73E+04	5.45E+03	kg
Doors	2691	67	m2
Transport	5.77E+06	1.12E+06	tonne km
Direct Construction	2,229,601	38,927	Euro
'Input-Output cradle-to-construction'			
Direct and Indirect Construction	24,296,174	168,695	Euro

[1]Standard Deviation

6.2.2 Ecoinvent Dataset Emissions Intensities

This section presents the uncertainties that have been identified and classified for the Ecoinvent process background data and IPCC GWPs. The uncertainty in each Ecoinvent dataset has been quantified using the methodology presented in Chapter 3, Section 3.4.3. The uncertainties for the IPCC GWPs are given in Table 15 in Chapter 5. The results of the emissions intensities and uncertainty for 245 Ecoinvent datasets are provided in Appendix IV. The quantified uncertainties are identified and classified in Table 22.

Table 22: Identified and classified uncertainty in Ecoinvent background data

Identified Uncertainty	Classification as per Figure 6	Quantified in study?	Key Issue as per Figure 7
Representativeness of background processes	Parameter practical irreducible qualitative	Yes	n/a
Temporal, geographical and technological variability of datasets	Parameter practical irreducible qualitative	Yes	n/a
Errors in dataset quantities	Parameter aggregated statistical	Yes	n/a
Choice of dataset	Scenario practical irreducible comparative	Yes	n/a
Error in IPCC GWPs quantities	Parameter aggregated statistical	Yes	n/a
Missing climate-carbon feedback impacts	Model ambiguity comparative	No	Perhaps a key issue
Choice of published GWPs	Scenario ambiguity recognized ignorance	No	Not a key issue

From Table 22, the first two uncertainties have been quantified using the additional uncertainty methodology of Ecoinvent using the DQI scores. The DQI scores used are provided in Appendix IV for each dataset. The third uncertainty (errors in dataset quantities) is the quantified basic uncertainty for the Ecoinvent datasets. The scenario uncertainty due to the choice of the dataset was also quantified in this study. This was done by randomly selecting a dataset from a list of potential datasets in Ecoinvent that are representative of the material being assessed. Monte Carlo analysis was used to calculate the result by first randomly selecting a dataset, and then choosing a value from the uncertainty distribution for that dataset. The resulting distributions combined with the IPCC GWPs and uncertainty are presented in Section 6.3 for all the materials in Table 21.

The uncertainties that have not been quantified include the missing climate-carbon feedbacks (see Section 5.2.4), and the choice of published GWPs. The latter is not considered a key issue for the GWPs. Although variation will occur according to the source and characterization model used, it is expected to be small compared to that of other impact categories where quantification of this uncertainty may result in significant changes in the results, such as with Abiotic Depletion Potential (see Section 2.4.2).

To assess the implications of the missing climate-carbon feedback impact, the LCIA result with feedback was extracted for each dataset from the Ecoinvent online database to compare it to the calculated LCIA from the extracted Ecoinvent LCI data without feedback. The complete results are provided in Appendix IV and are summarized below for each material. From Table 23, as expected the greatest variation (overestimation) in the emissions intensities is for wood products. The range reported in the table is for multiple datasets.

Table 23: Summary of variation in quantified emissions intensity per material

Material	Ratio of Ecoinvent[1] to Calculated[2] Emissions Intensity
In-Situ Concrete	0.91-0.93
Precast Concrete	0.67-0.93
Concrete roof tiles	0.88
Steel	0.79-0.94
Steel pipe	0.79
Bitumen	0.65-0.80
Stone	0.78-0.82
Glazing	0.72-0.73
Float glass	0.70-0.74
Medium Density Fibreboard	0.48-0.61
Paint	0.76-0.81
Plaster	0.56-0.92
Slate	0.59-0.86
Wood beam	0.25-0.85
Wood board	0.28-0.89
Polystyrene	0.85-0.96
Polyvinylchloride	0.93-0.94
Polyethylene	0.93-0.95
Doors	0.57-0.79
Transport	0.87-0.90

[1]LCIA data published in the Ecoinvent online database (with CCF).
[2]LCIA calculated using LCI data from the Ecoinvent online database and IPCC GWP_{100} without CCF.

6.2.3 Corrected Sectoral Emissions Intensity for NACE 45

This section first presents the uncertainties that have been identified and classified for the input-output data (Table 24) and then the results of the corrected sectoral emissions intensities (Table 25) using the disaggregated Leontief Inverse (Appendix III). The disaggregated energy sector emissions intensities in Table 18 are also presented and discussed.

Table 24: Identified and classified uncertainty in background input-output data

Identified Uncertainty	Classification as per Figure 6	Quantified in study?	Key Issue as per Figure 7
Inaccurate or unrepresentative data and measurement/reporting errors	Parameter aggregated statistical	Yes	n/a
Error is energy sector emissions intensities	(included in above aggregated uncertainty)	Yes	n/a
Missing data for imports	Model practical irreducible comparative	No	Key issue
Representativeness (aggregation) of sectors	Model practical irreducible qualitative	No	Perhaps a key issue
Error in disaggregation constants	Parameter practical irreducible statistical	No	Perhaps a key issue
Unrepresentative Disaggregation model/method	Model ambiguity qualitative	No	Perhaps a key issue
Choice of sector	Scenario ambiguity recognized ignorance	No	Not a key issue

From Table 24, the first two uncertainties have been quantified in this study using an estimation of the aggregated total uncertainty for EEIO analysis (see Sections 2.3.2.2 and 5.2.3). Ignoring imports for the Irish economy is a key issue for uncertainty in the input-output results (see Sections 2.3.2.1 and 5.2.3).

The identified uncertainties in Table 24 that are labelled as 'perhaps a key issue' include: the representativeness (aggregation) of the sectors, the error in the disaggregation constants, and the use of an unrepresentative disaggregation model/method. These uncertainties are potential 'key issues' since their impact on, or contribution to, the overall input-output results are unknown. Furthermore, the implications of not accounting for these uncertainties in this case study is dependent on the contribution of the input-output system to the overall result, which will be discussed in Section 6.6.

Table 25: Corrected Emission Factors and Sectoral Emissions Intensities

Sector	NACE Code (Rev1)	Q^1 (gCO_2/€)	CSEIs (gCO_2/€)
Agriculture, fishing, forestry	1-5	3,103	4202
Other, metal ores, quarrying	10-14	105	310
Coal	10-14	67	108
Peat	10-14	29	77
Crude oil	10-14	123	186
Food, beverage, tobacco	15-16	67	762
Textiles Clothing Leather & Footwear	17-19	182	194
Wood & wood products	20	51	182
Pulp, paper & print production	21-22	6	1045
Chemical production	24	22	224
Rubber & plastic production	25	33	312
Non-metallic mineral production	26	1,953	2545
Metal prod. excl. machinery & transport equip.	27-28	596	1127
Agriculture & industrial machinery	29	43	203
Office and data process machines	30	17	29
Electrical goods	31-33	61	230
Transport equipment	34-35	32	39
Other manufacturing	23,36-37	427	622
Petroleum	23,36-37	67	462
Electricity	40	28	4148
Natural gas	40	33	1152
Renewable energy	40	0	218
Water	41	54,780	55583
Construction	45	20	39
Services (excl. transport)	50-55,64-95	26	31213
Transport	60-63	1,065	2702

[1]Q = environmental intervention vector (refer to Equation 3)

The resulting corrected sector emissions intensities (CSEI) using the disaggregated Leontief inverse are presented in Table 25 and the results of the direct and indirect construction emissions intensities are summarized in Table 26. Table 14 in Chapter 5 gives the sectoral emissions intensities (uncorrected) for 19 aggregated sectors of the Irish economy.

Table 26: Domestic Emissions Intensities for the Irish Construction Sector

Construction (NACE 45)	Emissions Intensity	Unit
Direct construction emissions	39	gCO_2/€
Indirect construction emissions	165	gCO_2/€
Total direct and indirect (domestic)	204	gCO_2/€

The indirect and total construction emissions intensities in Table 26 do not include imports. For the Irish construction sector, ignoring imports has been found to underestimate the total CO_2-equivalents by approximately 42% (Acquaye and Duffy, 2010) (see Section 5.2.3). The values in Table 26 correspond well with, and are within error, of the values reported by Acquaye and Duffy (2010). These are 72 gCO_2/€ (weighted value), 173 gCO_2/€, and 245 gCO_2/€ for the direct, indirect and total domestic emissions, respectively.

The results from Acquaye and Duffy (2010) and Table 26 were compared to those obtained using a multi-regional environmentally extended world I-O database, Exiobase (see Section 5.2.3). The resulting emission intensity for the Irish construction sector was found to be 232 gCO_2/€. This value corresponds well with the values that do not include imports (within 5-14%). Resources were not available to explore this further, and therefore this result should be verified in further work.

The influence of the missing import emissions for this case study will be dependent on the contribution of the input-output system to the overall Tiered-hybrid result. This will be discussed further in Section 6.6.

6.3 Distributions for the Process System

The distributions presented include the uncertainties indicated as quantified in Table 22 for all materials in the process system and in Table 20 for the BOQ quantities. The uncertainties have been propagated as per the methodology in Chapter 5, Section 5.4. These input distributions are sampled to quantify the total emissions for the building presented in Section 6.5. The mean (μ), standard deviation (σ), coefficient of variation (ν), coefficient of skewness (γ_1), and excess kurtosis (γ_2) of the distributions in Figure 14 to Figure 38 were calculated using the Equations 23-27 in Chapter 5. The results are summarized in Table 27.

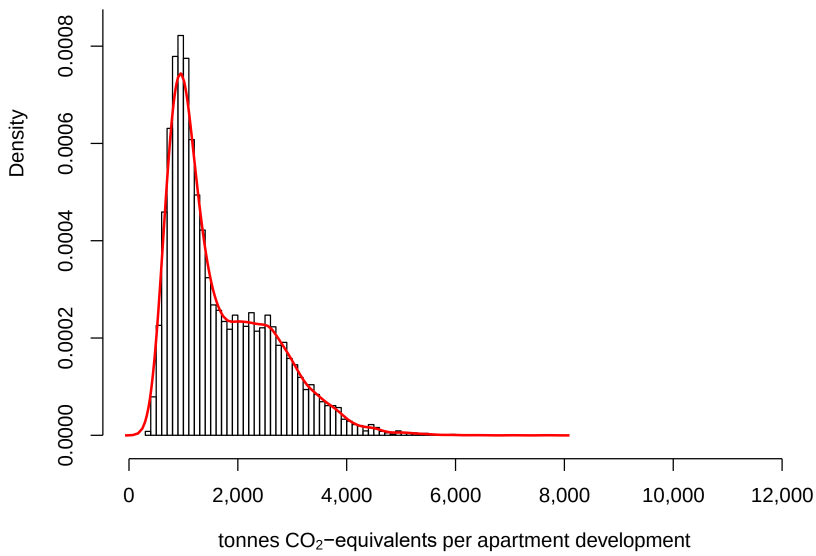


Figure 13: Input Distribution for Precast Concrete

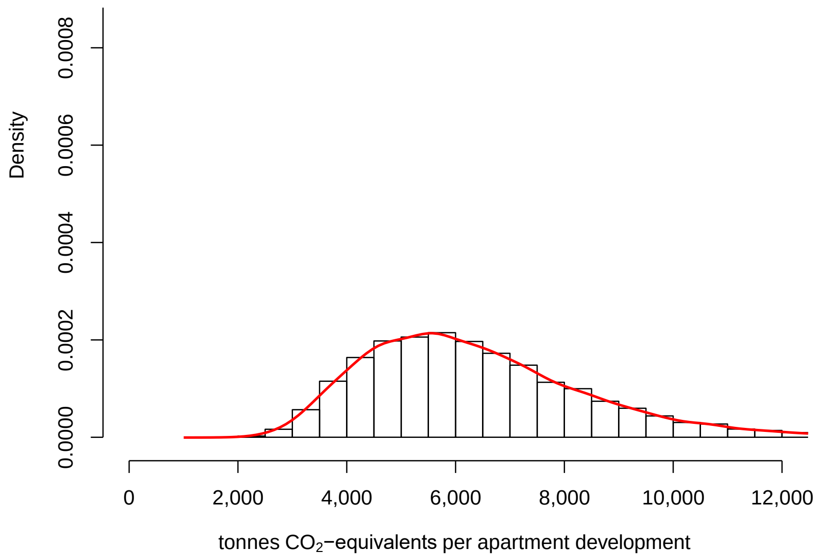


Figure 14: Input Distribution for In-Situ Concrete

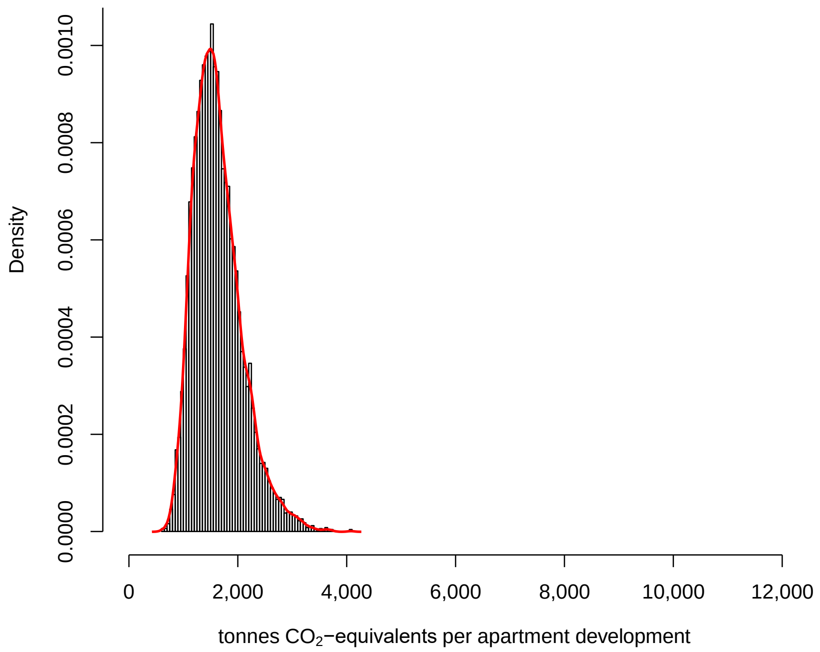


Figure 15: Input Distribution for Concrete Roof Tiles

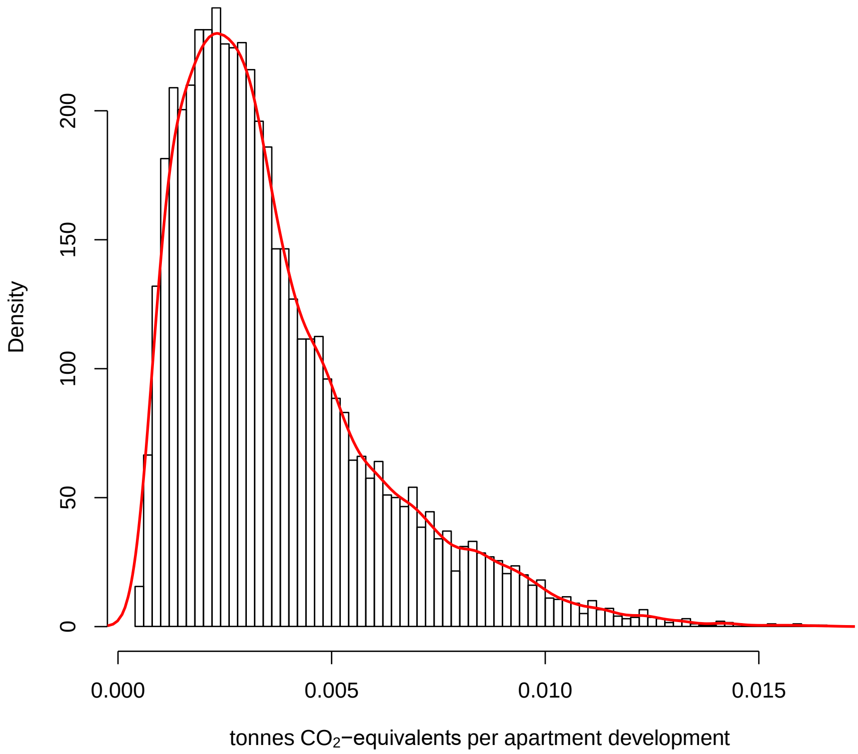


Figure 16: Input Distribution for Bitumen

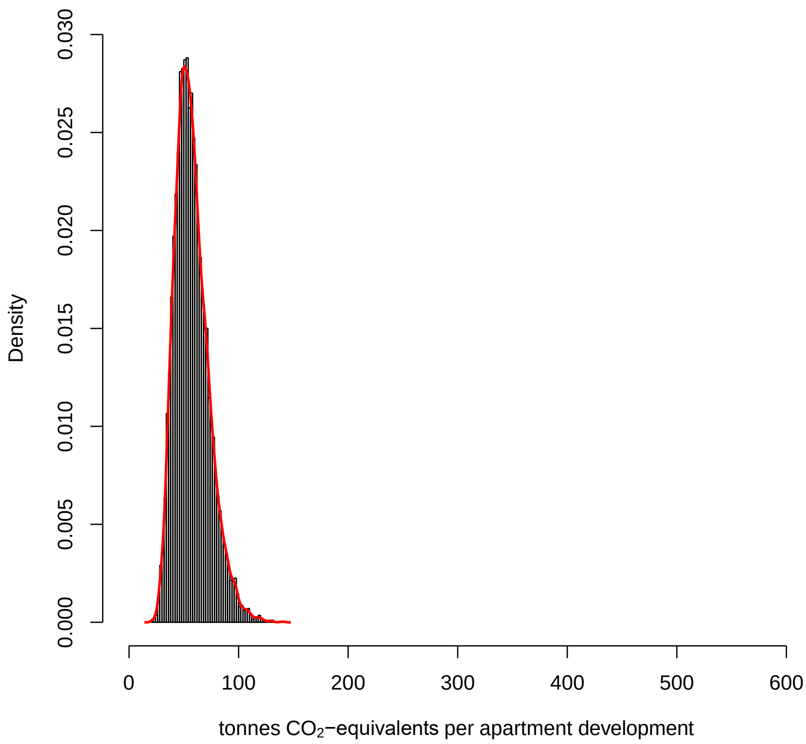


Figure 17: Input Distribution for Polyethylene

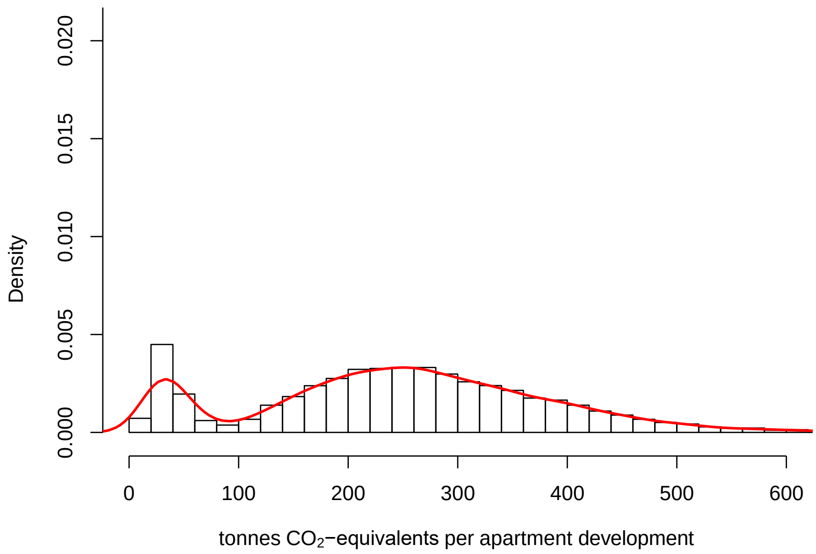


Figure 18: Input Distribution for Polystyrene

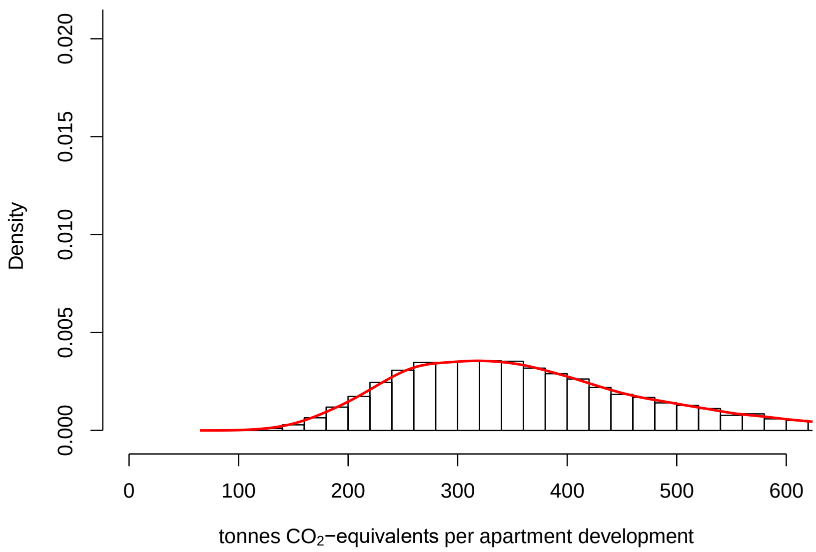


Figure 19: Input Distribution for Polyvinylchloride

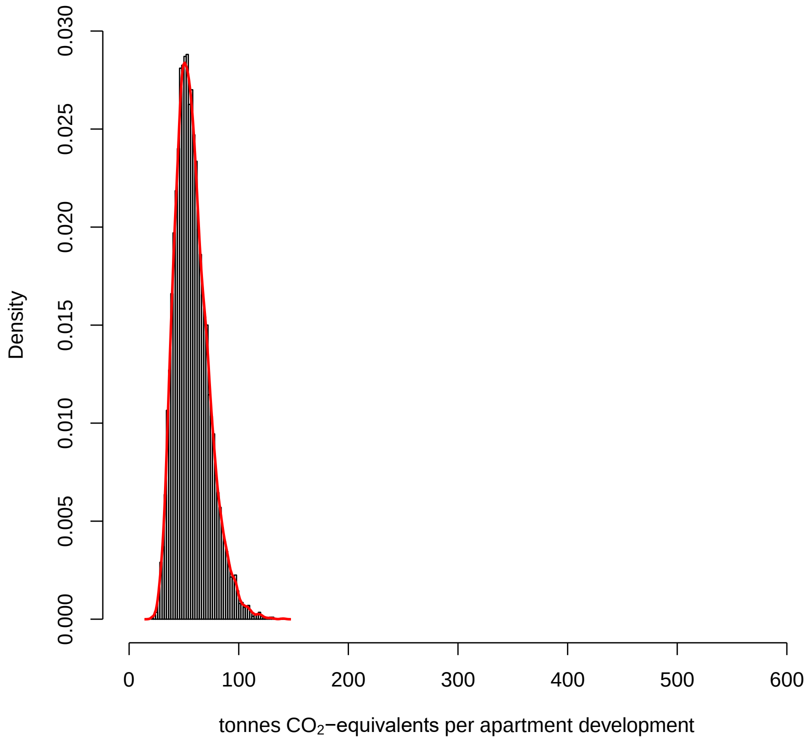


Figure 20: Input Distribution for Injection Moulding

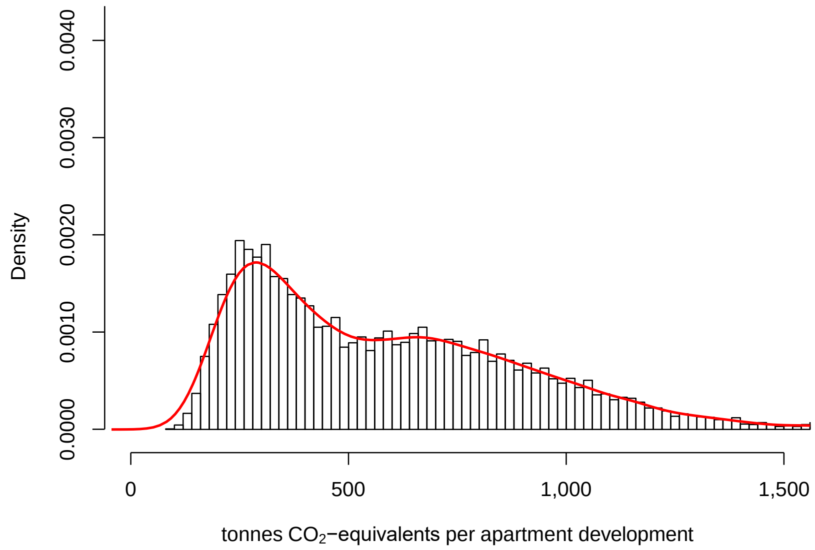


Figure 21: Input Distribution for Wood Beam

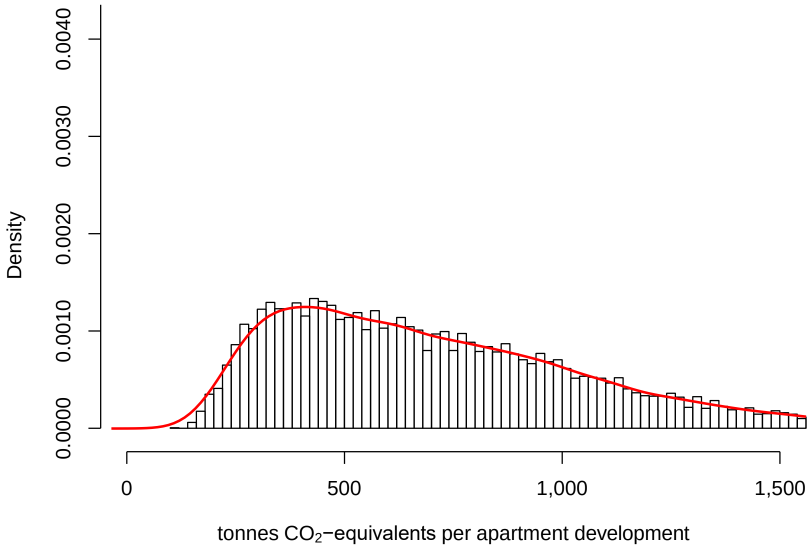


Figure 22: Input Distribution for Planing Wood Beam

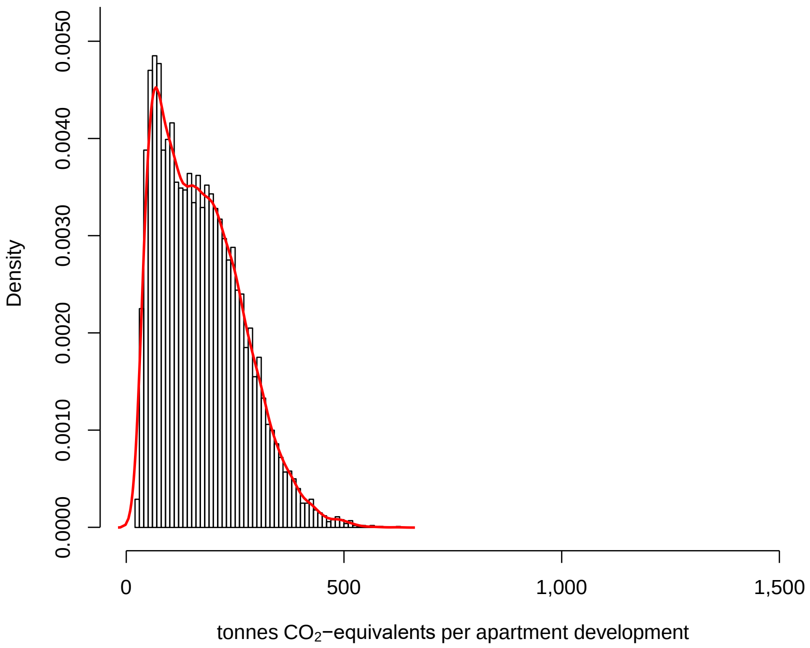


Figure 23: Input Distribution for Wood Board

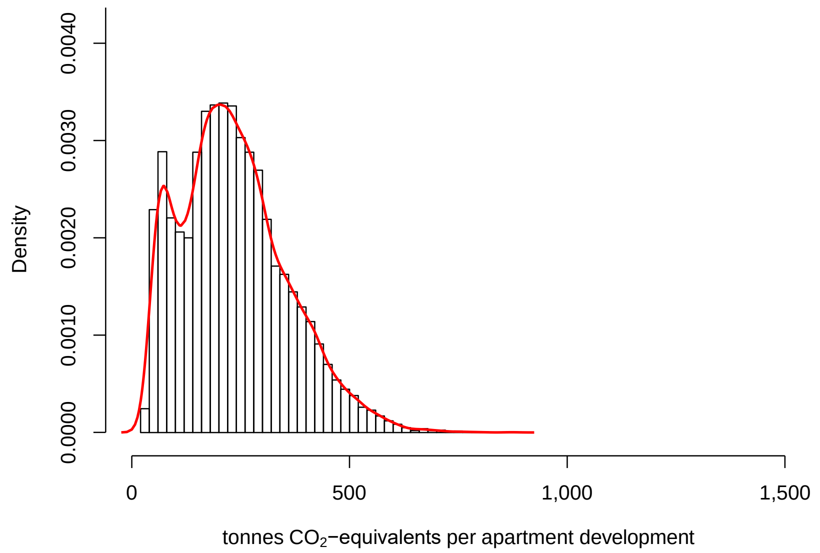


Figure 24: Input Distribution for Planing Wood Board

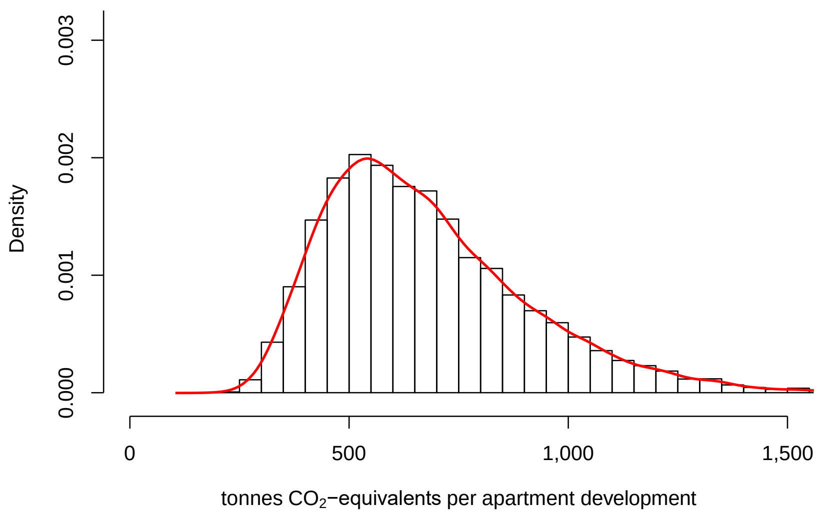


Figure 25: Input Distribution for Medium Density Fibreboard

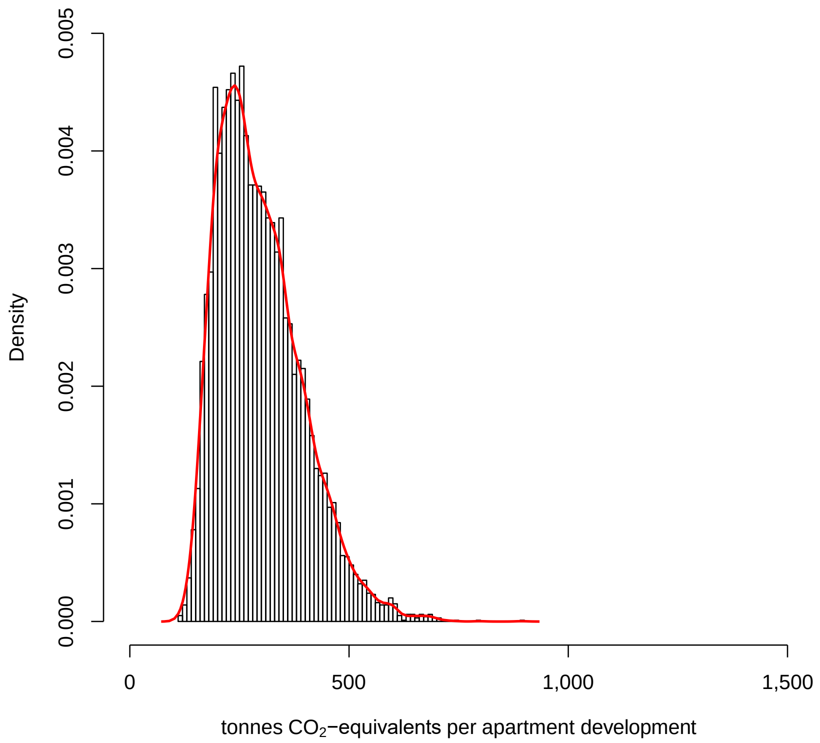


Figure 26: Input Distribution for Doors

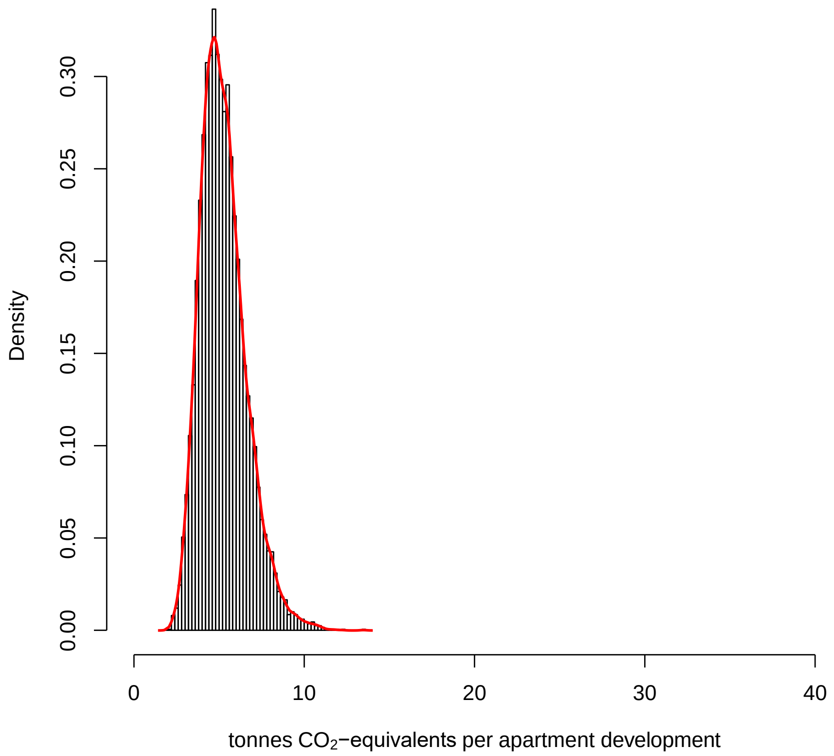


Figure 27: Input Distribution for Glazing

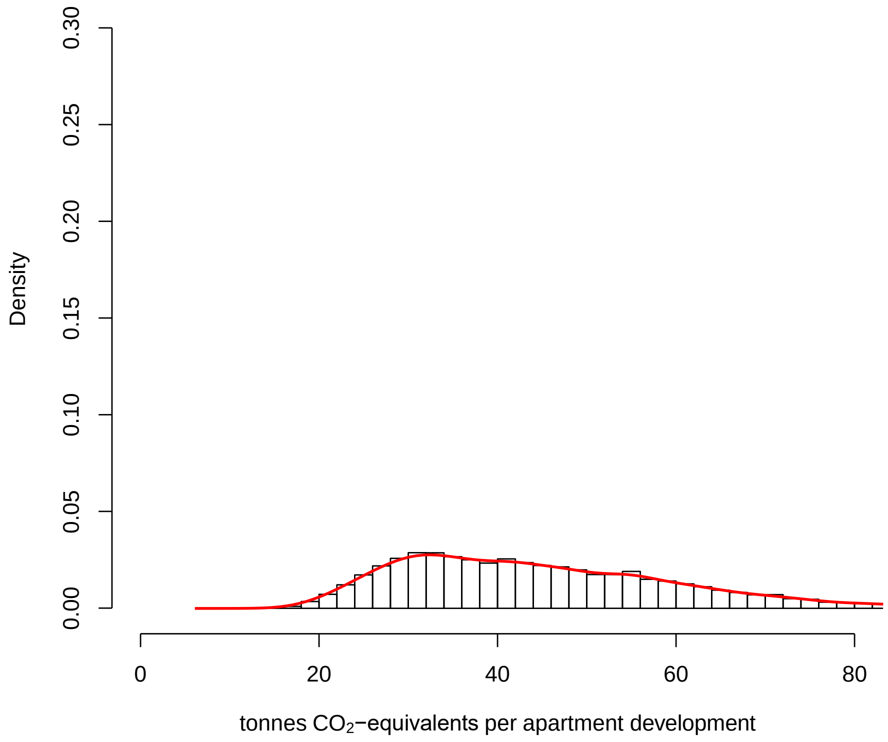


Figure 28: Input Distribution for Float Glass

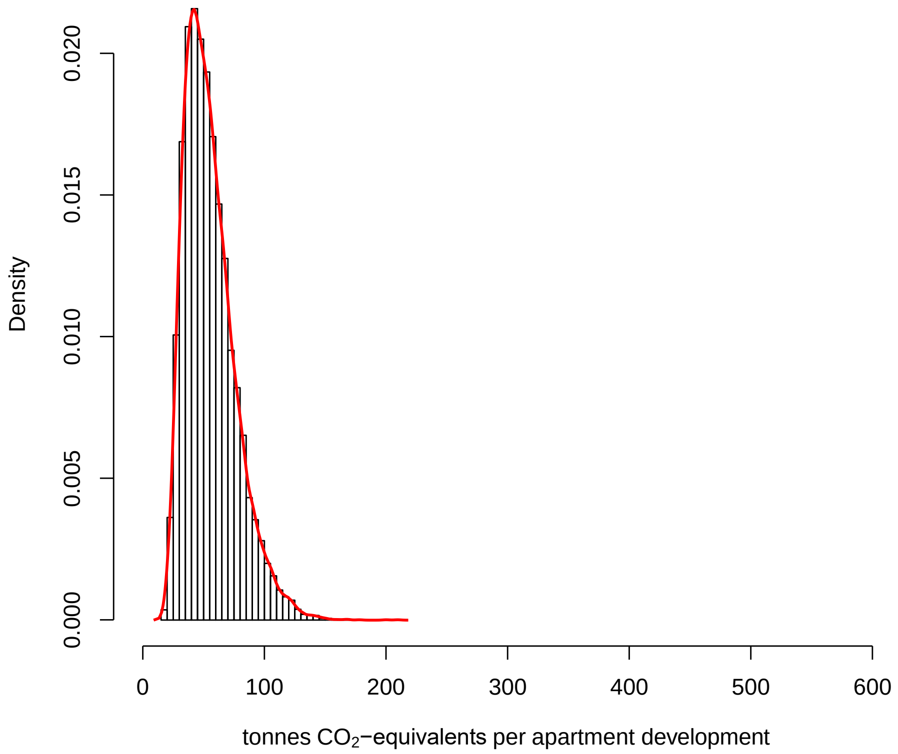


Figure 29: Input Distribution for Metal (excluding steel)

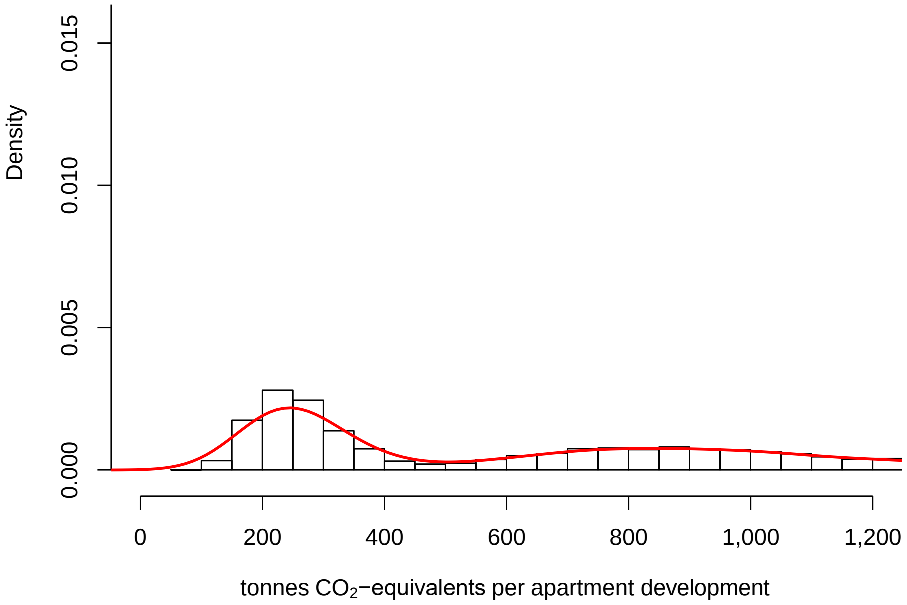


Figure 30: Input Distribution for Metal Casting (excluding steel)

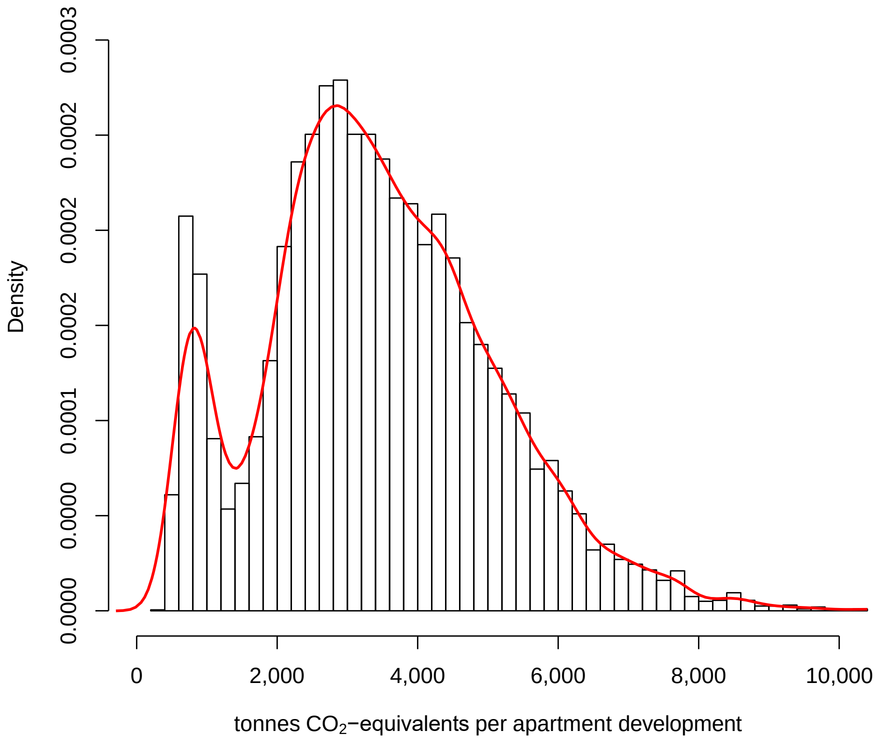


Figure 31: Input Distribution for Stone

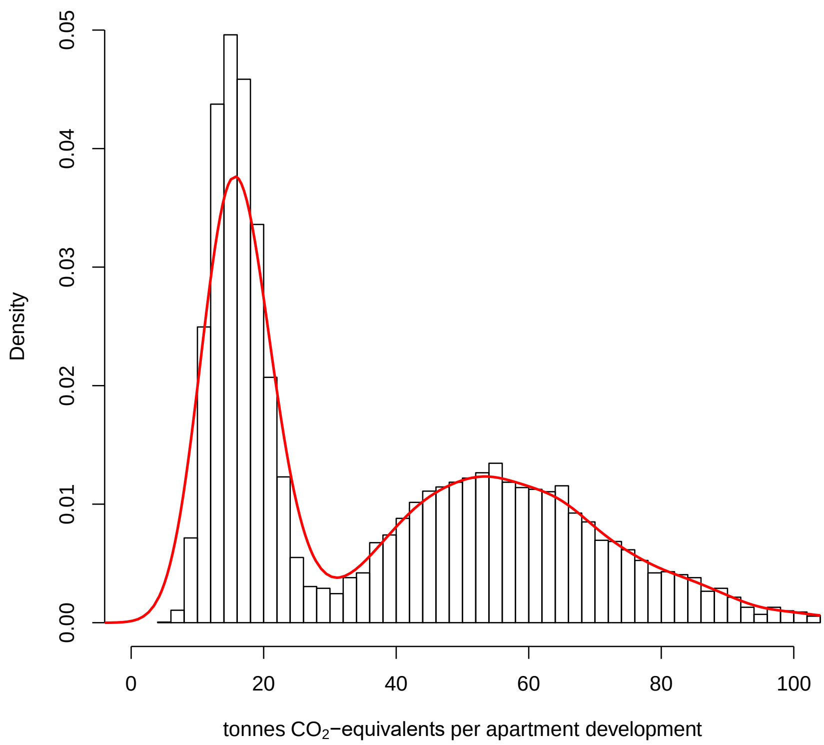


Figure 32: Input Distribution for Slate

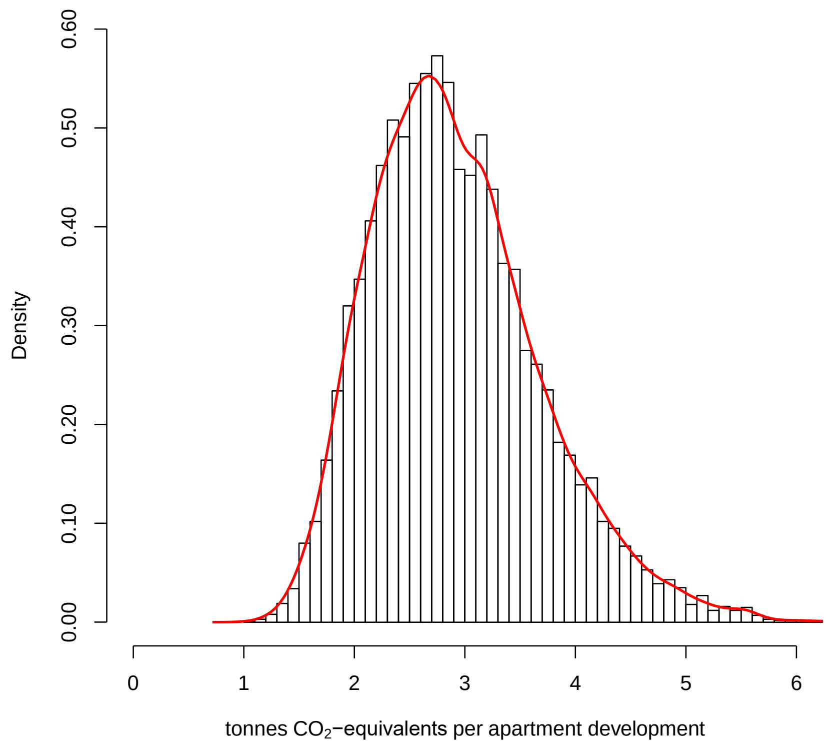


Figure 33: Input Distribution for Paint

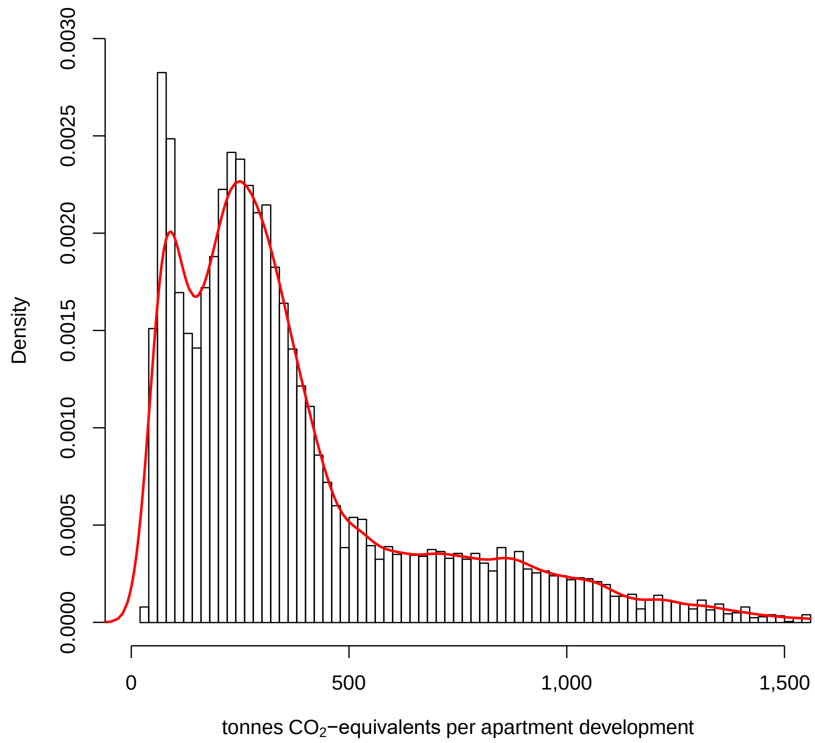


Figure 34: Input Distribution for Plaster

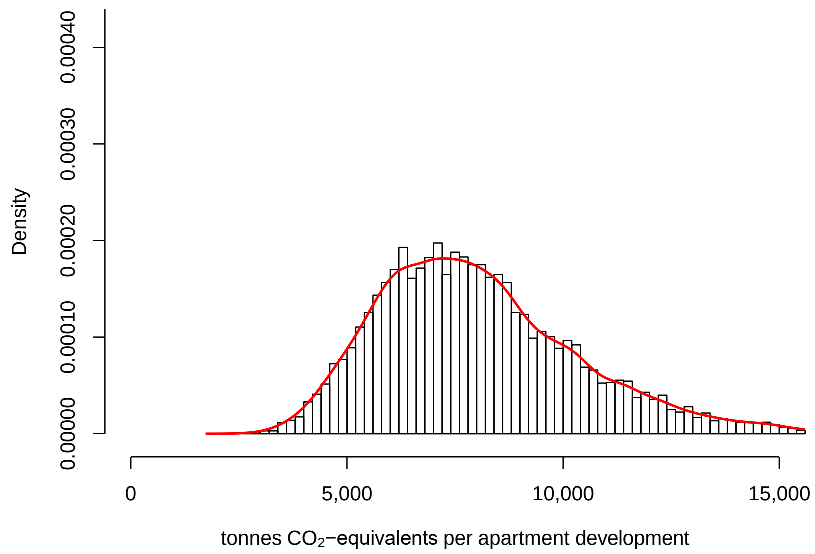


Figure 35: Input Distribution for Steel

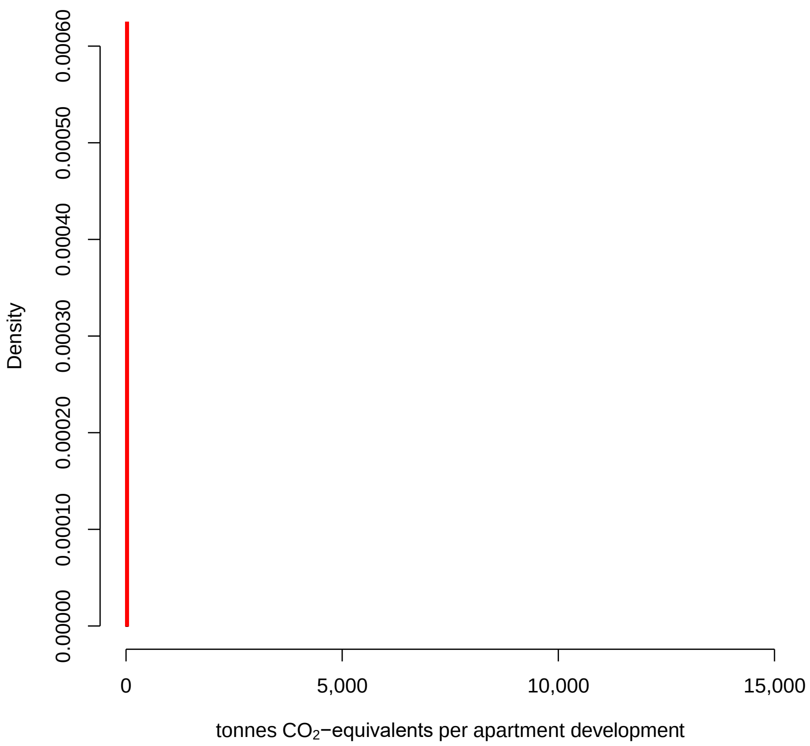


Figure 36: Input Distribution for Steel Pipe

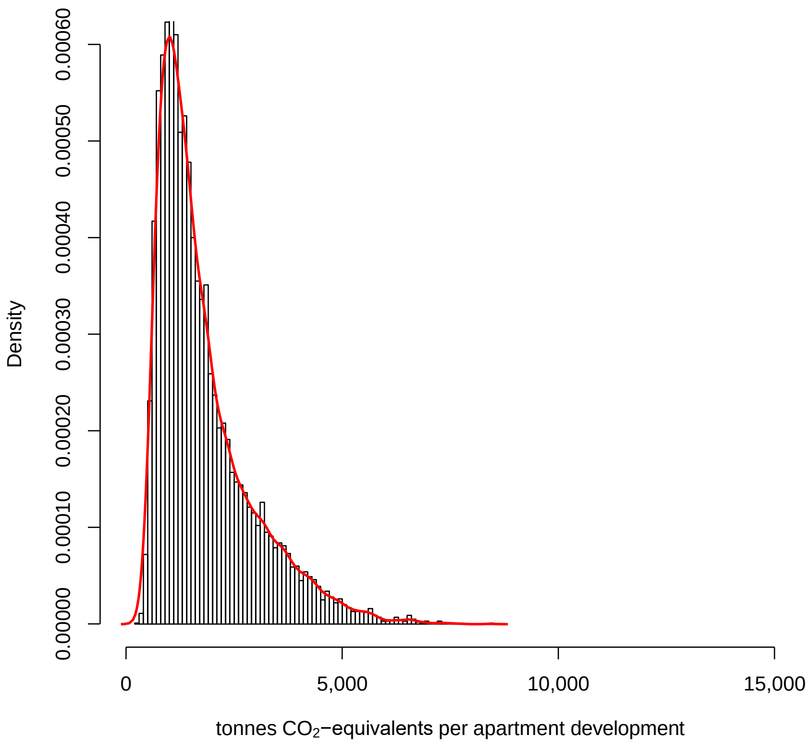


Figure 37: Input Distribution for Steel Rolling

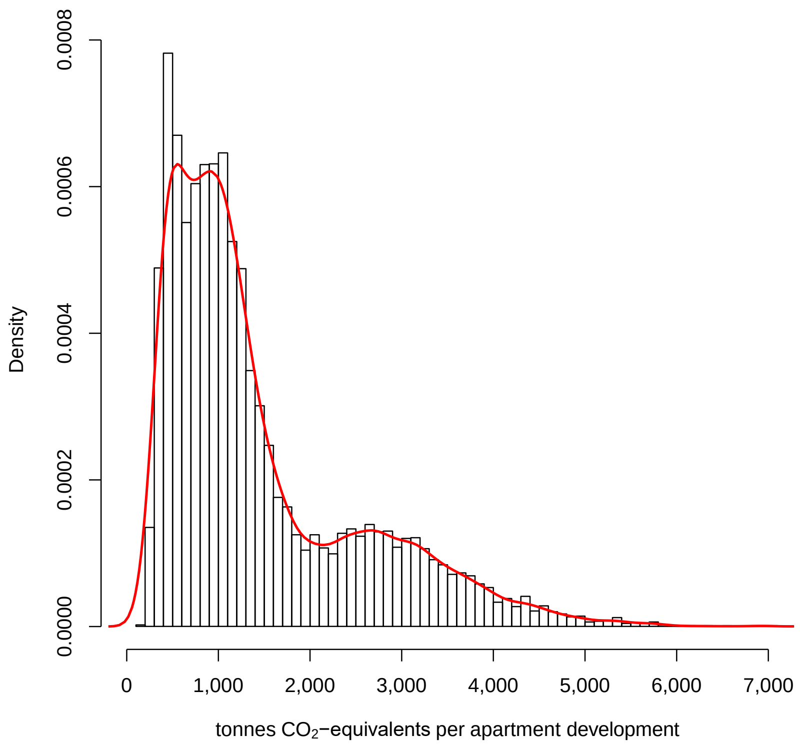


Figure 38: Input Distribution for Transport of materials to construction site

Table 27: Summary of process system results per building

Item	tonnes CO_2-equivalents		coefficients of		
	mean (μ)	standard deviation (σ)	variation (ν)	skewness (γ_1)	excess kurtosis (γ_2)
Metal (excluding steel)	55	21	0.38	1.20	2.66
Metal Casting (excluding steel)	621	500	0.81	2.94	18.51
In-Situ Concrete	6383	2069	0.32	1.01	1.85
Precast Concrete	1658	961	0.58	1.93	7.30
Concrete roof tiles	1630	441	0.27	0.83	1.26
Steel	8072	2388	0.30	0.91	1.52
Steel pipe	16	4	0.26	0.80	1.16
Steel rolling	1777	1081	0.61	2.05	8.29
Bitumen	0.004	0.003	0.70	2.45	12.33
Stone	3550	2300	0.65	2.22	9.83
Glazing	5.3	1.3	0.26	0.79	1.12
Float glass	45	16	0.36	1.11	2.27
Medium Density Fibreboard	679	232	0.34	1.06	2.08
Paint	2.9	0.8	0.26	0.81	1.19
Plaster	387	372	0.96	3.78	33.30
Slate	38	30	0.79	2.84	17.18
Wood beam	587	358	0.61	2.05	8.32
Wood board	175	120	0.69	2.40	11.70
Planing wood beam	716	399	0.56	1.84	6.59
Planing wood board	241	160	0.66	2.28	10.51
Polystyrene	276	281	1.02	4.12	40.67
Polyvinylchloride	367	124	0.34	1.05	2.03
Polyethylene	57	15	0.27	0.82	1.22
Injection moulding	274	83	0.30	0.93	1.58
Doors	297	96	0.32	1.00	1.83
Transport	1448	1158	0.80	2.91	18.12

6.4 Distributions for the Input-Output System

The distributions presented include the uncertainties indicated as quantified in Table 24 and Table 20 for the input-output system. The uncertainties have been propagated as per the methodology in Chapter 5, Section 5.4. These input distributions are sampled to quantify the total emissions for the building presented in Section 6.5. The mean (μ), standard deviation (σ), coefficient of variation (ν), coefficient of skewness (γ_1), and excess kurtosis (γ_2) (Equations 23-27 in Chapter 5) for the distributions in Figure 39, Figure 40, and Figure 41 are summarized in Table 28.

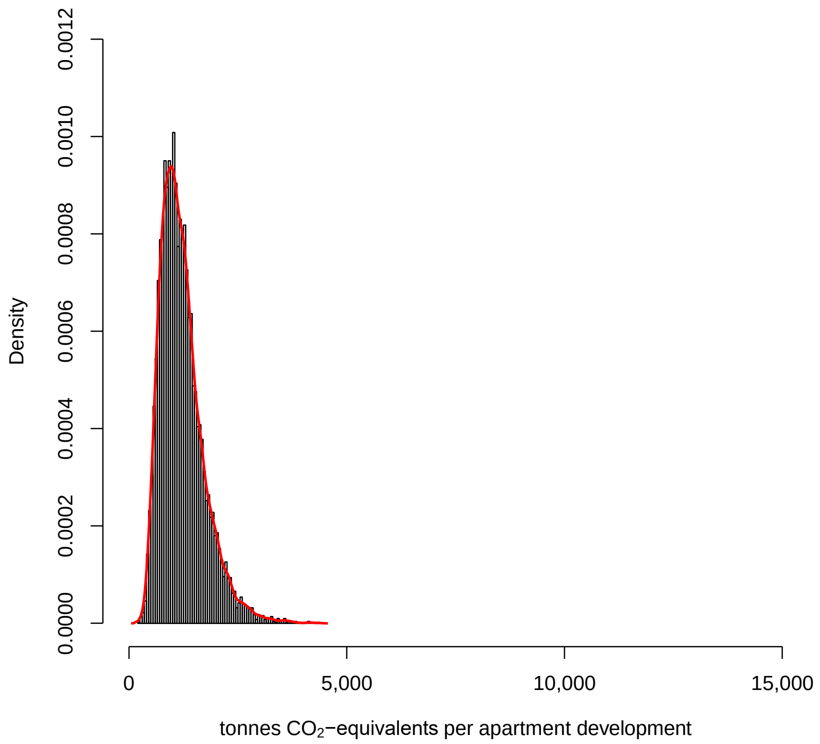


Figure 39: Process direct construction emissions per apartment development

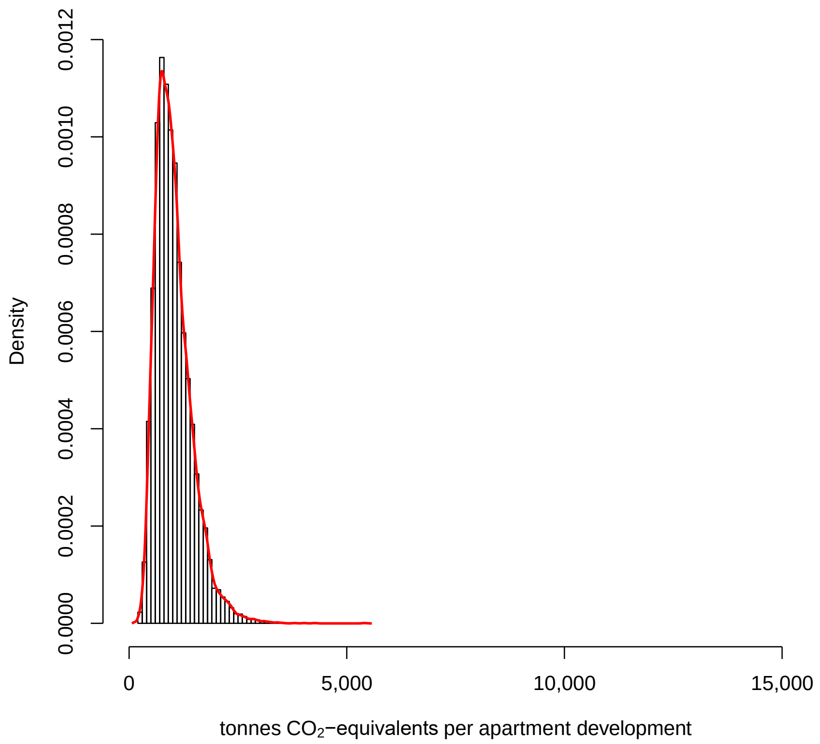


Figure 40: Input-Output direct construction emissions per apartment development

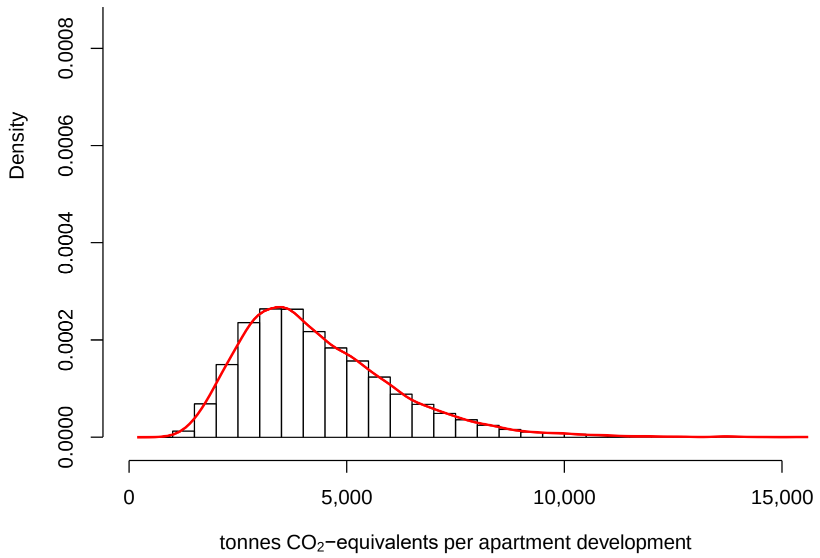


Figure 41: Input-Output indirect construction emissions per apartment development

Table 28: Summary of process and input-output system results per building

Construction emissions	tonnes CO_2-equivalents		coefficients		
	mean (μ)	standard deviation (σ)	variation (ν)	skewness (γ_1)	excess kurtosis (γ_2)
Direct (Process system)	1212	507	0.42	1.33	3.28
Direct (I-O system)	1022	424	0.42	1.32	3.24
Indirect (I-O system)	4365	1827	0.42	1.33	3.30

6.5 Total Emissions per Building

The total tonnes CO_2-equivalents for the building are presented in this section. In order to address the goal of the study of comparing the deterministic result to the stochastic result, the deterministic result was quantified ignoring all uncertainties and assigning the most suitable Ecoinvent dataset. The result per item is given in Table 29 along with the chosen representative Ecoinvent dataset for the process system.

The differences between the total tonnes CO_2-equivalents per item in Table 29 compared to the mean tonnes CO_2-equivalents per item in Table 27 and Table 28 are due to not accounting for the uncertainties that have propagated throughout the LCA model. In other words, the deterministic result is that for the selected data, assumptions and models without considering the possibility of other valid options for the chosen data, assumptions and models.

Table 29: Deterministic result per item (tonnes CO_2-equivalents)

Item	tonnes CO_2-eq.	Ecoinvent dataset
Materials:		
Metal (excluding steel)	59	aluminium alloy production, RER
Metal Casting	959	casting, aluminium, lost-wax RoW
In-Situ Concrete	4648	concrete production, normal CH
Precast Concrete	996	lightweight concrete block production, expanded clay CH
Concrete roof tiles	1097	concrete roof tile production CH
Steel	7816	reinforcing steel production RER
Steel pipe	16	chromium steel pipe production GLO
Steel rolling	2654	forging, steel, large open die RoW
Bitumen	0	bitumen seal production RER
Stone	857	natural stone plate production, cut CH
Glazing	5	flat glass production, coated RER
Float glass	54	glazing production, triple, U<0.5 W/m2K RER
Medium Density Fibreboard	511	medium density fibre board production, uncoated RER
Paint	3	alkyd paint production, white, solvent-based, product in 60% solution state RER
Plaster	139	gypsum plasterboard production CH
Slate	17	fibre cement roof slate production CH
Wood beam	699	beam, softwood, raw, kiln drying CH
Wood board	207	board, softwood, raw, kiln drying CH
Planing wood beam	756	planing, beam, softwood, kiln dried CH
Planing wood board	235	planing, board, softwood, kiln dried CH
Polystyrene	305	polystyrene foam slab for perimeter insulation CH
Polyvinylchloride	347	polyvinylchloride production, bulk polymerisation RER
Polyethylene	59	polyethylene production, low density, granulate RER
Injection moulding	241	injection moulding RER
Doors	238	door production, inner, wood RER
Transport	489	transport, freight, lorry >32 metric ton, EURO4 RER
Construction:		
Process system direct	1116	n/a
I-O system direct	943	n/a
I-O system indirect	4008	n/a

Table 30 shows the total deterministic result compared to the mean and standard deviation of the stochastic result. The stochastic result includes all propagated uncertainties for the case study as per the distributions previously quantified in Sections 6.3 and 6.4. Other central moments (coefficients of variation, skewness, and excess kurtosis) of the stochastic distribution are also shown in Table 30, and the distribution depicted in Figure 42. Table 30 also includes the results for a "reduced scenario". This scenario applies uncertainty reduction and is discussed in Section 6.6.1 and presented in Figure 46.

Table 30: Deterministic and Stochastic results (tonnes CO_2-equivalents)

Total Result	tonnes CO_2-equivalents		coefficients		
	Total/ mean (μ)	standard deviation (σ)	variation (ν)	skewness (γ_1)	excess kurtosis (γ_2)
Deterministic	29476	n/a	n/a	n/a	n/a
Stochastic	35801	4530	0.13	0.38	0.26
Reduced Scenario	31405	3279	0.10	0.31	0.18

In Figure 42, the blue vertical line indicates the deterministic value. Considering the uncertainties that were included in the study and are represented by the distribution in the figure, the probability that the deterministic value underestimates the total tonnes of CO_2-equivalents when uncertainty is ignored is approximately 93%. Therefore, the deterministic value, in this case, is highly likely to underestimate the potential impact. The reasons for this will be discussed in the interpretation section (Section 6.6).

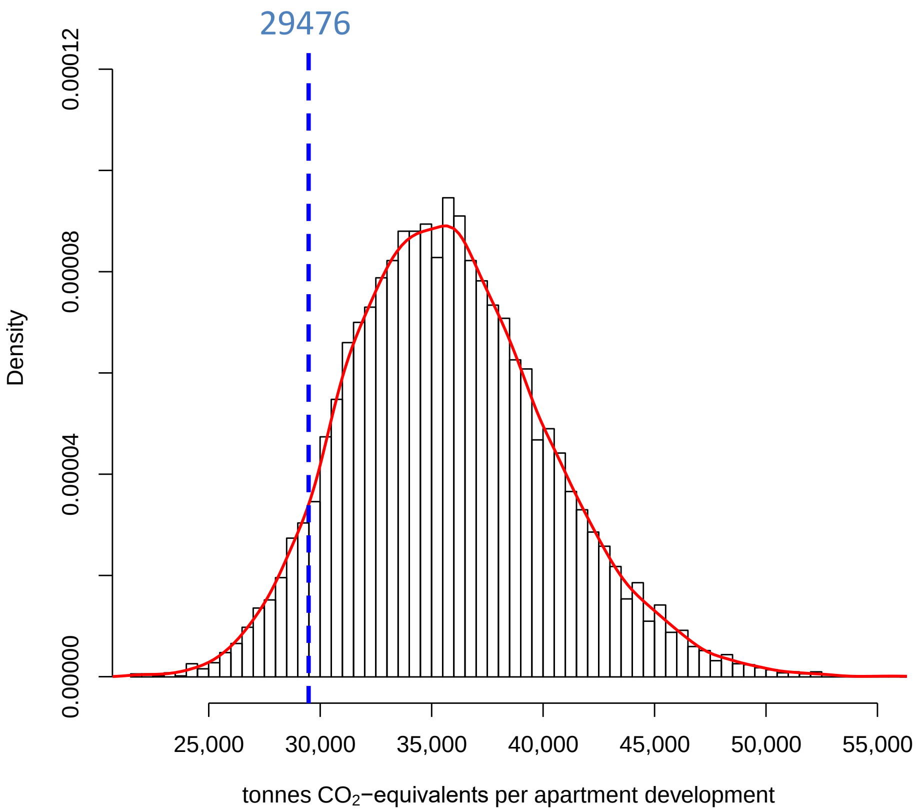


Figure 42: Total tonnes CO_2-equivalents per apartment development

6.6 Interpretation

This section presents the results of the contribution analysis of the inputs, and the uncertainty contribution ranking for each input using Equation 15 (see Section 3.5.2). A scenario for uncertainty reduction is also presented in Section 6.6.3. Table 31 shows the results for the aggregated materials and direct and indirect construction emissions. These results are also shown in Figure 43 and Figure 44.

Table 31: Contribution Analysis

Item	Total quantity (mean)	Total tonnes CO_2-equivalents (mean)	Contribution to total tonnes CO_2-equivalents	Uncertainty Ranking (Equation 15)
Materials:				
Steel	3390 tn	8072	22.4%	0.998
In-Situ Concrete	15900 m3	6383	17.8%	0.997
Stone	4650 tn	3550	9.9%	0.996
Steel rolling	3390 tn	1777	4.9%	0.990
Precast Concrete	1870 tn	1658	4.6%	0.987
Concrete roof tiles	5610 tn	1630	4.5%	0.946
Transport	5.8E+6 tn km	1448	4.0%	0.990
Planing wood beam	4449 m3	716	2.0%	0.919
Medium Density Fibreboard	437 m3	679	1.9%	0.838
Metal Casting	8.467 tn	621	1.7%	0.933
Wood beam	4449 m3	587	1.6%	0.898
Plaster	967 tn	387	1.1%	0.894
Polyvinylchloride	167 tn	367	1.0%	0.627
Polystyrene	73 tn	276	0.8%	0.574
Injection moulding	268 tn	274	0.8%	0.473
Doors	2691 m2	297	0.8%	0.529
Planing wood board	1525 m3	241	0.7%	0.601
Wood board	1525 m3	175	0.5%	0.507
Metal (excluding steel)	8 tn	55	0.2%	0.136
Polyethylene	27 tn	57	0.2%	0.100
Float glass	866 m2	45	0.1%	0.009
Slate	37 tn	38	0.1%	0.143
Steel pipe	3 tn	16	0.0%	0.027
Bitumen	0.005 tn	0.004	0.0%	0.000
Glazing	4691 m2	5	0.0%	0.100
Paint	0.5 tn	3	0.0%	0.005
Construction:	26.5 m€			
Indirect (I-O system)		4365	12.1%	0.996
Direct (Process system)		1212	3.4%	0.957
Direct (I-O system)		1022	2.8%	0.941

As can be seen in the figures, the top four items that contribute approximately 62% to the total result for the building are also the highest ranked uncertainties, being steel, in-situ concrete, indirect construction, and stone. These uncertainties will be discussed further in Sections 6.6.1 and 6.6.2. The percentage contributions of construction, materials, and transport is approximately 18%, 78%, and 4%, respectively. The total CO_2-equivalents per square meter of gross floor area for the building is approximately 1.1-1.4 tn CO_2-eq./m^2. Other studies have reported values between 0.05 tn CO_2-eq./m^2 and 4 tn CO_2-eq./m^2 (Seo and Hwang, 2001; Blengini and Di Carlo, 2010; Yan *et al.*, 2010; Acquaye, Duffy and Basu, 2011). However, these studies differ in the building type assessed (commercial, residential, standard house) and in the methodologies applied (see Section 2.2.6.1).

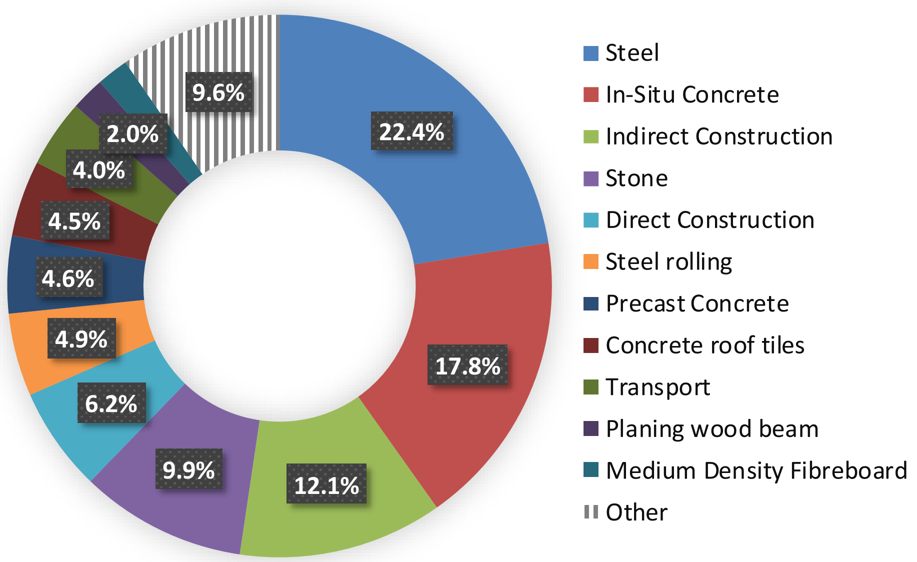


Figure 43: Percentage contribution to total tonnes CO_2-equivalents per building

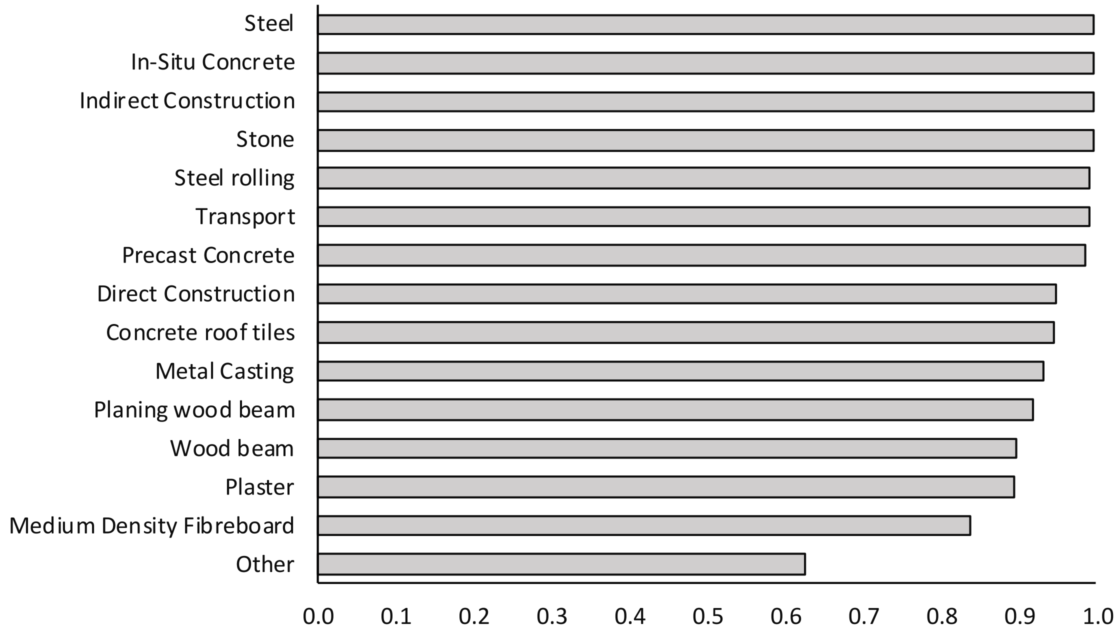


Figure 44: Rank of Uncertainty Contribution

6.6.1 Uncertainty Contributions of the Input-Output System

In order to assess the implications of ignoring the identified and classified uncertainties for the input-output system that were qualified as 'perhaps a key issue' in Table 24, the contribution of the input-output system to the total result for the Tiered-hybrid analysis was assessed. As can be seen in Table 31, the total contribution of the construction emissions that were modelled with Input-Output analysis is approximately 18.3%. This is quite high, considering that the top material contributions are concrete at 26.9% and steel at 27.3%. Therefore, the uncertainties for use of aggregated sectors particularly for the indirect construction emissions will influence the results. The representativeness of the disaggregation constants for the direct construction emissions need further investigation and their uncertainties should be addressed in future research.

6.6.2 Uncertainty Contributions of the Process System

The uncertainties that were included in the analysis for the process system were the BOQ aggregated input uncertainties (Table 20) and the uncertainties in the Ecoinvent background data (Table 22). For the items in Figure 44 with an uncertainty ranking of greater than 0.8, the contribution of the uncertainties in the foreground and background data were further assessed using Equation 15.

The results of the uncertainty ranking for the items in the process system are summarized in Table 32 and depicted in Figure 45. As can be seen in the figure, the uncertainties introduced due to the selection of the Ecoinvent dataset combined with the additional and basic uncertainties for each dataset and the IPCC GWP uncertainties (the background data) are ranked as the most significant contributors for all materials (uncertainty ranking of greater than 0.8). In comparison, the uncertainties in the BOQ data due to the measurement errors and unit conversions (the foreground data) were not as significant (uncertainty ranking of less than 0.5). This indicates where resources should be applied to reduce the uncertainty in the overall LCA result (Figure 42).

Table 32: Uncertainty Ranking of foreground versus background data

Item	BOQ Uncertainty (foreground data)	Dataset Uncertainty (background data)
Concrete roof tiles	0.075	0.997
Transport	0.132	0.983
Plaster	0.159	0.983
Steel rolling	0.166	0.977
Metal casting	0.232	0.963
Precast concrete	0.239	0.958
In-situ concrete	0.268	0.958
Stone	0.284	0.952
Steel	0.383	0.918
Wood beam	0.373	0.916
Planing wood beam	0.409	0.906
Medium Density Fibreboard	0.439	0.889

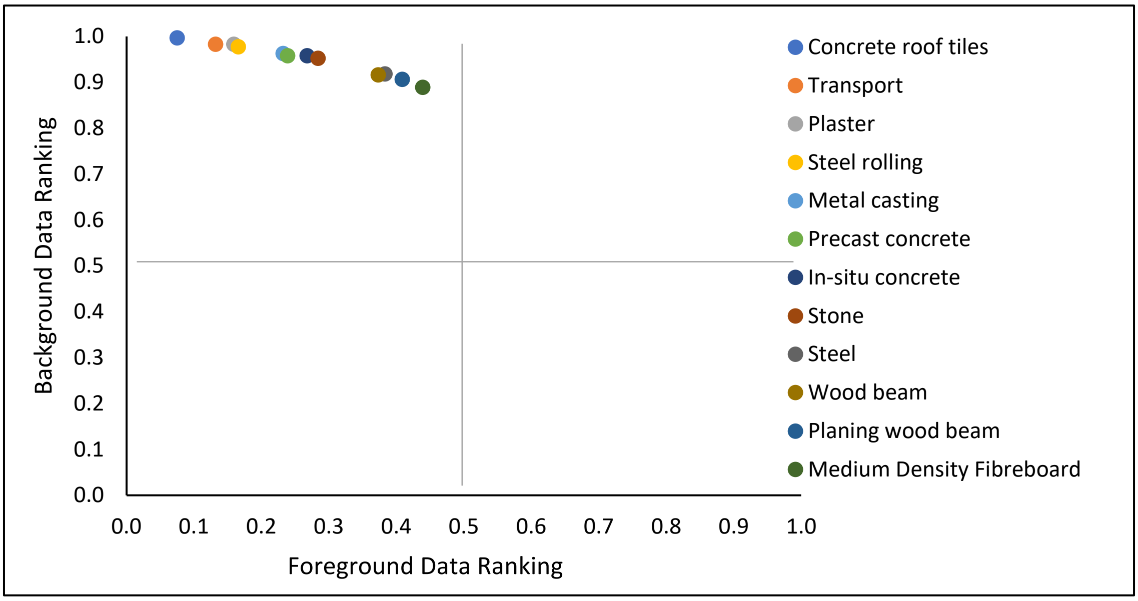


Figure 45: Uncertainty Ranking of background versus foreground data

To further assess which uncertainties contribute the most within the background data, particularly whether selection of the background dataset (Scenario Practical Irreducible Comparative uncertainty) or the uncertainty in the IPCC GWPs (Parameter Aggregated Statistical uncertainty) will contribute more to the reduction of the overall uncertainty, the two materials that contribute the most to the overall result (steel and in-situ concrete from Figure 43) were selected for further analysis. Table 33 shows the Ecoinvent dataset options used for steel production and in-situ concrete production in the LCA, along with the calculated kg CO_2-equivalents and the aggregated total uncertainty for each dataset (all Ecoinvent datasets used in the case study are listed in Appendix IV).

There were 18 optional datasets for steel with a range of 1.9 - 2.9 kg CO_2-equivalents per kg of steel, and 6 optional datasets for in-situ concrete with a range of 293 - 496 kg CO_2-equivalents per m^3 of concrete (Table 33). The DQI scores were quantified for each dataset to measure the appropriateness of the use of each dataset for this case study. The distributions for these materials were previously presented in Section 6.3, Figure 14 and Figure 35.

Table 33: Ecoinvent datasets for in-situ concrete and steel production

Dataset Name	kg CO_2-equivalents per *unit*	Uncertainty (±kg CO_2-equivalents per *unit*)
In-situ concrete (*unit* = m3):		
concrete production, normal CH	293	69
concrete production, high exacting requirements CH	361	85
concrete production, normal RoW	378	100
market for concrete, normal GLO	407	108
concrete production, high exacting requirements RoW	466	124
market for concrete, high exacting requirements GLO	496	131
Steel (*unit* = kg):		
market for steel, low-alloyed GLO	1.89	0.48
steel production, converter, unalloyed RER	2.14	0.50
steel production, converter, unalloyed RoW	2.17	0.56
steel production, low-alloyed, hot rolled RER	2.18	0.50
steel production, low-alloyed, hot rolled RoW	2.18	0.56
market for steel, low-alloyed, hot rolled GLO	2.18	0.56
market for steel, unalloyed GLO	2.21	0.57
metal working, average for steel product manufacturing RER	2.23	0.47
metal working, average for steel product manufacturing RoW	2.23	0.54
market for metal working, average for steel product manufacturing GLO	2.23	0.54
reinforcing steel production RER	2.39	0.55
reinforcing steel production RoW	2.39	0.61
market for reinforcing steel GLO	2.43	0.62
steel production, converter, low-alloyed RER	2.62	0.60
steel production, converter, low-alloyed RoW	2.64	0.67
metal working, average for chromium steel product manufacturing RER	2.88	0.61
metal working, average for chromium steel product manufacturing RoW	2.88	0.69
market for metal working, average for chromium steel product manufacturing GLO	2.88	0.69

Table 34 shows the uncertainty ranking for each dataset comparing the uncertainty in the Ecoinvent dataset (basic and additional uncertainties) to that of the IPCC GWPs, indicating that the uncertainty contributing most to the overall output uncertainty is from the latter for each individual dataset.

Table 34: Uncertainty Ranking of Ecoinvent LCI versus IPCC GWPs

Dataset Name	Ecoinvent LCI (basic and additional uncertainties)	IPCC GWPs
In-situ concrete:		
concrete production, normal CH	0.056	0.999
concrete production, high exacting requirements CH	0.025	0.999
market for concrete, high exacting requirements GLO	0.450	0.889
market for concrete, normal GLO	0.448	0.888
concrete production, high exacting requirements RoW	0.451	0.887
concrete production, normal RoW	0.453	0.881
Steel:		
steel production, converter, unalloyed RER	0.170	0.984
reinforcing steel production RER	0.181	0.983
steel production, low-alloyed, hot rolled RER	0.176	0.983
steel production, converter, low-alloyed RER	0.167	0.983
metal working, average for chromium steel product manufacturing RER	0.191	0.979
metal working, average for steel product manufacturing RER	0.209	0.979
steel production, converter, low-alloyed RoW	0.476	0.880
market for steel, unalloyed GLO	0.465	0.878
reinforcing steel production RoW	0.470	0.876
market for reinforcing steel GLO	0.474	0.876
market for steel, low-alloyed, hot rolled GLO	0.468	0.874
steel production, converter, unalloyed RoW	0.473	0.874
market for steel, low-alloyed GLO	0.467	0.873
steel production, low-alloyed, hot rolled RoW	0.483	0.872
metal working, average for chromium steel product manufacturing RoW	0.497	0.859
metal working, average for steel product manufacturing RoW	0.501	0.859
market for metal working, average for chromium steel product manufacturing GLO	0.506	0.858
market for metal working, average for steel product manufacturing GLO	0.506	0.854

To reduce the overall uncertainty, more specific information regarding the BOQ item should be collected to ensure that the most representative dataset or datasets are being used. This will reduce the uncertainty due to the choice of dataset (Scenario Practical Irreducible Comparative uncertainty), particularly for the case of in-situ concrete where a greater range in the kg CO_2-equivalents per m^3 for each dataset was observed.

The uncertainty in the IPCC GWPs (Parameter Aggregated Statistical uncertainty) cannot be reduced by the LCA practitioner; however, it does have a notable contribution to the overall uncertainty for each individual dataset. This further supports the fact that LCA studies cannot be compared when different methods have been applied. In this case, the results of this study should only be compared with studies that have also applied the IPCC GWPs, given that all other methods applied are also comparable.

6.6.3 Uncertainty Reduction Scenario

Uncertainty reduction was also tested for this case study (see Table 30, "reduced scenario"). It was assumed that the uncertainty due to the choice of the Ecoinvent dataset (refer to Table 22) could be reduced through selection of the most representative dataset. In practice, this could be done through discussions with the building designers and quantity surveyors regarding the building materials used and the data entered in the BOQ. Due to confidentiality of the BOQ data, this was not possible for this case study.

However, to simulate the elimination of this uncertainty, the same datasets used to quantify the deterministic result were selected as the most representative datasets. The result is shown as the histogram in Figure 46. In this figure, the shaded grey distribution is the stochastic result (Figure 42) and the deterministic value is the vertical blue line. The shift of the distribution and the reduction of σ, ν, γ_1, and γ_2 (see Table 30), indicate a reduction of uncertainty. With the reduced uncertainty, the probability of the deterministic value being an underestimate of the potential impact also reduces to 70%.

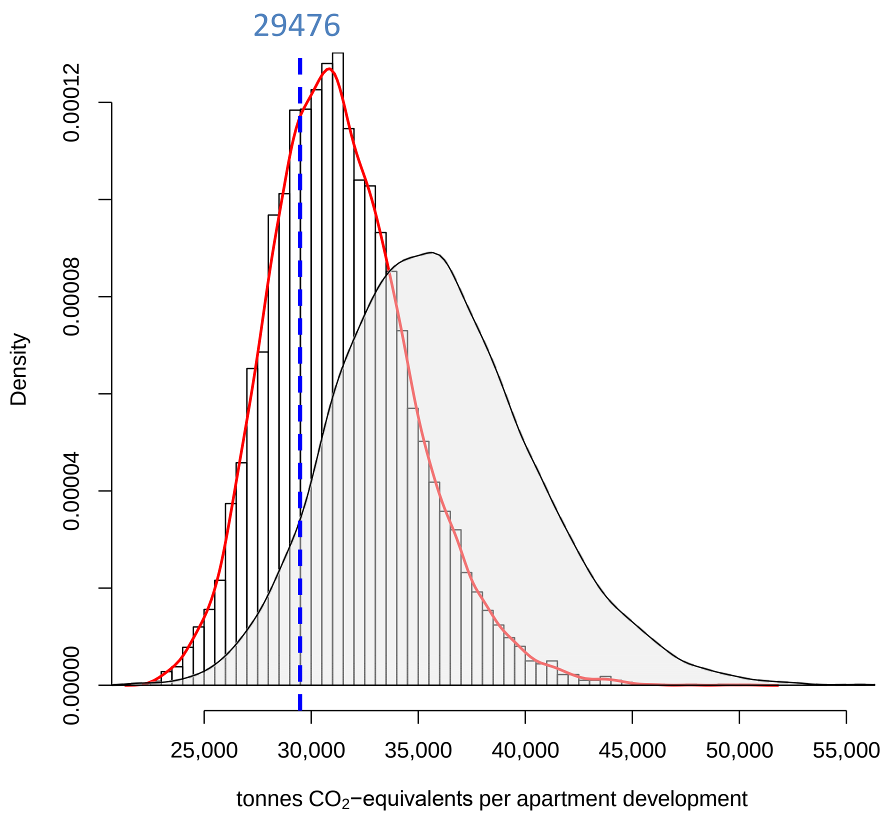


Figure 46: Reduced Scenario – Total tonnes CO_2-equivalents per apartment development

6.6.4 Limitations

The limitations of this study include:

- Lack of detailed information regarding the building materials used. This could reduce the uncertainty due to the choice of the background dataset.
- Missing data for imports in the Input-Output system for the construction sector. The construction emissions could be underestimated due to this missing data, although the uncertainty estimation has considered this. Further investigation is needed using an MR-IO approach.
- Lack of data for onsite construction emissions and energy consumption. This has been estimated though EEIO by disaggregating the Energy sectors.

- In terms of the uncertainty management method, this case study focused on the pre-occupancy stage of a building's life cycle. Other data sources and life cycle stages need to be assessed.
- Other uncertainties also need to be assessed, including those identified as 'key issue' and 'perhaps a key issue' according to Figure 7. These are summarized in Table 35.

Table 35: Summary of uncertainties identified as key issues but not quantified

Identified Uncertainty	Classification as per Figure 6	Key Issue as per Figure 7
Missing data for imports	Model practical irreducible comparative	Key issue
Missing climate-carbon feedback impacts	Model ambiguity comparative	Perhaps a key issue
Representativeness (aggregation) of sectors	Model practical irreducible qualitative	Perhaps a key issue
Error in disaggregation constants	Parameter practical irreducible statistical	Perhaps a key issue
Unrepresentative Disaggregation model/method	Model ambiguity qualitative	Perhaps a key issue
Inaccurate or unrepresentative BOQ data	Parameter practical irreducible comparative	Perhaps a key issue

6.7 Experience of using the uncertainty management method

The uncertainty management method presented in Chapter 4 provides a structured way in which to identify, classify, quantify/qualify, reduce, and report uncertainties in an LCA study. The Uncertainty Reduction step allows for significant uncertainties to be identified and ranked. This aims to identify where additional resources can be applied to reduce the total uncertainty of the LCA results. With integration of the uncertainty management method into the steps of an LCA, the results are presented as probability distributions along with a list of uncertainties.

To evaluate the experience of using the uncertainty management method in the case study, the criteria defined in Section 4.1 are used. However, it is noted here that this method needs to be implemented and evaluated by multiple researchers and across multiple case studies before it can be considered for potential integration into LCA standards.

The criteria and evaluation are listed below:

1. Unambiguous – it was found that the three-dimension classification was helpful in identifying unique uncertainties. The purpose of the classification within the LCA study was to be able to keep track of and report all uncertainties that have been identified, not only those that have been quantified within the study. However, the ease of which the uncertainties are classified into unique classes by multiple users needs to be tested.
2. Clear framework – the structured framework of the uncertainty management method allowed for uncertainties to be managed throughout the LCA study and reported. The iterative uncertainty ranking approach also identified where efforts to reduce the uncertainty should be focused.
3. Easy to use in practice – It was found that the method was easy to apply in practice and allowed for identification of various types of uncertainties. Therefore, focus is not only on parameter uncertainty. However, its usefulness across multiple types of case studies should be assessed. It might not always be useful to identify the model uncertainties in the Goal and Scope definition, for example. But this addresses key methodological differences between studies that may be useful for development of product-specific methods.
4. Additional resource requirement – the developed method requires the ability to write code for propagating the uncertainties. In this study, this was done in RStudio, but other statistical programs can also be used. However, as the

complexity of the case study increases, for example with assessment of multiple impact categories, implementation of this method in software should be investigated. It has further been reported that Monte Carlo simulations may take too long for this type of uncertainty analysis (Rosenbaum, Georgiadis and Fantke, 2018). In this case, analytical approaches to uncertainty analysis should be also be investigated (see Section 3.4.1.3).

5. Clear reporting to decision makers – the uncertainty management method reports the LCA results as a probability distribution with a list of uncertainties identified to be most significant to the total uncertainty in the result. This provides an assessment of the reliability of the results to the decision maker. However, more research is needed to determine the best way in which to report this information.

6.8 Conclusion

The case study successfully applied the developed uncertainty classification and uncertainty management methodology presented in Chapter 4. The uncertainties in the Tiered-hybrid model were identified and classified, and the quantified uncertainties were presented as distributions. Of the uncertainties quantified, the highest contributing uncertainties were found to be due to the choice of dataset in Ecoinvent, the uncertainty in the IPCC GWPs, and the uncertainty in the quantified sector emissions intensities for Ireland. The identified and classified uncertainties that were not quantified in this study were further reported and discussed.

The limitations of the study include lack of available data. BOQs are difficult to obtain due to being highly confidential. Furthermore, data on onsite construction emissions is not available for Ireland and was estimated through disaggregation of the sectors in the Irish I-O table. Although there have been efforts to harmonize the methods used in LCA studies in the buildings and construction sector, access to accurate and transparent sources of data will improve the reliability of study results. However, first the barriers to data accessibility need to be removed. Collection and reporting of BOQ data and onsite construction emissions data at a national level could lead to improvements in the analysis, if made publicly available. Furthermore, accessible disaggregated I-O tables for Ireland would also lead to better estimations.

The developed uncertainty management method is beneficial for LCA practitioners and decision makers. For LCA practitioners, the iterative uncertainty reduction step identifies uncertainties where resources for reduction should be focused. This was demonstrated in the study with the elimination of the uncertainty due to the choice of a representative background dataset. The uncertainty reduction step ranks the uncertainties by their contribution. This ensures that resources are being applied effectively to improve the reliability of the study results. This step can also be implemented into LCA software in future work.

The results of this study also highlight the need for further information regarding uncertainty to be reported to decision makers. This was demonstrated in the case study by comparing the uncertainty distributions to the deterministic result. It was found that the probability of the deterministic value underestimating the potential impact was 93% and 70% for the initial uncertainty assessment and the reduced uncertainty assessment, respectively. Therefore, care must be taken in making decisions based on only the deterministic result. By providing a distribution and a list of uncertainties that influence the result, decision makers can make better informed decisions or allocate further resources to reduce the uncertainty and improve the reliability of the results.

Lastly, for data providers to LCA databases, such as Ecoinvent, the results of this study further indicate the need to report all uncertainties along with limitations for use of the data in LCA case studies. Datasets that transparently report the product system assessed, the system boundary that has been included (with a flow diagram), the source of the data, the assumptions that have been made, and all methodological considerations, are less likely to be misused. Furthermore, datasets should include a data quality assessment and reported uncertainties. This also requires that LCA databases allow for a coherent platform in which this information is displayed. This will lead to improvements in the reliability of the background system.

The developed uncertainty management method allows for a standardized way to identify, classify, quantify/qualify, reduce, and report uncertainties in an LCA study. Further work is needed to test the method in a variety of case studies. However, integration of the uncertainty management steps into the steps of an LCA allows for the management of resources available for reduction measures. By effectively reporting uncertainties and indicating where to focus uncertainty reduction efforts, the uncertainty management method aims to improve the reliability, robustness, and repeatability of case study results.

CHAPTER 7. CONCLUSION AND RECOMMENDATIONS

This chapter summarizes the research presented in this thesis and discusses the key findings (Section 7.1). It further reviews the contributions to knowledge (Section 7.2) and provides recommendations for future research (Section 7.3).

7.1 Research Summary

The intent of this research was to develop an uncertainty classification and uncertainty management methodology for LCA that improves identification, classification, quantification/qualification, reduction, and reporting of uncertainties in case studies. The developed methods aimed to address the main barriers preventing uncertainty reporting, being lack of resources, lack of expertise and lack of guidance (Ross, Evans and Webber, 2002; Ciroth, Fleischer and Steinbach, 2004; Rosenbaum, Georgiadis and Fantke, 2018). The objectives of the research were to:

1. review the methods used to construct the Life Cycle Inventory Analysis (LCI) model and clearly define the best practice;
2. clearly define the weaknesses in the current practice for assessing uncertainty in LCA;
3. develop a practical method for assessing uncertainty in LCA which addresses these weaknesses;
4. propose a potential integration of this method into the international standard for LCA studies (ISO 14044:2006), or other product-specific standards; and
5. demonstrate the usability and effectiveness of the developed method by applying it in an LCA case study that uses the best practice approach for constructing the LCI model.

For objectives 1 and 2, critical reviews were conducted on the approaches used to construct an LCI model and on how uncertainties are dealt with in practical LCA case studies. In Chapter 2 it was concluded that although the Integrated hybrid is seen as the state-of-the-art approach, Tiered-hybrid along with a method to account for double counting errors could be considered best practice. This is due to its ease of application in practical case studies (Nakamura and Nansai, 2016; Yang, Heijungs and Brandão, 2017). However, this is also dependent of the data available for a case study. Objective 2 was addressed in Chapter 3, concluding that there is a lack of guidance on how to conduct an uncertainty assessment in LCA and ambiguity in the uncertainty classes and definitions. Therefore, improvement in uncertainty reporting first requires clarification of the definitions and standard guidance on how to proceed.

Following this, objective 3 was achieved through the development of structured uncertainty classification and uncertainty management methods. The developed uncertainty management method for LCA studies standardizes the identification and classification steps to ensure that the methods and definitions can be applied uniformly amongst all LCA studies. These methods were presented in Chapter 4, along with a framework of how to integrate the uncertainty management methodology into the steps of an LCA as defined by ISO (objective 4). The intent of the integration was to improve the efficiency of uncertainty management and allow for iterative uncertainty reduction as resources become available. A case study was conducted to test the developed methods (objective 5).

For objective 5, the best practice LCI approach from objective 1 was used in a case study of an apartment development in Ireland. Since process data for construction emissions were not available, a Tiered-hybrid approach that allowed for use of input-output data for these emissions was suitable to fill in data gaps. This case study was used to demonstrate the usability and effectiveness of the developed uncertainty classification and the uncertainty management method. The result of the study was presented as a distribution along with a list of significant uncertainties that should be taken into consideration by decision makers. Comparison of this result to the deterministic result showed that the probability of the deterministic value underestimating the potential impact is approximately 93%. Uncertainty reduction was also demonstrated in the case study, indicating a shift towards the deterministic value and a reduction in the spread of the distribution.

7.2 Contributions to Knowledge

The research in this thesis resulted in the achievement of three contributions to knowledge, including:

(1) A practical application of a three-dimensional uncertainty classification for LCA in a Tiered-hybrid case study that defines and separates aggregated uncertainties and connects to the identification and quantification steps in uncertainty management (Chapter 4, Section 4.2).

This was achieved through defining a three-dimensional classification for use in practical case studies, building from previous work that applied a three-dimensional classification in environmental modelling. The novel addition of aggregated uncertainty is specific to LCA. Furthermore, the identification and classification steps have been connected to ensure unique uncertainties are identified. The resulting classification included the following dimensions and classes: location (parameter, model, scenario), nature (aggregated, practical irreducible, ambiguous, epistemic), and level (statistical, comparative, qualitative, recognized ignorance).

(2) A structured uncertainty management method for LCA that provides a detailed way to report uncertainties to the decision maker and is integrated into the steps of an LCA as defined by ISO 14044:2006 (Chapter 4, Section 4.3).

Building on a concept of knowledge abstraction through the modelling steps, a structured identification step was developed for LCA and connected to the classification step in uncertainty management. Through classification of unique uncertainties, double counting in the quantification and qualification step is avoided. The uncertainty reduction step was further developed based on the equation for correlation and can be iteratively applied to rank uncertainties according to their contribution. This step also allows for information regarding both quantified and qualified uncertainties to be reported to the decision maker. These steps are further conducted within the steps of an LCA.

(3) The first application of a detailed and structured uncertainty management method in a Tiered-hybrid case study that identifies and classifies uncertainties in all steps of an LCA and demonstrates an iterative approach to uncertainty reduction (Chapters 5 and 6).

The uncertainty management method and the uncertainty classification were applied to a tiered-hybrid case study of an Irish apartment development. The case study was also used to demonstrate the iterative uncertainty reduction method.

7.3 Recommendations for Future Research

This thesis presented a practical uncertainty management method for LCA studies that aims to improve the assessment and communication of uncertainty in LCA case study results. However, further evaluation of the developed method is required. This section recommends some areas for further work that extends from the work in this thesis.

7.3.1 Data and Modelling

As was discussed throughout the thesis, certain assumptions and methodological decisions were made for the case study that should be addressed with further research. This includes the assessment of correlation and covariance, climate-carbon feedback, and imports in Ireland’s economy.

Correlation and covariance were ignored in the case study as it was assumed that all input uncertainty distributions were independent. However, particularly for the aggregated uncertainties where correlation may be high, independent sampling of the distributions could potentially lead to underestimating the uncertainty (Lesage *et al.*, 2018).

The climate-carbon feedback (CCF) was also ignored in the case study, which can lead to an underestimated impact and uncertainty. The GWPs that account for CCF have larger uncertainty ranges compared to those without CCF due to the large uncertainties in the CCF model (Myhre *et al.*, 2013). Furthermore, the IPCC GWP_{100} values with CCF have slightly higher values for the 100-year time period compared to the IPCC GWP_{100} values without CCF.

Lastly, ignoring imports in the Irish economy can lead to an underestimation of the result since the economy relies heavily on imports, which have been estimated to account for approximately 42% of the total CO_2-equivalents for the construction sector in Ireland (Acquaye and Duffy, 2010). Accounting for these factors may lead to changes in both the deterministic result obtained for the case study and the resulting output distribution.

7.3.2 Uncertainty Quantification and Qualification

Further work should also quantify or qualify the key uncertainties that were identified and classified but not measured in the case study. These include the uncertainties listed in

Table 35 (Chapter 6). This will further give a better representation of the total uncertainty of the case study result.

Moreover, one aim of classification is to apply quantification, qualification, and reduction measures uniformly across uncertainty classes. Further work can identify the best practice for uncertainty quantification and qualification for each class of uncertainty. In the case study presented, Monte Carlo analysis was used, however, other methods could potentially result in less time for the analysis. For example, Taylor Series Expansion may be suitable for some uncertainty classes and Bayesian Model Averaging for others.

7.3.3 Further Testing of the Uncertainty Management Method

The uncertainty management method further needs to be tested by multiple LCA practitioners and applied in multiple LCA case studies that assess multiple impact categories. Other impact categories, besides climate change, may not report a quantified uncertainty in the characterization factors or may have multiple valid ways to derive the characterization factors. Furthermore, the implications of using independent sampling of the classified aggregated uncertainties for other impact categories should also be assessed as there is a higher potential for correlation in other impact categories due to reliance on data from the same few sources (Lesage *et al.*, 2018). The reduction of time and effort will also become more apparent with the assessment of multiple impact categories per case study, and therefore, implementing the uncertainty management method in LCA software should also be assessed.

7.4 Concluding Remarks

The intent of this research is to improve uncertainty management and reporting in LCA case studies, and in turn, improve the reliability, robustness, and repeatability of the results, allowing for better informed decisions to be made.

This research aims to be applicable to all types of LCA studies and across all life cycle stages. This includes, for example, comparative studies, EPDs, 'hot spot' analysis and studies on emerging or innovative technologies. For comparative studies, probability distributions may overlap indicating the probability of one alternative performing better than another. Decision makers can use this information to apply strategic reduction measures. EPDs are used in business-to-business and business-to-consumer communication. In this case, reporting uncertainties in an understandable way to the final user should be considered. This should also be considered for 'hot spot' analysis, which highlights the most contributing processes within the system boundary for the product system being assessed. For LCA studies of innovative and emerging technologies, the uncertainty management method can be used to demonstrate the uncertainty contribution of unknown aspects, such as scale-up to industrial scale production. The uncertainty reduction step can also be used to demonstrate scenarios for improved reliability of the data and models used.

The developed uncertainty management methodology provides the necessary guidance for managing uncertainties in LCA studies. This method is interconnected with the steps of an LCA and can therefore be integrated in the same way into LCA standards, such as the international standards or product-specific standards. The next step is to test this method across practitioners, researchers, and case studies. Afterwards, meetings can be held with technical committees to discuss the potential integration into LCA standards.

The overall aim being to make uncertainty management and uncertainty reporting common practice in LCA.

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GLOSSARY OF TERMS

Term	Definition	Reference
activity data	see foreground data	SAIC (2006)
allocation	partitioning the input or output flows of a process or a product system between the product system under study and one or more other product systems	ISO 14044:2006
attributional	An attributional model uses average data for all processes included in the system boundary	Plevin, Delucchi and Creutzig (2013)
background data	data for the processes within the background system	EC-JRC-IES (2010); Bjørn et al. (2018)
background system	consists of the processes within the system boundary that are not included in the foreground system	EC-JRC-IES (2010); Bjørn et al. (2018)
CAS number	(Chemical Abstracts Service number) a numerical identifier assigned to unique substances, such as inorganic and organic chemicals, metals, minerals, etc.	CAS.org
category endpoint	Attribute or aspect of natural environment, human health or resources, identifying an environmental issue giving cause for concern	ISO 14044:2006
category indicator	Quantifiable representation of an impact category	ISO 14044:2006
characterization factor	Factor derived from a characterisation model which is applied to convert an assigned life cycle inventory analysis result to the common unit of the category indicator	ISO 14044:2006
characterization model	Reflects the environmental mechanism by describing the relationship between the LCI results, category indicators and, in some cases, category endpoint(s). The characterisation model is used to derive the characterisation factors.	ISO 14044:2006
climate change	refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer.	Myhre et al. (2013)
consequential	Consequential models determine how the inputs and outputs within a system change according to a decision.	Plevin, Delucchi and Creutzig (2013)
correlation	Correlation is a scaled version of covariance that indicates the relative strength of the covariance as well as the direction.	Morgan and Henrion (1990)
covariance	Covariance occurs when two or more random variables are not completely independent, meaning that one variable changes with changes in another variable.	Morgan and Henrion (1990)
co-product	any of two or more products coming from the same unit process or product system	ISO 14044:2006
cut-off criteria	specification of the amount of material or energy flow or the level of environmental significance associated with unit processes or a product system to be excluded from the study	ISO 14044:2006
data quality	characteristics of data that relate to their ability to satisfy stated requirements	ISO 14044:2006

Term	Definition	Reference
direct energy	energy consumed in various on-site and off-site operations like construction, prefabrication, transportation, and administration.	Dixit et al. (2010)
emerging technologies	technologies that are in an early stage of development	Caduff et al. (2014); Olsen, Borup and Andersen (2018)
endpoint indicator	see category endpoint	
environmental impact	a set of environmental changes, positive or negative, due to an anthropogenic intervention	Rosenbaum et al. (2018)
environmental mechanism	System of physical, chemical and biological processes for a given impact category, linking the life cycle inventory analysis results to category indicators and to category endpoints	ISO 14044:2006
foreground data	data for the processes within the foreground system	EC-JRC-IES (2010); Bjørn et al. (2018)
foreground system	consists of the processes within the system boundary that are specific to the product system being assessed	EC-JRC-IES (2010); Bjørn et al. (2018)
functional unit	quantified performance of a product system for use as a reference unit	ISO 14044:2006
global warming potential	An index, based on radiative properties of greenhouse gases, measuring the radiative forcing following a pulse emission of a unit mass of a given greenhouse gas in the present-day atmosphere integrated over a chosen time horizon, relative to that of carbon dioxide.	Myhre et al. (2013)
goal and scope definition	The first step of an LCA study that defines the intended application, the reasons for carrying out the study, the intended audience, how the results will be used, and explicitly states all methodological considerations and limitations.	ISO 14044:2006
greenhouse gas	Greenhouse gases are those gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths. For example, Carbon dioxide (CO_2), Dinitrogen oxide (N_2O), Methane (CH_4).	Myhre et al. (2013)
hot spots	identifies the significant processes within the system boundary for the product system being assessed	
impact category	Class representing environmental issues of concern to which life cycle inventory analysis results may be assigned	ISO 14044:2006
impact pathway	Cause–effect chain of an environmental mechanism	Rosenbaum et al. (2018)
indicator result	the result of the conversion of LCI results to common units and the aggregation of the converted results within the same impact category. This conversion uses characterization factors.	ISO 14044:2006
indirect energy	energy mostly used during the manufacturing of building materials, in the main process, upstream processes and downstream processes and during renovation, refurbishment, and demolition.	Dixit et al. (2010)
interpretation	The last step in an LCA which includes: the identification of significant issues; completeness, sensitivity, and consistency checks; formulation of the final conclusions and recommendations.	ISO 14044:2006
inventory data	data compiled during the LCI step	

Term	Definition	Reference
Life Cycle Assessment (LCA)	compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle	ISO 14044:2006
Life Cycle Impact Assessment (LCIA)	phase of life cycle assessment aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts for a product system throughout the life cycle of the product	ISO 14044:2006
Life Cycle Inventory Analysis (LCI)	phase of life cycle assessment involving the compilation and quantification of inputs and outputs for a product throughout its life cycle	ISO 14044:2006
LCA model	LCA can be considered as a model with the inputs defined as the inputs used in the various steps of an LCA and the output being the final result(s). This has been defined in this thesis to visualise how uncertainty management can be integrated into the steps of an LCA in accordance with the international standards.	
LCI model	The constructed model consisting of the inventory data inputs and the output LCI result	
LCI result	outcome of a life cycle inventory analysis that catalogues the flows crossing the system boundary and provides the starting point for life cycle impact assessment	ISO 14044:2006
midpoint indicator	Impact category indicator located somewhere along the impact pathway between emission and category endpoint	Rosenbaum et al. (2018)
normalisation	calculating the magnitude of category indicator results relative to reference information	ISO 14044:2006
process	set of interrelated or interacting activities that transforms inputs into outputs	ISO 14044:2006
product flow	products entering from or leaving to another product system	ISO 14044:2006
product category	Group of products that can fulfil equivalent functions	ISO 14025:2006
product system	collection of unit processes with elementary and product flows, performing one or more defined functions, and which models the life cycle of a product	ISO 14044:2006
RStudio	an open source software for statistical programming	RStudio Team (2016)
raw material	primary or secondary (including recycled) material that is used to produce a product	ISO 14044:2006
reference flow	measure of the outputs from processes in a given product system required to fulfil the function expressed by the functional unit	ISO 14044:2006
sensitivity analysis	systematic procedures for estimating the effects of the choices made regarding methods and data on the outcome of a study	ISO 14044:2006
significant	has a high contribution and influence	
significant issues	Significant issues in LCA studies can include: inventory data, such as energy, emissions, discharges, waste; impact categories, such as resource use, climate change; and significant contributions from life cycle stages to LCI or LCIA results, such as individual unit processes or groups of processes like transportation and energy production.	ISO 14044:2006
system boundary	set of criteria specifying which unit processes are part of a product system	ISO 14044:2006
transparency	open, comprehensive and understandable presentation of information	ISO 14044:2006

Term	Definition	Reference
uncertainty	can be defined as any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system	Walker et al. (2003)
uncertainty contribution rank	The ranking of input uncertainties from most significant to least significant based on their contribution to the total output uncertainty.	Morgan and Henrion (1990)
unit process	smallest element considered in the life cycle inventory analysis for which input and output data are quantified	ISO 14044:2006
value-choice	Value-choices (also known as value judgement) are decisions made based on implicit or recognized opinions, beliefs, or bias. Often used (although should be minimized) during the selection of impact categories, category indicators, characterization models and in weighting.	EC-JRC-IES (2010); De Schryver et al. (2011)
variability	is defined as the fluctuation in value of a parameter due to real world scenarios	Huijbregts (1998a)
weighting	converting and possibly aggregating indicator results across impact categories using numerical factors based on value-choices (not scientifically based)	ISO 14044:2006

APPENDICES

Appendix I. Uncertainty Distributions and Propagation Equations

Probability distributions can be used to represent the likeliness that a variable has different possible values (Morgan and Henrion, 1990). Probabilistic results are often considered more reliable than deterministic results, particularly for studies where large data uncertainties are present (Sonnemann, Schuhmacher and Castells, 2003; Wang and Shen, 2013). Probability distributions can be described by cumulative distribution functions, probability density functions, or by selected moments such as the median, mean, standard deviation, coefficient of variation, coefficient of skewness, or coefficient of kurtosis (Morgan and Henrion, 1990).

The cumulative distribution function (CDF) gives the cumulative probability from 0 to 1 that a random variable, *X*, will have any possible value less than or equal to *x*. The probability density function (PDF) is the derivative of the CDF and gives the probability that *X* is within a small increment, Δ*x*, hence within the range $x \pm \frac{\Delta x}{2}$. The mode, or peak of the PDF, is the value of *X* with the maximum probability. The PDF has units of X^{-1} (probability per units of *X*). The median (or 50th percentile) is the value of *X* where there is a 50% probability that the actual value is less than *X*. The median can easily be obtained from the CDF. The mean (μ), on the other hand, is also defined as the first central moment (μ_1) of the PDF and can be derived by Equation E_1 for *N* = 1, where *N* represents the N^{th} central moment and μ is 0 (Morgan and Henrion, 1990).

$$\mu_N = \int_X (x-\mu)^N f(x)dx \qquad (E_1)$$

The standard deviation (σ) is the square root of the variance (σ^2), which is also known as the second central moment (μ_2) of the PDF (Equation E_1, $N = 2$). These values can be used to calculate the coefficient of variation (ν), the coefficient of skewness (γ_1), and the coefficient of kurtosis (γ_2), as below:

$$\nu = \frac{\sigma}{\mu_1} \qquad (E_2)$$

$$\gamma_1 = \frac{\mu_3}{\sigma^3} \qquad (E_3)$$

$$\gamma_2 = \frac{\mu_4}{\sigma^4} \qquad (E_4)$$

Where the coefficient of variation (ν) is the ratio of the standard deviation to the mean, represents the spread of the distribution and is dimensionless; the coefficient of skewness (γ_1) is based on the third central moment (μ_3) and represents the shift of the distribution mode positively or negatively, being zero for symmetric distributions; and the coefficient of kurtosis (γ_2) is based on the fourth central moment (μ_4) and indicates the degree to which the outliers are similar to that of a normal distribution, which has a kurtosis of 3 (Morgan and Henrion, 1990).

Four common types of distributions identified in LCA studies are uniform, triangular, normal, or lognormal, which are defined in Table I along with equations for the PDF for each distribution. The latter three distributions are used when a central tendency of the data is expected, whereas a uniform distribution is used when there is no central tendency expected (Coulon *et al.*, 1997). If the distribution is unknown, expert opinion can be used to estimate the distribution or uncertainty ranges (Coulon *et al.*, 1997; Huijbregts, 1998a).

Other existing distributions, such as Poisson, Weibull, Beta, Gamma, and Exponential are not addressed in this thesis, although they could be considered in further research. In particular, the Weibull distribution may be valuable for some LCA studies that require estimations of failure rates.

Table I: Uncertainty Distributions

Distribution	Probability distribution function (Morgan and Henrion, 1990)
Uniform	$f(x) = \frac{1}{b-a};\ \ a \leq x \leq b$
Triangular	$f(x) = \frac{b - \lvert x-a \rvert}{b^2};\ \ a-b \leq x \leq a+b$
Normal	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right);\ \ \infty \geq x \geq -\infty$
Lognormal	$f(x) = \frac{1}{\sigma^* x\sqrt{2\pi}} exp\left(-\frac{[\ln(\mathrm{x}) - \mu^*]^2}{2\sigma^{*2}}\right);\ \ 0 \leq x \leq \infty$ where $\mu^* = \frac{1}{n}\sum_{i=1}^{n} ln(x_i)$ and $\sigma^* = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ln(x_i) - \mu^*)^2}$

In order to propagate the uncertainties from distributions, sampling of the input distributions can be performed and the calculations conducted with the sampled inputs multiple times to produce an output distribution of the results obtained (JCGM 101, 2008). When sampling from an input distribution, the distribution of the means of each sample will tend towards a normal distribution as the number of samples taken from the original input distribution increases (Morgan and Henrion, 1990). This is known as the Central Limit Theorem, and is true for all types of input distributions, not only those that are originally normally distributed.

The rule for combining uncertainties through addition or subtraction is given by Equation E_5, for multiplication or division by Equation E_6, and for power equations (for example: $f(x) = x^a$, where a is any whole number except -1) by Equation E_7. $\delta f(x, y, \ldots z)$ or $\delta f(x)$ denotes the total calculated uncertainty (δ) for each function, and δx, δy and δz represent the uncertainties in *x*, *y* and *z*, respectively.

$$\delta f(x, y, \dots z) = \sqrt{(\delta x)^2 + (\delta y)^2 + \dots + (\delta z)^2} \qquad (E_5)$$

$$\frac{\delta f(x, y, \dots z)}{|f(x, y, \dots z)|} = \sqrt{\left(\frac{\delta x}{x}\right)^2 + \left(\frac{\delta y}{y}\right)^2 + \dots + \left(\frac{\delta z}{z}\right)^2} \qquad (E_6)$$

$$\frac{\delta f(x)}{|f(x)|} = |a| \frac{\delta x}{|x|}, \quad for\ a \neq -1 \qquad (E_7)$$

Appendix II. Bill of Quantities

Description	Qty	Unit	Total
<u>Substructures</u>			
<u>Excavation and Earthworks</u>			
Excavating shallow trench	341	m3	2,710.95
Excavating pits - Pile caps	231	m3	2,326.17
Excavating pits - Lift Pits	314	m3	3,161.98
Working space	308	m2	10,447.36
disposal water	1	item	incl
disposal water	1	item	incl
Disposal excavated material	886	m3	17,888.34
filling to make up levels	2,669	m3	84,367.09
Blinding	8,895	m2	18,857.40
Blinding lift pits	200	m2	530.00
<u>Piling</u>			
Mobilisation	1	item	5,300.00
Precast driven piles	1	item	1,383,300.00
Cutting down surplus lengths	1	item	78,153.80
Preparing heads for capping	1	item	116,553.36
Testing	1	item	53,000.00
Allowance for additional piling due to increased loadings	1	item	159,000.00
<u>Concrete Work</u>			
Blinding on earth	668	m3	75,764.56
Blinding in lift pits	11	m3	1,247.62
40N to edge slabs	310	m3	35,572.50
40n to isolated fdns	200	m3	22,950.00
40N to slab	2,669	m3	315,395.73
40N to lift slab	59	m3	6,972.73
40N to lift pit base	16	No	1,272.00
Joints- longitudinal	1,000	m	16,960.00
pointing	1,000	m	8,200.00
Waterstops	1,200	m	52,056.00
Powerfloating	8,700	m2	38,019.00
Powerfloating	75	m2	651.00
Rebar	410	tn	306,081.40
Formwork pile caps	1,380	m	36,570.00
Formwork edge of slab	600	m	15,900.00
Kickers to walls	1,630	m	27,384.00
Kickers to columns	230	nr	3,864.00
Radon	9,177	m2	58,365.72
Waterproofing	308	m2	8,192.00
joints	item		15,900.00
insulation	500	m2	5,300.00
			2,988,214.71
<u>Retaining Walls</u>			
<u>Concrete</u>			
To walls	814	m3	104,102.46
E.O. for pouring against secant wall	904	m2	10,820.88
<u>Sundries</u>			
Joints	275	m	4,620.00
Pointing	275	m	1,952.50

Description	Qty	Unit	Total
<u>Roof</u>			
Screed on roof	326	m3	37,926.84
Over lift shafts	34	m3	3,955.56
Trowelling	112	m2	646.24
Powerfloat	4,337	m2	19,993.57
Mesh	4,337	m2	16,697.45
Formwork	112	m2	17,976.00
Precast Floor Slabs	4,337	m2	189,570.27
Concrete edge filling	1,083	m	48,648.36
Breaking out cores	230	m	7,695.80
Opgs in slabs	1	item	2,140.00
			345,250.09
<u>Frame</u>			
Beams, Columns, Walls, Rebar and F/W	Item		1,489,784.95
F/W, kickers, edges, steelwork	Item		1,323,927.05
Steelwork	Item		27,893.83
			2,841,605.83
<u>External Walls Completions</u>			
Window Boards	580	m	11,721.80
Door/Screen thresholds	2,650	m	79,553.00
Windows	427	m2	184,715.93
Glazed Screens	3,921	m2	1,696,185.39
Patio screens	1,490	m2	644,559.10
Doors	132	m2	57,101.88
Cladding grnd-first - Stone -Phase 1 complete, Phase 2 complete	1,003	m2	305,864.85
Cladding 2nd-6th	480	m2	146,376.00
Single balcony doors	57	No	91,485.00
Double exterior doors	8	No	15,408.00
ESB Doors	4	No	12,840.00
Stairwell lobby curtain walling	16	No	438,534.08
Stairwell lobby curtain walling	15	No	411,125.70
Glazed screens and doors to retail units	622	m2	232,939.00
Associated builders work	1	item	71,904.00
Balconies			
Balconies			
Balconies including Balustrade	514	m	412,485.00
Steelwork framework to balconies	514	m	109,996.00
Privacy panels	154	No	41,524.56
Timber decking to balconies	1,678	m2	269,319.00
Steel structure for balconies	1	item	1,660,281.22
Window pressed cills	580	m	27,927.00
Flashings	2,650	m	70,887.50
			6,992,734.01

Description	Qty	Unit	Total	Description	Qty	Unit	Total
Waterstops	275	m	11,929.50	**Internal Walls Completions**			
Reinforcement							
Rebar	163	Tn		Apartment doors	205	No	70,376.50
			121,686.02				
				Vision panels	16	No	1,284.00
Formwork				Apartment doors	68	No	23,344.40
				Staircore doors	98	No	33,643.40
Walls	1,452	m2		vision panels	98	No	7,864.50
			53,869.20				
E.O. corbel	520	m		Flush internal apartment doors	1,023	No	154,166.10
			52,364.00				
One sided only	904	m2		Hot press doors	249	No	37,524.30
			57,494.40				
				Duplex internal doors	38	No	11,452.82
Sundries				Frames	8,692	m	293,094.24
				Architraves	17,432	m	87,682.96
Breaking through secant walling	1	Item	26,500.00				
Provide flanges in retaining wall	1	Item	15,900.00	Ironmongery, all onsite	1	item	378,000.00
Additional joints	1	Item	15,900.00				
E.O for over 4.0m	1	Item	17,808.00				
Tanking to retail units	1,079	m2	40,030.90	Fixing only:			
				door closers	5,805	No	121,324.50
(Note: the following grilles have been				Hinges	1,680	No	46,821.60
replaced by insitu concrete walls)				lever handles	3,166	No	22,067.02
				mortice lock	1,680	No	70,224.00
Phase 1and 2 complete				pull handle	287	No	3,997.91
Vent grilles 17000*1000mm	1	no	4,218.32	finger plate	287	No	3,997.91
Vent grilles 12000*1000mm	1	no	2,977.64	Kick plate	287	No	3,997.91
Vent grilles 5000*1000mm	4	no	5,955.28	door stops	1,690	No	23,541.70
Vent grilles 3000*1000mm	25	no	22,332.25	signs	600	No	4,182.00
				numerals	909	No	6,335.73
			570,461.35	intumescent strips	3,169	m	10,679.53
Internal Walls				Painting door frames	8,692	m	51,195.88
Concrete				Painting doors	7,614	m2	89,616.78
Walls	600	m3	76,734.00				**1,556,415.69**
Ramp walls	96	m3	12,277.44	**Stairs Completions**			
Lift pits	65	m3	8,312.85	Handrails	537	m	51,713.10
Sundries				Handrails	163	m	15,696.90
Joints	200	m	3,360.00	Balustrade to main stairwells	531	m	198,859.50
Reinforcement							
Rebar	153	Tn	114,220.62				**266,269.50**
Formwork							
				Roof Completions			
Walls	6,468	m2	239,962.80				
Ramps	520	m2	19,292.00	Stucco or similar rooflights	16	No	158,874.88
Lift pits	345	m2	12,799.50	Latchway	1	item	50,000.00
Door opgs	16	Nr	1,865.60				
(changed substantially from block to concrete walls therefore claiming							**208,874.88**
blockwork to offset cost of change)				**Wall finishes Externally**			
215mm block walls	450	m2	23,791.50				
100mm block walls	1,200	m2	38,376.00	External applied finish to courtyard	808	m2	77,810.40
EO for exposed blockwork	1,650	m2	8,992.50	Ext. angles	300	m	2,601.00
Bonding	500	m	3,900.00	Stops	100	m	696.00
Bonding	200	m	1,560.00	Plaster to walls	1,320	m2	29,238.00
Bonding	500	m	3,900.00	Ditto bellcast	1,090	m	6,256.60
DPC	1	item	1,590.00				**116,602.00**
				Wall finishes internally			
			570,934.81				
Floors							
				Plaster to walls	1,820	m2	49,449.40
Concrete Work				Ditto >300mm	31,282	m2	633,773.32
40N suspended slab	2,490	m3	304,228.20	Drylining to walls	7,000	m2	428,750.00
Attached beams	850	m3	132,991.00	Plaster to walls	1,950	m2	57,154.50
Downstands for tree bases	55	no	81,885.10	Ditto >300mm	16,530	m2	370,272.00
				ditto to beams	1,820	m2	49,449.40
Sundries				reveals	2,229	m2	65,331.99
Longitudinal joints	1,000	m	26,500.00	Plaster stops	18,036	m	69,077.88
Sealant	1,000	m	7,100.00	Painting to reveals	7,795	m2	45,912.55
Movement joints	1,500	m	63,570.00	Painting to walls	51,632	m2	304,112.48
Powerfloating	8,300	m2	36,271.00	Painting to walls	31,411	m2	185,010.79
				Allowance for narrow widths, casings, boxing outs	1	item	80,250.00
Reinforcement							**2,338,544.31**
Rebar	668	tn	498,688.72				

Description	Qty	Unit	Total
Formwork			
Soffits of slabs	7,000	m2	296,800.00
Beams	3,445	m2	164,326.50
edges of slab	520	no	13,780.00
opgs in slab	13	no	1,791.40
opgs in slab	25	m2	1,802.00
holes for pipes	50	nr	2,385.00
holes for pipes	50	nr	2,915.00
Sundries			
Additional cost of substructure for increased loadings	1	Item	156,000.00
			1,791,033.92
Stairs and Ramps			
Concrete Work			
Suspended slabs	120	m3	14,661.60
Upstand kerbs	27	m3	3,298.86
Powerfloating	400	m2	1,748.00
Reinforcement			
Rebar	30	tn	22,396.20
Formwork			
Soffits	400	m2	38,160.00
Edges 250-500	149	m	3,948.50
edges 100-250	327	m	6,932.40
250 -500 upstands	298	m	7,897.00
holes 55-110	20	no	954.00
holes >110	20	no	1,166.00
Precast Concrete			
Stairs - 1100 wide	10	no	20,754.80
Stairs - 2200 wide	1	no	4,290.88
Angles	1	item	3,180.00
			129,388.24
Frame			
Concrete			
Columns	56	m3	9,177.28
Reinforcement			
Rebar	14	Tn	10,451.56
Formwork			
Columns	573	m2	39,479.70
Chamfers	2,900	m	27,666.00
			86,774.54
Internal Wall Completions			
Architraves	984	m	8,118.00
Storage doors	27	No	6,068.25
E.O. for fire	27	No	12,798.00
Corridor/lobby doors	54	No	13,060.98
Corridor/lobby doors	1	No	483.74
E.O. for viewing panel	56	No	4,494.00
Frames	492	m	14,912.52
Supply Ironmongery	1	item	18,725.00
Hinges	249	Nr	3,468.57
Door closers	83	Nr	2,313.21
Mortice locks	82	Nr	2,285.34
Pull handles	83	Nr	578.51
Finger plates	82	Nr	571.54
Kicking plates	83	Nr	693.88
signs	54	Nr	376.38
Painting frames	492	m	2,897.88
Painting architraves	983	m	3,686.25
Painting doors	409	m2	4,813.93
Allowance for plant doors	1	item	10,700.00
			111,045.98
Stair Completions			
Sloping Balustrade	36	m	10,593.00

Description	Qty	Unit	Total
Floor Finishes			
MDF Skirting	27,534	m	316,916.34
Corridor Floor Finish - vinyl	1,660	m2	106,572.00
Stone tiling to entrance lobbies	500	m2	50,825.00
Skirting to entrance lobbies	450	m	21,667.50
Acoustic matting	25,372	m2	418,130.56
Matwells	19	no	40,663.61
Labours	1	item	26,750.00
Floor Tiling (claiming to cover cost of high spec lobby finishes)	298	no	74,500.00
			1,056,025.01
Stairs Finishes			
Floor Finishes			
Vinyl to landings	280	m2	28,462.00
Vinyl to threads/risers	583	m	28,071.45
Circular cutting	44	m	423.72
Skirting	245	m	6,553.75
Skirting Curved	57	m	2,744.55
Skirting to steps	135	m	13,722.75
Carpet/Linoleum	526	m2	28,141.00
Carpet/Linoleum to threads/risers	2,160	m	57,780.00
nosings	1,152	m	55,468.80
circular cutting to tiles	182	m	778.96
Skirtings	495	m	13,241.25
Ditto curved	182	m	8,763.30
Skirtings to profile of steps	375	m	10,031.25
Skirtings to open end of stairs	548	m	20,522.60
Wall Finishes			
Plaster to walls	176	m2	4,781.92
ditto >300mm	3,734	m2	67,660.08
Drylining to precast	896	m2	9,587.20
Curved work	930	m2	34,828.50
drylining curved stairs	930	m2	19,902.00
angles	2,727	m	10,882.26
Painting to reveals	176	m2	1,036.64
Painting to walls	3,734	m2	21,993.26
Painting to curved walls	930	m2	5,477.70
Ceiling Finishes			
Plaster to ceilings	1,479	m2	28,389.39
>300mm	652	m2	17,449.23
Painting to ceilings	2,132	m2	12,555.67
Allowance for labours	1	item	42,800.00
Allowance for finishes ground floor lobby	1	item	53,500.00
			605,549.23
Ceiling Finishes			
MF system to ceilings	24,442	m2	1,046,117.60
E.O. for moisture resistant plasterboard	2,000	m2	7,500.00
Boxing in	1,500	m	44,940.00
Painting to ceilings	24,442	m2	143,963.38
Labours	1	item	37,450.00
			1,279,970.98
Roof Finishes			
Screed laid to fall on roof	4,337	m2	79,670.69
Sheet Coverings			
Roof covering	4,337	m2	300,727.58
Ditto to balconies	445	m2	30,856.30
Upstands	1,524	m	19,568.16
Upstands to balconies	750	m	9,630.00
Cutting around openings	350	No	24,342.50
Flashings	1,524	m	73,380.60
Flashings	750	m	36,112.50
Finishes to penthouse roof (balau)	450	m2	50,395.50
Ditto to terraces (balau)	445	m2	49,835.55
Railings to roof	200	m	53,500.00

Description	Qty	Unit	Total	Description	Qty	Unit	Total
Horzi. Balustrade	7	m	2,059.75	Allowances for outlets etc	1	item	53,500.00
E.O for ends	6	No	-	Roof outlets in slab	1	item	26,750.00
Bends	27	No	-	Allowances for screenings at roof level	1	item	48,150.00
Sloping handrail	50	m	4,681.50				
Horiz. Handrail	15	m	1,284.00				**856,419.38**
E.O for ends	12	No	-	**Mechanical Installation**			
Painting balustrades	126	m2	1,685.88				
Painting handrails	65	m	208.65	Mechanical installation	298	No	3,284,258.00
				Distribution system/Ventilation			765,841.00
			20,512.78	Controls			345,943.00
Floor, Wall and Ceiling Finishes				Combination unit			625,412.00
Dust sealer to basement	8,700	m2	67,686.00	Plumbing (incl rising mains)			698,562.00
ditto to slopes	400	m2	3,112.00	Wastes and soils			848,500.00
Floor finish to lift lobby	250	m2	14,592.50				3,284,258.00
Ditto skirtings	275	m	6,688.00	Builders work	298	No	328,425.80
Matwells (replaced by floor finish)	16	No	7,781.92				**3,612,683.80**
Carparking lines 100mm wide	1,600	m	2,832.00				
Letters	30	No	1,219.80	Lift installation	16	no	941,600.00
Letters	24	No	975.84	Builders work	16	no	17,120.00
Letters	469	No	1,758.75	EO for fire lifts (Dry risers complete)	5	no	250,000.00
Letters	3	No	144.45				**1,208,720.00**
Letters	6	No	288.90	**Electrical Installation**			
Letters	1	item	2,675.00				
Insulation				Electrical Installation	298	No	2,739,832.86
"Kingspan Kooltherm K10" fixed to				Main and Sub-board installation			352,415.00
basement soffit (Under living areas)				Sub-distribution			390,000.00
Soffits of slabs	5,200	m2	68,432.00	Trunking and trays			198,089.00
Sides of beams	750	m2	9,870.00	Consumer unit and general services			925,500.00
Holes < 150mm	100	Nr	1,605.00	Lighting installation			535,356.86
Holes > 150mm	100	Nr	1,605.00	Emergency lighting			55,041.00
Plaster to walls in lift lobby	245	m2	4,963.70	Fire detection and alarm			149,520.00
Painting walls in lift lobby	245	m2	1,443.05	IT and Data installation			63,589.00
Plaster to ceilings	300	m2	6,078.00	Electro-mechanical installation			59,760.00
Ditto sloping	150	m2	4,012.50	Earthing and bonding			10,562.00
Paint ceilings	300	m2	1,767.00				2,739,832.86
Ditto sloping	150	m2	883.50				
Additional finishes in lobbies	1	item	34,240.00	Builders work	298	No	239,145.00
Sealing plant rooms	1	item	10,094.34	EO for increased quantity	1	item	8,560.00
			254,749.25				**2,987,537.86**
Storage, Screening Fittings				**Prefabricated Pods**			
Impact barriers (excluded replaced by extra lighting)	1	item	10,700.00				
Impact barriers	1	item	10,700.00	Bathrooms Pods	516	No	3,253,070.40
Signage	1	item	10,700.00				
Bicycle racks	5	No	2,675.00				
bike rack	1	item	5,350.00	**Sanitary Fittings**			
Sliding gates	1	item	10,700.00				
				WHB	36	No	7,704.00
			50,825.00	WC Pan	36	No	9,630.00
Mechanical Installation				Mirrors etc	36	No	5,778.00
Mechanical Installation basement area	1	item	243,181.82				**23,112.00**
Builders work	1	item	24,318.18	Surface water	item		260,094.71
Extra over for retail units	1	item	51,589.29	Foul water	item		138,424.26
Add. costs for sliding gates	1	item		Watermain	item		46,522.07
			16,050.00				
				Gas supply	item		31,999.12
			335,139.29	Services	item		172,619.82
Electrical Installation							**649,659.98**
Electrical installation	1	Item	121,590.91	**Siteworks**			
Builders work	1	Item	12,159.09				
Extra for retail units	1	item	51,589.29	Break up, remove pathways, pavings	2,200	m2	33,066.00
				ditto kerbing	350	m	8,767.50
			185,339.29	ditto road surface	450	m2	4,509.00
				Existing light poles	1	item	2,675.00
Superstructure				Filling in to make up levels	5,320	m3	175,879.20
				Precast concrete paviours	2,128	m2	95,951.52
External Walls				Eden Granite to courtyard areas	3,460	m2	191,303.40
				Threads	203	m	5,430.25
Parapet/Copings	1,576	m	274,491.92	Risers	227	m	6,072.25
Blockwork			89,780.09	Flexible waterproofing membrane	1,010	m2	22,583.60
Blockwork			32,030.00	Granite paving	1,000	m2	247,470.00
Blockwork			32,030.00	Mastic pointing	1,480	m	12,668.80
EO for blockwork			22,508.09	Courtyard waterproofing system	3,950	m2	401,517.50

Description	Qty	Unit	Total
Ancon			1,804.52
Forming cavities			25,198.97
Closing cavities			11,265.00
Techcrete precast panels			1,700,000.00
Fixings etc.			300,000.00
Techcrete precast panels	1	item	1,798,900.00
xtra for glass balustrade	175	m	140,437.50
			4,428,446.09
Internal Walls			
Lintels			5,998.47
Blockwork			1,004,909.22
Blockwork			141,060.12
EO on blockwork			55,093.83
EO on blockwork			141,657.30
EO on blockwork			35,342.10
Ancon			112,747.04
Total for internal walls structure			1,496,808.08
Stud Partitions			
Partitions 2700mm high	15,761	m2	910,670.58
E.O for insulation	15,761	m2	126,560.83
E.O. for moisture board	8,246	m2	22,099.28
Abutments	6,480	m	40,564.80
Forming opgs	1,255	nr	40,285.50
angle beads	17,690	m	56,784.90
Boxing out	1,000	m	69,550.00
Filling gap at pods	2,810	m	75,167.50
Packing tops of walls	5,229	m	55,950.30
			2,894,441.77
Floors			
Screed to slabs ne 150mm	2,134	m3	248,269.56
Transfer floor - 2nd floor			
Suspended slabs 150-300mm	1,158	m3	134,721.72
Suspended slabs 450-600mm	1,700	m3	197,778.00
Powerfloating	24,991	m2	115,208.51
Mesh in screed	17,048	m2	65,634.80
Bar rebar in suspended slabs	548	Tn	412,961.84
F/W to edges fo slab >500mm	441	m2	23,593.50
F/W to edges fo slab 250-500mm	1,365	m	51,119.25
FW to edges <250	3,551	m	94,989.25
Formwork soffit < 300mm thick	4,565	m2	190,497.45
Formwork soffit < 500mm thick	3,390	m2	181,365.00
Holes for pipes 55-110mm	550	Nr	26,482.50
Holes for pipes >110mm	275	Nr	16,183.75
Design joints	1	item	32,100.00
Forming recess for bathroom pods	1	item	39,376.00
Floor slabs	17,013	m2	759,970.71
Edge filling	4,085	m2	183,498.20
Allowance for opgs	item		5,885.00
Raking cutting		m2	8,025.00
			2,787,660.04
Stairs			
Screed to landings	173	m3	20,126.82
Rebar	26	tn	19,593.08
FW to soffits of landings	692	m2	55,533.00
FW to edges 250-500mm	1,356	m	50,782.20
FW to edges 250-500mm - curved	181	m	13,556.90
Powerfloat	692	m2	3,190.12
Staircases	203	No	225,790.81
Staircases	1	No	1,853.78
Softwood staircases	1	No	1,926.00
Staircases	35	No	67,410.00
Softwood staircases	6	No	12,840.00
Steel angles for stairs	item		16,050.00
			488,652.71

Description	Qty	Unit	Total
Linemarking	1	item	1,459.09
Granite Kerbing	812	m	122,035.48
Ditto curved	120	m	21,039.60
35N in retaining walls	228	m3	27,841.08
Rebar to above	46	tn	34,664.68
Formwork to wall	1,518	m2	48,727.80
Blockwork to external walls (concrete)	392	m2	25,111.52
Stone walling to wall facades	1,015	m2	279,683.25
Coping to walls	300	m	49,971.00
Concrete ramps incl balustrade 19000*2000m	2	No	9,016.24
Concrete ramps incl balustrade 19000*2000m	1	No	438.17
Concrete ramps incl balustrade 19000*2000m	2	No	1,887.48
Concrete external stairs	3	No	6,066.90
Concrete external stairs	2	No	2,696.40
Concrete external stairs	1	No	4,470.03
Concrete external stairs	1	No	7,793.88
Concrete external stairs	3	No	5,561.34
Concrete external stairs	1	No	1,898.72
Concrete external stairs	1	No	8,089.20
Mild steel balustrades to ramps	136	m	40,382.48
Ditto as above	226	m	67,106.18
Louvred Ventilation grilles	250	m2	133,750.00
Mild steel sloping balustrade	30	m	8,827.50
Mild steel sloping handrail	215	m	15,643.40
Mild steel railings	103	m	25,348.30
Pedestrian gates	4	no	4,708.00
Ditto as above	1	no	1,845.75
Vehicular gates	2	no	3,691.50
Small retaining walls in courtyard	172	m	50,518.12
Granite bollards	45	m	16,828.65
Granite seating	149	m	67,598.32
Tree grilles	54	no	72,225.00
Bollards	6	No	3,852.00
Bicycle racks			3,745.00
litter bins			3,745.00
Forming tree pits	54	no	11,556.00
Tree planting	1	item	72,954.55
Sprinkler system	1	item	5,350.00
Sprinkler system	1	item	3,210.00
Screen walls	1	item	80,250.00
Patio Gardens	34	No	145,520.00
Patio Gardens	1	No	4,815.00
Patio Gardens	3	No	19,260.00
Patio Gardens	1	No	3,210.00
Painting balustrades	66	m2	776.82
Painting handrail	215	m	1,266.35
Painting railings	473	m2	5,567.21
			2,767,862.53

Appendix III. Irish Input-Output Tables and Leontief Inverse

2005 Symmetric Input-Output Table of domestic product flows €m

	NACE	1-5	10-13	14	15	16	17	18	19	20
	products	Agriculture, forestry and fishing	Coal, peat, petroleum and metal ore extraction	Other mining and quarrying	Manufacture of food and beverages	Tobacco products	Textiles	Wearing apparel	Leather and leather products	Wood and wood products (excl furniture)
NACE	*products*									
1 - 5	Agriculture, forestry and fishing	1,424	0	0	3,993	2	1	0	0	107
10 - 13	Coal, peat, petroleum and metal ore extraction	1	49	6	1	-	0	0	0	0
14	Other mining and quarrying	25	2	117	0	-	0	0	-	0
15	Manufacture of food and beverages	525	-	-	917	-	0	-	-	0
16	Tobacco products	0	-	-	-	2	-	-	-	-
17	Textiles	1	0	0	0	-	10	3	0	0
18	Wearing apparel	0	0	0	0	-	0	2	-	0
19	Leather and leather products	0	0	-	0	-	0	-	0	0
20	Wood and wood products (excl furniture)	1	1	0	10	1	0	0	-	127
21	Pulp, paper and paper products	2	0	0	91	2	1	0	0	2
22	Printed matter and recorded media	13	0	0	1	0	0	0	0	1
23&36	Petroleum and other manufacturing products	45	2	12	25	0	1	0	0	2
24	Chemical products and man-made fibres	48	1	1	1	0	3	0	0	5
25	Rubber and plastics	3	1	1	57	0	0	0	0	2
26	Other non-metallic mineral products	2	1	26	24	-	0	-	-	0
27	Basic metals	0	0	0	5	-	0	0	-	1
28	Fabricated metal products	47	5	2	45	0	1	1	0	19
29	Machinery and equipment n.e.c.	6	1	0	2	0	0	0	0	1
30	Office machinery and computers	0	0	0	0	-	0	-	-	0
31	Electrical machinery and apparatus n.e.c.	0	0	0	0	-	0	0	0	0
32	Radio, television and communications apparatus	0	0	0	0	-	0	-	-	0
33	Medical, precision and optical instruments	0	0	0	0	-	0	0	0	0
34	Motor vehicles and trailers	0	0	0	0	-	0	0	-	0
35	Other transport equipment	0	-	-	0	-	0	0	-	0
37	Recycling	0	-	0	9	-	-	0	0	4
40	Electricity and gas	93	24	21	174	1	5	1	0	29
41	Water collection and distribution	5	0	0	10	0	1	0	-	3
45	Construction work	77	16	20	17	0	0	0	0	13
50	Motor fuel and vehicle trade and repair	29	7	6	13	0	0	0	0	1
51	Wholesale trade	362	15	32	482	2	13	5	1	45
52	Retail trade and repair of household goods	0	-	0	-	-	0	-	0	0
55	Hotel and restaurant services	43	2	12	133	4	4	2	1	10
60	Land transport services	18	29	178	352	2	7	2	1	41
61	Water transport services	5	0	2	4	0	0	0	0	0
62	Air transport services	2	2	24	67	2	1	0	0	-
63	Auxiliary transport services and travel agencies	6	0	1	5	1	0	0	0	0
64	Post and telecommunication services	32	1	6	69	3	3	1	0	8
65	Financial intermediation services	176	34	26	383	3	7	3	1	6
66	Insurance and pension services	115	12	15	55	5	5	4	1	12
67	Services auxiliary to financial intermediation	0	3	2	37	0	1	0	0	1
70	Real estate services	13	1	0	5	1	0	0	0	1
71	Renting services of machinery and equipment	12	2	58	19	0	0	1	0	4
72	Computer and related services	3	15	9	32	4	3	0	1	6
73	Research and development services	2	0	0	7	-	1	0	0	2
74	Other business services	28	48	2	671	3	6	16	1	40
75	Public administration and defence	43	1	1	9	0	1	1	0	2
80	Education	0	0	-	1	0	0	0	0	0
85	Health and social work services	93	0	-	8	0	0	0	0	0
90	Sewage and refuse disposal services	4	1	1	36	1	2	2	1	8
91	Membership organisation services n.e.c.	13	-	0	1	0	-	0	-	-
92	Recreation	8	0	1	12	0	1	0	0	0
93	Other services	7	5	5	18	0	1	0	0	3
95	Private households with employed persons	-	-	-	-	-	-	-	-	-
	Intermediate consumption	3,337	285	587	7,804	40	82	48	10	503
	Imports	1,316	111	52	4,968	39	135	91	9	249
	Product taxes less subsidies	-94	7	27	-402	1	3	2	0	4
	Total consumption at purchasers' prices	4,559	403	666	12,369	80	220	142	20	757
	Compensation of employees	462	147	67	1,537	29	122	46	6	235
	net operating surplus	2,775	114	21	2,375	102	15	11	3	139
	Consumption of fixed capital	691	20	2	251	11	20	11	1	41
	Non-product taxes less subsidies	-1,287	6	6	87	1	4	3	-0	7
	Value added	2,641	288	96	4,250	142	161	71	10	422
	Total inputs (=Total outputs column)	7,200	690	762	16,619	221	381	213	29	1,179

NACE	products	21	22	23, 36	24	25	26	27	28	29
	products	Pulp, paper and paper products	Printed matter and recorded media	Petroleum and other manufacturing products	Chemical products and man-made fibres	Rubber and plastics	Other non-metallic mineral products	Basic metals	Fabricated metal products	Machinery and equipment n.e.c.
NACE	*products*									
1 - 5	Agriculture, forestry and fishing	0	1	0	9	0	0	0	0	0
10 - 13	Coal, peat, petroleum and metal ore extraction	-	0	35	4	0	5	68	0	0
14	Other mining and quarrying	-	0	1	17	0	78	7	0	0
15	Manufacture of food and beverages	0	0	0	39	1	0	-	0	0
16	Tobacco products	-	-	-	0	-	-	0	-	-
17	Textiles	1	1	1	0	0	0	0	0	0
18	Wearing apparel	0	0	0	0	0	0	-	0	0
19	Leather and leather products	-	0	0	0	0	0	-	0	0
20	Wood and wood products (excl furniture)	1	1	77	1	10	3	0	1	0
21	Pulp, paper and paper products	64	57	7	32	2	8	0	2	1
22	Printed matter and recorded media	8	401	1	16	0	1	0	0	1
23&36	Petroleum and other manufacturing products	0	1	135	3	8	10	14	0	0
24	Chemical products and man-made fibres	3	9	0	382	10	4	2	1	0
25	Rubber and plastics	4	1	27	22	93	4	0	4	8
26	Other non-metallic mineral products	0	4	36	7	14	238	0	10	4
27	Basic metals	0	1	11	1	4	7	1	76	4
28	Fabricated metal products	2	2	25	18	35	20	8	91	103
29	Machinery and equipment n.e.c.	1	1	0	6	2	2	1	4	3
30	Office machinery and computers	0	1	0	0	0	0	0	0	0
31	Electrical machinery and apparatus n.e.c.	0	0	1	0	0	0	0	0	0
32	Radio, television and communications apparatus	0	0	0	0	0	0	0	0	1
33	Medical, precision and optical instruments	0	0	0	1	0	0	0	0	0
34	Motor vehicles and trailers	0	0	0	0	0	0	0	0	0
35	Other transport equipment	0	0	0	0	0	0	0	0	0
37	Recycling	5	-	0	-	-	-	28	12	-
40	Electricity and gas	8	8	17	134	36	83	27	15	15
41	Water collection and distribution	1	16	2	30	1	1	5	1	6
45	Construction work	1	8	5	11	2	0	1	5	2
50	Motor fuel and vehicle trade and repair	1	1	2	5	3	4	4	2	1
51	Wholesale trade	12	24	76	267	56	114	28	67	72
52	Retail trade and repair of household goods	0	-	0	-	-	-	0	0	-
55	Hotel and restaurant services	9	44	25	90	23	19	3	15	18
60	Land transport services	17	34	26	10	41	66	3	29	24
61	Water transport services	0	1	0	1	1	1	0	0	0
62	Air transport services	3	63	12	103	7	26	6	7	5
63	Auxiliary transport services and travel agencies	0	2	2	3	2	2	0	1	0
64	Post and telecommunication services	4	16	9	26	23	32	2	12	14
65	Financial intermediation services	8	138	28	315	2	79	17	62	58
66	Insurance and pension services	12	57	29	133	32	25	5	19	27
67	Services auxiliary to financial intermediation	1	9	3	28	0	7	2	6	5
70	Real estate services	1	4	1	2	3	1	0	1	0
71	Renting services of machinery and equipment	1	6	2	10	5	19	1	16	3
72	Computer and related services	6	37	20	544	15	11	0	10	8
73	Research and development services	1	17	1	18	4	2	1	3	2
74	Other business services	26	107	92	83	91	102	9	43	9
75	Public administration and defence	1	1	4	6	2	3	2	4	2
80	Education	0	0	0	4	0	0	0	0	0
85	Health and social work services	0	3	2	46	2	1	0	2	2
90	Sewage and refuse disposal services	1	1	1	12	4	3	11	27	0
91	Membership organisation services n.e.c.	0	1	0	1	1	-	0	0	0
92	Recreation	1	3	1	11	1	3	0	1	1
93	Other services	4	2	4	4	5	7	0	6	3
95	Private households with employed persons	-	-	-	-	-	-	-	-	-
	Intermediate consumption	207	1,082	723	2,455	541	992	258	557	406
	Imports	191	8,322	1,586	17,525	430	325	217	635	719
	Product taxes less subsidies	2	134	19	516	19	27	25	6	8
	Total consumption at purchasers' prices	400	9,538	2,327	20,496	990	1,345	500	1,198	1,133
	Compensation of employees	163	602	360	1,528	401	444	112	515	455
	net operating surplus	56	2,736	47	8,712	153	317	83	262	310
	Consumption of fixed capital	3	78	63	838	57	176	25	76	64
	Non-product taxes less subsidies	5	10	10	50	9	20	6	37	47
	Value added	227	3,425	480	11,128	619	957	225	890	876
	Total inputs (=Total outputs column)	627	12,963	2,806	31,625	1,609	2,302	726	2,088	2,009

NACE	*products*	30 Office machinery and computers	31 Electrical machinery and apparatus n.e.c.	32 Radio, television and communi cations apparatus	33 Medical, precision and optical instruments	34 Motor vehicles and trailers	35 Other transport equipmen t	37 Recycling	40 Electricit y and gas	41 Water collection and distributi on
1 - 5	Agriculture, forestry and fishing	3	1	0	0	0	0	0	0	-
10 - 13	Coal, peat, petroleum and metal ore extraction	0	0	0	0	0	0	-	50	0
14	Other mining and quarrying	-	0	0	0	0	0	-	-	-
15	Manufacture of food and beverages	-	0	0	1	0	-	-	3	0
16	Tobacco products	-	-	-	-	-	-	-	-	-
17	Textiles	0	0	0	0	0	0	-	-	-
18	Wearing apparel	0	0	0	0	-	-	-	-	-
19	Leather and leather products	0	0	0	0	-	0	-	-	-
20	Wood and wood products (excl furniture)	0	0	2	1	0	0	-	0	0
21	Pulp, paper and paper products	2	0	4	5	0	0	0	1	0
22	Printed matter and recorded media	11	0	5	3	0	0	0	12	4
23&36	Petroleum and other manufacturing products	1	1	1	1	0	0	0	168	1
24	Chemical products and man-made fibres	5	1	14	15	0	0	0	1	1
25	Rubber and plastics	1	4	5	48	5	1	0	0	1
26	Other non-metallic mineral products	1	1	4	1	0	0	-	0	0
27	Basic metals	2	1	1	5	8	3	6	0	0
28	Fabricated metal products	26	6	25	24	11	0	0	19	1
29	Machinery and equipment n.e.c.	2	0	6	3	1	0	0	2	1
30	Office machinery and computers	225	2	6	1	0	0	-	1	0
31	Electrical machinery and apparatus n.e.c.	44	59	25	18	5	3	-	4	0
32	Radio, television and communications apparatus	145	20	248	13	28	0	-	1	0
33	Medical, precision and optical instruments	0	0	5	130	0	0	-	1	0
34	Motor vehicles and trailers	0	0	0	0	1	0	-	0	0
35	Other transport equipment	0	0	0	0	0	1	-	-	-
37	Recycling	0	-	-	-	0	-	5	0	-
40	Electricity and gas	6	12	55	25	4	5	1	952	19
41	Water collection and distribution	0	0	1	6	9	0	0	-	4
45	Construction work	2	16	15	2	0	4	0	25	18
50	Motor fuel and vehicle trade and repair	2	7	6	1	11	1	0	0	2
51	Wholesale trade	120	31	67	68	32	6	4	131	6
52	Retail trade and repair of household goods	-	0	-	-	0	-	-	0	0
55	Hotel and restaurant services	63	13	5	40	8	3	-	4	3
60	Land transport services	89	18	4	13	6	1	7	0	1
61	Water transport services	1	0	0	0	0	0	0	0	-
62	Air transport services	24	17	34	14	6	2	-	0	-
63	Auxiliary transport services and travel agencies	2	3	26	5	0	1	-	0	1
64	Post and telecommunication services	5	10	1	19	5	0	-	8	4
65	Financial intermediation services	64	15	14	14	13	5	2	135	6
66	Insurance and pension services	10	15	16	42	10	6	3	1	6
67	Services auxiliary to financial intermediation	5	1	1	1	1	0	0	13	0
70	Real estate services	0	1	0	2	1	0	0	1	4
71	Renting services of machinery and equipment	0	2	5	1	0	0	0	10	4
72	Computer and related services	41	87	27	31	4	0	2	16	8
73	Research and development services	17	12	24	48	2	0	0	-	1
74	Other business services	126	28	14	62	17	3	2	41	49
75	Public administration and defence	3	2	2	3	1	1	0	2	0
80	Education	1	0	2	0	0	0	-	0	1
85	Health and social work services	7	2	8	5	0	0	-	3	0
90	Sewage and refuse disposal services	0	0	0	1	1	0	-	19	10
91	Membership organisation services n.e.c.	0	0	0	1	0	0	-	0	1
92	Recreation	9	1	4	6	0	1	-	1	0
93	Other services	1	2	1	2	1	1	1	1	0
95	Private households with employed persons	0	-	-	-	-	-	-	-	-
	Intermediate consumption	1,065	392	683	679	193	50	34	1,626	158
	Imports	10,918	956	1,965	2,326	259	162	37	992	29
	Product taxes less subsidies	129	19	6	32	23	3	0	36	4
	Total consumption at purchasers' prices	12,112	1,366	2,654	3,037	475	214	71	2,655	190
	Compensation of employees	343	276	392	784	128	213	12	582	90
	net operating surplus	386	24	1,042	1,389	16	12	7	310	1
	Consumption of fixed capital	108	19	192	279	36	14	4	564	1
	Non-product taxes less subsidies	2	46	27	1	2	4	1	12	0
	Value added	839	365	1,653	2,453	182	243	25	1,468	92
	Total inputs (=Total outputs column)	12,952	1,732	4,307	5,491	657	457	97	4,122	283

NACE	*products*	45 Construction work	50 Motor fuel and vehicle trade and repair	51 Wholesale trade	52 Retail trade and repair of household goods	55 Hotel and restaurant services	60 Land transport services	61 Water transport services	62 Air transport services	63 Auxiliary transport services and travel agencies
NACE	*products*									
1 - 5	Agriculture, forestry and fishing	63	0	2	9	236	0	2	0	0
10 - 13	Coal, peat, petroleum and metal ore extraction	0	0	0	0	0	0	-	0	0
14	Other mining and quarrying	372	0	1	0	2	0	0	0	3
15	Manufacture of food and beverages	5	1	4	38	1,290	1	1	4	6
16	Tobacco products	0	0	0	0	2	-	-	-	-
17	Textiles	9	0	0	2	2	0	0	0	0
18	Wearing apparel	1	0	0	0	0	0	-	0	0
19	Leather and leather products	1	1	0	0	1	0	0	0	0
20	Wood and wood products (excl furniture)	447	0	0	2	7	0	0	0	1
21	Pulp, paper and paper products	18	0	3	4	7	1	0	0	1
22	Printed matter and recorded media	170	6	7	15	32	5	0	3	16
23&36	Petroleum and other manufacturing products	149	7	26	13	25	67	4	87	14
24	Chemical products and man-made fibres	36	0	1	2	3	0	0	0	0
25	Rubber and plastics	298	7	10	7	3	10	0	1	3
26	Other non-metallic mineral products	1,395	2	11	4	4	2	0	1	1
27	Basic metals	37	0	0	1	0	1	0	0	0
28	Fabricated metal products	774	4	2	4	2	5	0	0	1
29	Machinery and equipment n.e.c.	33	1	0	1	0	0	0	0	0
30	Office machinery and computers	5	0	0	0	0	0	0	0	0
31	Electrical machinery and apparatus n.e.c.	127	0	0	1	0	2	0	0	0
32	Radio, television and communications apparatus	17	0	1	0	0	1	0	0	1
33	Medical, precision and optical instruments	10	0	0	0	0	0	0	0	0
34	Motor vehicles and trailers	1	2	0	0	0	1	0	0	0
35	Other transport equipment	1	0	0	0	0	0	0	2	0
37	Recycling	19	-	-	-	-	0	0	0	0
40	Electricity and gas	131	20	42	127	158	13	1	7	21
41	Water collection and distribution	22	1	3	4	6	0	0	0	1
45	Construction work	10,062	2	8	24	29	3	0	2	41
50	Motor fuel and vehicle trade and repair	66	42	16	13	18	32	2	8	13
51	Wholesale trade	1,153	14	14	54	725	45	3	78	19
52	Retail trade and repair of household goods	0	0	0	0	0	5	0	0	0
55	Hotel and restaurant services	114	8	15	272	103	20	5	102	67
60	Land transport services	89	34	135	84	64	95	7	3	117
61	Water transport services	3	4	12	1	14	1	54	15	25
62	Air transport services	12	5	9	6	32	3	1	217	82
63	Auxiliary transport services and travel agencies	17	32	300	74	137	215	54	210	423
64	Post and telecommunication services	62	39	114	104	198	17	5	27	51
65	Financial intermediation services	327	49	78	153	142	56	6	61	152
66	Insurance and pension services	51	52	129	128	125	25	4	68	43
67	Services auxiliary to financial intermediation	25	1	5	12	8	2	2	11	2
70	Real estate services	648	44	126	411	176	20	5	31	54
71	Renting services of machinery and equipment	580	16	17	38	48	115	1	23	47
72	Computer and related services	152	29	74	85	78	88	12	97	166
73	Research and development services	15	0	12	3	2	4	1	3	5
74	Other business services	1,179	117	39	335	577	121	10	23	220
75	Public administration and defence	239	8	11	37	24	65	1	1	3
80	Education	3	0	1	2	18	2	0	1	14
85	Health and social work services	18	1	4	4	28	2	0	3	2
90	Sewage and refuse disposal services	192	10	26	44	55	4	1	5	8
91	Membership organisation services n.e.c.	1	0	0	0	9	1	0	1	3
92	Recreation	7	1	5	6	62	5	0	7	31
93	Other services	2	1	1	1	71	3	1	12	6
95	Private households with employed persons	-	-	-	-	-	-	-	-	-
	Intermediate consumption	19,158	566	1,268	2,122	4,526	1,058	186	1,117	1,665
	Imports	4,978	140	701	340	1,708	305	63	840	1,819
	Product taxes less subsidies	305	66	95	67	223	275	12	215	83
	Total consumption at purchasers' prices	24,440	771	2,063	2,528	6,457	1,638	261	2,173	3,567
	Compensation of employees	9,380	839	3,804	3,303	2,177	1,365	105	375	696
	net operating surplus	4,246	559	6,492	1,742	699	399	26	263	264
	Consumption of fixed capital	351	61	715	201	347	427	27	279	280
	Non-product taxes less subsidies	24	65	268	190	119	25	4	18	30
	Value added	14,001	1,523	11,279	5,436	3,343	2,215	163	935	1,270
	Total inputs (=Total outputs column)	38,442	2,294	13,342	7,964	9,800	3,853	424	3,108	4,838

	NACE	64	65	66	67	70	71	72	73	74
	products	Post and telecommunication services	Financial intermediation services	Insurance and pension services	Services auxiliary to financial intermediation	Real estate services	Renting services of machinery and equipment	Computer and related services	Research and development services	Other business services
NACE	*products*									
1 - 5	Agriculture, forestry and fishing	0	-	-	0	4	0	0	3	1
10 - 13	Coal, peat, petroleum and metal ore extraction	0	0	0	0	0	0	0	0	0
14	Other mining and quarrying	0	-	-	0	6	-	-	0	1
15	Manufacture of food and beverages	6	3	1	3	0	0	8	2	24
16	Tobacco products	0	-	-	-	-	-	-	0	0
17	Textiles	0	0	0	0	2	0	0	0	1
18	Wearing apparel	0	0	0	0	0	0	0	0	0
19	Leather and leather products	0	0	0	0	0	0	0	0	1
20	Wood and wood products (excl furniture)	2	0	0	0	30	1	1	0	4
21	Pulp, paper and paper products	1	1	1	2	3	1	1	1	16
22	Printed matter and recorded media	14	28	13	15	16	4	21	4	193
23&36	Petroleum and other manufacturing products	6	1	3	2	4	9	12	2	31
24	Chemical products and man-made fibres	0	0	0	0	1	0	0	1	3
25	Rubber and plastics	25	1	0	1	8	1	9	1	7
26	Other non-metallic mineral products	7	0	0	0	59	0	1	0	2
27	Basic metals	1	0	0	0	-	0	1	0	0
28	Fabricated metal products	3	0	0	1	9	1	3	0	2
29	Machinery and equipment n.e.c.	1	0	0	0	1	4	1	0	2
30	Office machinery and computers	0	0	0	0	1	0	2	0	0
31	Electrical machinery and apparatus n.e.c.	13	0	0	0	1	1	8	0	2
32	Radio, television and communications apparatus	117	0	0	0	1	1	16	1	2
33	Medical, precision and optical instruments	3	0	0	0	0	0	3	0	1
34	Motor vehicles and trailers	0	0	0	0	0	1	1	0	1
35	Other transport equipment	0	0	0	0	0	0	0	0	0
37	Recycling	1	-	-	0	-	0	-	4	2
40	Electricity and gas	27	1	2	8	19	24	53	11	135
41	Water collection and distribution	1	0	0	0	1	1	2	1	4
45	Construction work	56	24	20	0	465	5	1	2	62
50	Motor fuel and vehicle trade and repair	6	5	11	2	16	69	32	3	40
51	Wholesale trade	287	8	6	8	52	20	17	7	128
52	Retail trade and repair of household goods	0	0	0	0	1	2	0	0	1
55	Hotel and restaurant services	73	15	8	11	23	10	111	6	299
60	Land transport services	51	16	11	6	10	66	53	9	97
61	Water transport services	20	1	1	2	0	3	-	-	4
62	Air transport services	56	33	11	4	8	15	10	5	171
63	Auxiliary transport services and travel agencies	57	36	19	22	37	44	7	9	203
64	Post and telecommunication services	1,586	149	43	153	89	57	401	22	490
65	Financial intermediation services	123	754	333	289	1,490	132	370	33	518
66	Insurance and pension services	17	87	30	66	236	72	241	7	148
67	Services auxiliary to financial intermediation	9	851	1,203	832	8	9	60	16	145
70	Real estate services	55	62	53	4	65	19	46	14	267
71	Renting services of machinery and equipment	16	3	4	5	11	42	102	6	84
72	Computer and related services	36	146	65	62	82	45	1,722	45	323
73	Research and development services	5	3	1	1	3	1	0	152	5
74	Other business services	265	128	188	0	618	223	1,486	174	3,025
75	Public administration and defence	10	7	4	3	91	2	7	2	89
80	Education	3	1	1	1	28	0	33	13	12
85	Health and social work services	4	4	9	2	1	1	6	5	15
90	Sewage and refuse disposal services	11	1	1	6	21	13	27	5	39
91	Membership organisation services n.e.c.	5	3	1	0	1	1	2	0	31
92	Recreation	23	9	6	3	9	6	60	2	71
93	Other services	11	7	2	2	3	22	6	7	76
95	Private households with employed persons	0	-	-	-	-	-	-	-	0
	Intermediate consumption	3,015	2,386	2,055	1,516	3,536	930	4,941	577	6,781
	Imports	1,008	3,701	6,163	597	187	1,329	4,624	49	3,533
	Product taxes less subsidies	54	289	224	109	224	64	208	12	399
	Total consumption at purchasers' prices	4,077	6,377	8,443	2,221	3,947	2,324	9,773	639	10,713
	Compensation of employees	1,532	2,636	1,344	687	339	296	1,265	286	4,605
	net operating surplus	638	4,334	1,749	1,597	7,065	2,225	1,268	63	2,860
	Consumption of fixed capital	670	871	377	347	3,398	1,080	639	30	1,438
	Non-product taxes less subsidies	39	38	30	6	1	-1	-3	0	-5
	Value added	2,879	7,878	3,501	2,637	10,803	3,600	3,168	379	8,898
	Total inputs (=Total outputs column)	6,956	14,255	11,944	4,858	14,750	5,924	12,941	1,018	19,611

NACE	*products*	75	80	85	90	91	92	93	95	
		Public administration and defence	Education	Health and social work services	Sewage and refuse disposal services	Membership organisation services n.e.c.	Recreation	Other services	Private households with employed persons	Total inter-industry
NACE	*products*									
1 - 5	Agriculture, forestry and fishing	7	35	18	-	1	2	0	-	5,925
10 - 13	Coal, peat, petroleum and metal ore extraction	9	0	-	0	0	0	0	-	231
14	Other mining and quarrying	2	0	-	4	0	1	0	-	642
15	Manufacture of food and beverages	17	1	19	3	13	9	0	-	2,946
16	Tobacco products	-	0	-	-	0	0	-	-	4
17	Textiles	1	0	3	0	0	0	0	-	38
18	Wearing apparel	1	0	0	0	0	0	0	-	6
19	Leather and leather products	0	0	-	0	0	0	0	-	7
20	Wood and wood products (excl furniture)	1	5	1	0	1	1	0	-	741
21	Pulp, paper and paper products	8	20	25	2	1	1	0	-	401
22	Printed matter and recorded media	36	82	10	12	5	14	8	-	1,206
23&36	Petroleum and other manufacturing products	37	17	60	3	1	3	3	-	1,018
24	Chemical products and man-made fibres	6	3	109	5	1	2	2	-	684
25	Rubber and plastics	10	1	63	5	1	1	1	-	765
26	Other non-metallic mineral products	17	0	2	12	2	4	0	-	1,902
27	Basic metals	1	0	-	0	0	0	0	-	180
28	Fabricated metal products	17	13	1	3	0	1	0	-	1,385
29	Machinery and equipment n.e.c.	1	0	0	0	0	0	0	-	90
30	Office machinery and computers	1	1	0	0	0	0	0	-	249
31	Electrical machinery and apparatus n.e.c.	0	0	4	0	0	0	0	-	321
32	Radio, television and communications apparatus	1	0	3	0	0	2	0	-	624
33	Medical, precision and optical instruments	2	3	36	0	0	0	0	-	200
34	Motor vehicles and trailers	0	0	0	0	0	0	0	-	11
35	Other transport equipment	0	0	0	0	0	0	0	-	7
37	Recycling	-	0	0	2	-	0	0	-	93
40	Electricity and gas	150	134	34	20	4	27	14	-	2,952
41	Water collection and distribution	1	0	-	2	9	2	1	-	164
45	Construction work	487	88	8	18	3	6	1	-	11,679
50	Motor fuel and vehicle trade and repair	25	2	2	7	2	4	5	-	550
51	Wholesale trade	83	50	266	21	11	18	9	-	5,234
52	Retail trade and repair of household goods	-	1	0	0	0	0	0	-	11
55	Hotel and restaurant services	135	63	77	8	16	23	5	-	2,187
60	Land transport services	218	29	43	37	3	6	7	-	2,308
61	Water transport services	4	0	-	10	1	2	0	-	193
62	Air transport services	30	58	21	2	4	7	2	-	1,232
63	Auxiliary transport services and travel agencies	1	5	-	16	8	13	8	-	2,009
64	Post and telecommunication services	204	69	-	26	24	26	25	-	4,292
65	Financial intermediation services	118	34	8	43	52	72	31	-	7,041
66	Insurance and pension services	29	76	57	27	2	23	10	-	2,424
67	Services auxiliary to financial intermediation	0	0	-	3	0	1	2	-	3,335
70	Real estate services	803	39	41	10	4	64	38	-	3,146
71	Renting services of machinery and equipment	10	5	-	37	4	26	25	-	1,450
72	Computer and related services	277	29	123	63	31	24	26	-	4,817
73	Research and development services	20	31	63	28	4	6	1	-	534
74	Other business services	699	234	133	133	125	155	102	-	12,026
75	Public administration and defence	25	1	14	1	3	9	7	-	761
80	Education	37	259	130	4	2	2	1	-	577
85	Health and social work services	5	4	2,726	5	2	2	6	-	3,049
90	Sewage and refuse disposal services	44	9	21	372	3	9	9	-	1,084
91	Membership organisation services n.e.c.	0	0	2	0	70	32	1	-	187
92	Recreation	72	163	0	8	82	133	6	-	844
93	Other services	9	54	17	33	11	13	69	-	526
95	Private households with employed persons	-	0	-	-	-	-	0	-	0
	Intermediate consumption	3,661	1,618	4,141	987	506	749	430	-	94,289.88
	Imports	448	229	1,661	120	45	219	58	-	89,428
	Product taxes less subsidies	562	105	210	17	10	54	12	-	4,451
	Total consumption at purchasers' prices	4,671	1,952	6,011	1,124	562	1,022	499	-	188,169
	Compensation of employees	4,850	5,816	8,100	245	351	939	442	136	65,963
	net operating surplus	0	36	1,454	58	26	558	113	0	60,155
	Consumption of fixed capital	1,382	4	56	26	12	252	51	-	16,965
	Non-product taxes less subsidies	-	30	59	14	9	17	18	-	108
	Value added	6,232	5,886	9,669	342	397	1,766	624	136	143,191
	Total inputs (=Total outputs column)	10,903	7,838	15,680	1,466	958	2,788	1,124	136	331,360

NACE	products	Household consumption expenditure	NPISH consumption expenditure	Government consumption expenditure	Gross fixed capital formation and valuables	Changes in inventories	Exports (f.o.b)	Total Final uses	Total uses
NACE	*products*								
1 - 5	Agriculture, forestry and fishing	570	-	-	-	26	678	1,275	7,200
10 - 13	Coal, peat, petroleum and metal ore extraction	124	-	-	33	14	288	459	690
14	Other mining and quarrying	-	-	-	97	-14	37	120	762
15	Manufacture of food and beverages	1,251	37	-	-	2	12,383	13,673	16,619
16	Tobacco products	124	-	-	-	-0	93	217	221
17	Textiles	26	-	-	-	25	291	342	381
18	Wearing apparel	32	-	-	-	0	175	207	213
19	Leather and leather products	17	-	-	-	3	2	22	29
20	Wood and wood products (excl furniture)	29	-	-	-	34	375	438	1,179
21	Pulp, paper and paper products	43	-	-	-	-6	188	226	627
22	Printed matter and recorded media	400	-	-	-	44	11,313	11,757	12,963
23&36	Petroleum and other manufacturing products	573	-	-	60	-17	1,173	1,788	2,806
24	Chemical products and man-made fibres	55	-	-	-	18	30,868	30,941	31,625
25	Rubber and plastics	88	-	-	-	-6	762	844	1,609
26	Other non-metallic mineral products	14	-	-	-	-12	397	399	2,302
27	Basic metals	-	-	-	-	10	535	545	726
28	Fabricated metal products	79	-	-	94	-5	536	703	2,088
29	Machinery and equipment n.e.c.	24	-	-	108	4	1,783	1,919	2,009
30	Office machinery and computers	5	-	-	30	13	12,655	12,703	12,952
31	Electrical machinery and apparatus n.e.c.	21	-	-	49	37	1,303	1,411	1,732
32	Radio, television and communications apparatus	35	-	-	57	-26	3,617	3,683	4,307
33	Medical, precision and optical instruments	2	-	-	25	2	5,262	5,291	5,491
34	Motor vehicles and trailers	52	-	-	90	1	504	646	657
35	Other transport equipment	1	-	-	58	-5	397	451	457
37	Recycling	-	-	-	-	-0	4	4	97
40	Electricity and gas	1,154	-	-	-	-	17	1,171	4,122
41	Water collection and distribution	13	-	106	-	-	-	119	283
45	Construction work	246	-	-	26,517	-	-	26,762	38,442
50	Motor fuel and vehicle trade and repair	1,261	-	-	483	-	-	1,744	2,294
51	Wholesale trade	1,420	11	0	567	55	6,055	8,108	13,342
52	Retail trade and repair of household goods	7,954	-	-	-	-	-	7,954	7,964
55	Hotel and restaurant services	5,109	-	-	-	-	2,503	7,613	9,800
60	Land transport services	1,407	-	-	-	-	138	1,545	3,853
61	Water transport services	42	-	-	-	-	188	231	424
62	Air transport services	246	-	-	-	-	1,629	1,875	3,108
63	Auxiliary transport services and travel agencies	2,476	-	-	-	-	352	2,829	4,838
64	Post and telecommunication services	2,220	-	-	-	-	443	2,663	6,956
65	Financial intermediation services	2,020	-	-	-	-	5,194	7,214	14,255
66	Insurance and pension services	2,611	-	-	-	-	6,909	9,520	11,944
67	Services auxiliary to financial intermediation	623	-	-	-	-	900	1,523	4,858
70	Real estate services	11,134	-	-	470	-	-	11,604	14,750
71	Renting services of machinery and equipment	234	-	-	-	-	4,240	4,474	5,924
72	Computer and related services	-	-	-	402	-	7,722	8,123	12,941
73	Research and development services	-	-	150	-	-	333	484	1,018
74	Other business services	280	-	-	2,517	-	4,788	7,585	19,611
75	Public administration and defence	74	-	9,967	66	-	36	10,142	10,903
80	Education	705	2,071	4,485	-	-	-	7,260	7,838
85	Health and social work services	2,014	533	10,084	-	-	-	12,631	15,680
90	Sewage and refuse disposal services	270	-	112	-	-	-	382	1,466
91	Membership organisation services n.e.c.	310	461	-	-	-	-	772	958
92	Recreation	1,427	-	-	155	-	363	1,944	2,788
93	Other services	519	-	-	-	-	79	598	1,124
95	Private households with employed persons	136	-	-	-	-	-	136	136
	Intermediate consumption	49,471	3,113	24,904	31,876	198	127,508	237,070	331,360
	Imports	10,547	42	-	7,317	626	4,860	23,391	112,819
	Product taxes less subsidies	10,605	-	-	3,921	-	-	14,526	18,977
	Total consumption at purchasers' prices	70,623	3,155	24,904	43,113	824	132,368	274,987	463,156

2005 Leontief Inverse (Aggregated Irish Sectors)

NACE	*products*	Agriculture, forestry and fishing	Coal, peat, petroleum, metal ores, quarrying	Food, beverage, tobacco	Textiles Clothing Leather & Footwear	Wood & wood products	Pulp, paper & print production	Chemical production	Rubber & plastic production	Non-metallic mineral production	Metal prod. excl. machinery & transport equip.	Agriculture & industrial machinery	Office and data process machines	Electrical goods	Transport equipment	Other manufacturing	Fuel, power, water	Construction	Services (excl. transport)	Transport
1 - 5	Agriculture, forestry and fishing	1.277	0.003	0.322	0.003	0.131	0.000	0.001	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.005	0.002	0.006	0.007	0.002
10-14	Coal, peat, petroleum, metal ores, quarrying	0.007	1.140	0.002	0.002	0.002	0.000	0.001	0.002	0.047	0.034	0.002	0.000	0.001	0.001	0.016	0.018	0.019	0.001	0.001
15-16	Food, beverage, tobacco	0.101	0.004	1.085	0.003	0.012	0.001	0.002	0.004	0.003	0.002	0.002	0.001	0.001	0.002	0.002	0.003	0.003	0.013	0.004
17-19	Textiles Clothing Leather & Footwear	0.000	0.000	0.000	1.025	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	Wood & wood products	0.001	0.002	0.001	0.001	1.122	0.000	0.000	0.008	0.002	0.001	0.000	0.000	0.000	0.000	0.031	0.002	0.018	0.001	0.001
21-22	Pulp, paper & print production	0.005	0.003	0.008	0.003	0.005	1.041	0.002	0.003	0.006	0.002	0.002	0.001	0.002	0.001	0.004	0.007	0.008	0.005	0.004
24	Chemical production	0.009	0.002	0.003	0.006	0.006	0.001	1.012	0.007	0.002	0.002	0.000	0.000	0.003	0.001	0.001	0.001	0.002	0.001	0.000
25	Rubber & plastic production	0.002	0.003	0.005	0.001	0.002	0.001	0.001	1.062	0.003	0.002	0.005	0.000	0.006	0.006	0.011	0.001	0.012	0.002	0.002
26	Non-metallic mineral production	0.002	0.026	0.003	0.001	0.002	0.001	0.000	0.011	1.117	0.006	0.003	0.000	0.001	0.001	0.016	0.002	0.056	0.002	0.001
27-28	Metal prod. excl. machinery & transport equip.	0.010	0.009	0.006	0.004	0.023	0.001	0.001	0.029	0.016	1.068	0.057	0.003	0.006	0.022	0.018	0.008	0.033	0.001	0.002
29	Agriculture & industrial machinery	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.002	0.001	0.002	1.002	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.000
30	Office and data process machines	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.018	0.001	0.000	0.000	0.000	0.000	0.000	0.000
31-33	Electrical goods	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.001	0.016	1.047	0.035	0.001	0.002	0.006	0.002	0.001
34-35	Transport equipment	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.002	0.000	0.000	0.000	0.000	0.000
23,36-37	Other manufacturing	0.011	0.018	0.007	0.003	0.010	0.001	0.001	0.009	0.010	0.024	0.003	0.000	0.001	0.003	1.053	0.053	0.009	0.003	0.018
40-41	Fuel, power, water	0.027	0.052	0.024	0.019	0.044	0.004	0.008	0.036	0.058	0.027	0.016	0.001	0.013	0.023	0.014	1.288	0.015	0.011	0.008
45	Construction	0.022	0.045	0.009	0.004	0.022	0.002	0.001	0.005	0.006	0.007	0.004	0.001	0.005	0.007	0.006	0.020	1.359	0.014	0.009
50-55,64-95	Services (excl. transport)	0.260	0.407	0.244	0.213	0.236	0.060	0.071	0.261	0.317	0.216	0.168	0.053	0.101	0.179	0.179	0.208	0.262	1.309	0.271
60-63	Transport	0.016	0.222	0.039	0.027	0.052	0.012	0.006	0.046	0.068	0.031	0.022	0.012	0.016	0.020	0.029	0.010	0.018	0.024	1.148

2005 Leontief Inverse (Disaggregated Energy Sectors)

NACE	*products*	Agriculture, forestry and fishing	Other, metal ores, quarrying	Coal	Peat	Crude oil	Food, beverage, tobacco	Textiles Clothing Leather & Footwear	Wood & wood products	Pulp, paper & print production	Chemical production	Rubber & plastic production	Non-metallic mineral production	Metal prod. excl. machinery & transport equip.	Agriculture & industrial machinery	Office and data process machines	Electrical goods	Transport equipment
1 – 5	Agriculture, forestry and fishing	1.277	0.003	0.003	0.003	0.003	0.322	0.003	0.131	0.000	0.001	0.003	0.002	0.001	0.001	0.001	0.001	0.001
10-14	Other, metal ores, quarrying	0.004	1.080	0.080	0.080	0.080	0.001	0.001	0.001	0.000	0.001	0.001	0.027	0.019	0.001	0.000	0.000	0.001
10-14	Coal	0.001	0.016	1.016	0.016	0.016	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.004	0.000	0.000	0.000	0.000
10-14	Peat	0.001	0.019	0.019	1.019	0.019	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.005	0.000	0.000	0.000	0.000
10-14	Crude oil	0.001	0.024	0.024	0.024	1.024	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.006	0.000	0.000	0.000	0.000
15-16	Food, beverage, tobacco	0.101	0.004	0.004	0.004	0.004	1.085	0.003	0.012	0.001	0.002	0.004	0.003	0.002	0.002	0.001	0.001	0.002
17-19	Textiles Clothing Leather & Footwear	0.000	0.000	0.000	0.000	0.000	0.000	1.025	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	Wood & wood products	0.001	0.002	0.002	0.002	0.002	0.001	0.001	1.122	0.000	0.000	0.008	0.002	0.001	0.000	0.000	0.000	0.000
21-22	Pulp, paper & print production	0.005	0.003	0.003	0.003	0.003	0.008	0.003	0.005	1.041	0.002	0.003	0.006	0.002	0.002	0.001	0.002	0.001
24	Chemical production	0.009	0.002	0.002	0.002	0.002	0.003	0.006	0.006	0.001	1.012	0.007	0.002	0.002	0.000	0.000	0.003	0.001
25	Rubber & plastic production	0.002	0.003	0.003	0.003	0.003	0.005	0.001	0.002	0.001	0.001	1.062	0.003	0.002	0.005	0.000	0.006	0.006
26	Non-metallic mineral production	0.002	0.026	0.026	0.026	0.026	0.003	0.001	0.002	0.001	0.000	0.011	1.117	0.006	0.003	0.000	0.001	0.001
27-28	Metal prod. excl. machinery & transport equip.	0.010	0.009	0.009	0.009	0.009	0.006	0.004	0.023	0.001	0.001	0.029	0.016	1.068	0.057	0.003	0.006	0.022
29	Agriculture & industrial machinery	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.002	1.002	0.000	0.001	0.001
30	Office and data process machines	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.018	0.001	0.000
31-33	Electrical goods	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.001	0.016	1.047	0.035
34-35	Transport equipment	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.002
23,36-37	Other manufacturing	0.003	0.006	0.006	0.006	0.006	0.002	0.001	0.006	0.001	0.000	0.003	0.003	0.018	0.001	0.000	0.001	0.001
23,36-37	Petroleum	0.007	0.013	0.013	0.013	0.013	0.004	0.002	0.004	0.000	0.000	0.006	0.007	0.006	0.001	0.000	0.001	0.001
40	Electricity	0.020	0.039	0.039	0.039	0.039	0.017	0.012	0.031	0.002	0.005	0.026	0.044	0.019	0.010	0.001	0.009	0.010
40	Natural gas	0.005	0.011	0.011	0.011	0.011	0.005	0.003	0.008	0.000	0.001	0.007	0.012	0.005	0.003	0.000	0.003	0.003
40	Renewable energy	0.001	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.000	0.000	0.001	0.002	0.001	0.001	0.000	0.000	0.001
41	Water	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.001	0.001	0.001	0.001	0.002	0.003	0.000	0.001	0.009
45	Construction	0.000	0.000	0.045	0.045	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
50-55,64-95	Services (excl. transport)	0.260	0.406	0.406	0.406	0.406	0.244	0.214	0.236	0.060	0.071	0.260	0.316	0.217	0.169	0.053	0.101	0.181
60-63	Transport	0.016	0.222	0.222	0.222	0.222	0.039	0.027	0.052	0.012	0.006	0.046	0.068	0.031	0.022	0.012	0.016	0.020

2005 Leontief Inverse (Disaggregated Energy Sectors continued)

NACE	*products*	Other manufacturing	Petroleum	Electricity	Natural gas	Renewable energy	Water	Construction	Services (excl. transport)	Transport
1 - 5	Agriculture, forestry and fishing	0.004	0.005	0.002	0.002	0.002	0.004	0.006	0.007	0.002
10-14	Other, metal ores, quarrying	0.009	0.009	0.011	0.011	0.011	0.002	0.011	0.000	0.001
10-14	Coal	0.002	0.002	0.002	0.002	0.002	0.000	0.002	0.000	0.000
10-14	Peat	0.002	0.002	0.003	0.003	0.003	0.000	0.003	0.000	0.000
10-14	Crude oil	0.003	0.003	0.003	0.003	0.003	0.001	0.003	0.000	0.000
15-16	Food, beverage, tobacco	0.002	0.002	0.003	0.003	0.003	0.007	0.003	0.013	0.004
17-19	Textiles Clothing Leather & Footwear	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	Wood & wood products	0.029	0.032	0.002	0.002	0.002	0.002	0.018	0.001	0.001
21-22	Pulp, paper & print production	0.004	0.004	0.005	0.005	0.005	0.018	0.008	0.005	0.004
24	Chemical production	0.001	0.001	0.000	0.000	0.000	0.003	0.002	0.001	0.000
25	Rubber & plastic production	0.010	0.011	0.001	0.001	0.001	0.005	0.012	0.002	0.002
26	Non-metallic mineral production	0.015	0.016	0.002	0.002	0.002	0.006	0.056	0.002	0.001
27-28	Metal prod. excl. machinery & transport equip.	0.021	0.016	0.008	0.008	0.008	0.007	0.033	0.001	0.002
29	Agriculture & industrial machinery	0.000	0.000	0.001	0.001	0.001	0.003	0.001	0.000	0.000
30	Office and data process machines	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
31-33	Electrical goods	0.001	0.001	0.002	0.002	0.002	0.003	0.006	0.002	0.001
34-35	Transport equipment	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
23,36-37	Other manufacturing	1.021	0.016	0.017	0.017	0.017	0.003	0.004	0.001	0.005
23,36-37	Petroleum	0.033	1.037	0.040	0.040	0.040	0.006	0.005	0.002	0.012
40	Electricity	0.010	0.010	1.229	0.229	0.229	0.071	0.010	0.008	0.006
40	Natural gas	0.003	0.003	0.062	1.062	0.062	0.019	0.003	0.002	0.002
40	Renewable energy	0.001	0.001	0.012	0.012	1.012	0.004	0.001	0.000	0.000
41	Water	0.001	0.001	0.000	0.000	0.000	1.014	0.001	0.000	0.000
45	Construction	0.000	0.006	0.014	0.014	0.014	0.000	1.359	0.000	0.000
50-55,64-95	Services (excl. transport)	0.183	0.177	0.179	0.179	0.179	0.529	0.262	1.309	0.270
60-63	Transport	0.033	0.026	0.009	0.009	0.009	0.021	0.018	0.024	1.148

Appendix IV. Ecoinvent Datasets

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit	DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
bitumen adhesive compound production, cold RER	RER	01/01/1994	31/12/2014	1 kg	4,4,3,4,4	0.47	0.097	0.35448	76%
bitumen adhesive compound production, cold RoW	RoW	01/01/1994	31/12/2014	1 kg	4,4,3,5,5	0.49	0.116	0.37077	76%
bitumen adhesive compound production, hot RER	RER	01/01/1994	31/12/2014	1 kg	4,4,3,4,4	0.69	0.139	0.46493	68%
bitumen adhesive compound production, hot RoW	RoW	01/01/1994	31/12/2014	1 kg	4,4,3,5,5	0.64	0.147	0.41553	65%
bitumen seal production RER	RER	01/01/1992	31/12/2014	1 kg	4,4,3,4,4	1.22	0.251	0.96803	80%
bitumen seal production RoW	RoW	01/01/1992	31/12/2014	1 kg	4,4,3,5,5	1.25	0.294	0.99022	79%
market for bitumen adhesive compound, cold GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.50	0.117	0.37613	76%
market for bitumen adhesive compound, hot GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.67	0.154	0.44261	66%
market for bitumen seal GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	1.25	0.295	0.99363	79%
autoclaved aerated concrete block production CH	CH	01/01/1995	31/12/2014	1 kg	4,4,3,4,3	0.40	0.093	0.36907	92%
autoclaved aerated concrete block production RoW	RoW	01/01/1995	31/12/2014	1 kg	4,4,3,5,5	0.51	0.134	0.46225	90%
lightweight concrete block production, expanded clay CH	CH	01/01/1995	31/12/2014	1 kg	4,4,3,4,3	0.53	0.110	0.39676	75%
lightweight concrete block production, expanded clay RoW	RoW	01/01/1995	31/12/2014	1 kg	4,4,3,5,5	0.56	0.135	0.42456	75%
lightweight concrete block production, expanded perlite CH	CH	01/01/1995	31/12/2014	1 kg	4,4,3,4,3	1.40	0.285	1.0216	73%
lightweight concrete block production, expanded perlite RoW	RoW	01/01/1995	31/12/2014	1 kg	4,4,3,5,5	1.43	0.339	1.0499	73%
lightweight concrete block production, expanded vermiculite CH	CH	01/01/1995	31/12/2014	1 kg	4,4,3,4,3	0.62	0.133	0.40905	67%
lightweight concrete block production, expanded vermiculite RoW	RoW	01/01/1995	31/12/2014	1 kg	4,4,3,5,5	0.65	0.160	0.43686	68%
lightweight concrete block production, polystyrene CH	CH	01/01/1995	31/12/2014	1 kg	4,4,3,4,3	1.17	0.263	1.0892	93%
lightweight concrete block production, polystyrene RoW	RoW	01/01/1995	31/12/2014	1 kg	4,4,3,5,5	1.43	0.365	1.3143	92%
market for autoclaved aerated concrete block GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.52	0.137	0.47217	90%
market for lightweight concrete block, expanded clay GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.58	0.139	0.43503	76%
market for lightweight concrete block, expanded perlite GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	1.44	0.342	1.0604	74%
market for lightweight concrete block, expanded vermiculite GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.66	0.163	0.44732	68%
market for lightweight concrete block, polystyrene GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	1.44	0.368	1.3231	92%
concrete production, high exacting requirements CH	CH	01/01/1997	31/12/2014	1 m3	4,4,3,4,3	360.71	85.181	334.7	93%
concrete production, high exacting requirements RoW	RoW	01/01/1997	31/12/2014	1 m3	4,4,3,5,5	466.49	123.730	428.82	92%
concrete production, normal CH	CH	01/01/1997	31/12/2014	1 m3	4,4,3,4,3	293.12	69.175	271.34	93%
concrete production, normal RoW	RoW	01/01/1997	31/12/2014	1 m3	4,4,3,5,5	378.37	100.334	347.24	92%
concrete roof tile production CH	CH	01/01/2004	31/12/2014	1 kg	4,4,3,4,3	0.25	0.057	0.21891	88%
concrete roof tile production RoW	RoW	01/01/2004	31/12/2014	1 kg	4,4,3,5,5	0.31	0.079	0.26832	88%
market for concrete, high exacting requirements GLO	GLO	01/01/2011	31/12/2014	1 m3	4,4,3,5,5	495.56	131.446	454.13	92%
market for concrete, normal GLO	GLO	01/01/2011	31/12/2014	1 m3	4,4,3,5,5	406.88	107.900	372.06	91%
market for concrete roof tile GLO	GLO	01/01/2011	31/12/2014	1 kg	4,4,3,5,5	0.32	0.082	0.27861	88%
door production, inner, glass-wood RER	RER	01/01/1997	31/12/2014	1 m2	4,4,3,4,4	81.29	15.746	54.115	67%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
door production, inner, wood RoW	RoW	01/01/1997	31/12/2014	1	m2	4,4,3,5,5	90.17	19.324	55.035	61%
door production, inner, wood RER	RER	01/01/1997	31/12/2014	1	m2	4,4,3,4,4	75.31	13.626	43.026	57%
door production, outer, wood-aluminium RER	RER	01/01/1997	31/12/2014	1	m2	4,4,3,4,4	129.75	27.588	100.88	78%
door production, outer, wood-aluminium RoW	RoW	01/01/1997	31/12/2014	1	m2	4,4,3,5,5	138.90	33.214	106.31	77%
door production, outer, wood-glass RER	RER	01/01/1997	31/12/2014	1	m2	4,4,3,4,4	128.20	27.870	101.03	79%
door production, outer, wood-glass RoW	RoW	01/01/1997	31/12/2014	1	m2	4,4,3,5,5	134.48	32.780	104.81	78%
market for door, inner, glass-wood GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	92.13	20.675	61.026	66%
market for door, inner, wood GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	86.61	18.586	53.2	61%
market for door, outer, wood-aluminium GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	138.19	33.175	106.38	77%
market for door, outer, wood-glass GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	134.19	32.802	105.07	78%
flat glass production, coated RER	RER	01/01/2000	31/12/2014	1	kg	4,4,3,4,4	1.14	0.265	0.80877	71%
flat glass production, coated RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	1.16	0.300	0.82292	71%
flat glass production, uncoated RER	RER	01/01/1996	31/12/2014	1	kg	4,4,3,4,4	1.04	0.243	0.76884	74%
flat glass production, uncoated RoW	RoW	01/01/1996	31/12/2014	1	kg	4,4,3,5,5	1.06	0.275	0.74884	71%
market for flat glass, coated GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.23	0.319	0.88475	72%
market for flat glass, uncoated GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.08	0.275	0.75225	70%
glazing production, double, U<1.1 W/m2K RER	RER	01/01/1996	31/12/2014	1	m2	4,4,3,4,4	37.65	8.401	27.202	72%
glazing production, double, U<1.1 W/m2K RoW	RoW	01/01/1996	31/12/2014	1	m2	4,4,3,5,5	38.63	9.667	27.888	72%
glazing production, triple, U<0.5 W/m2K RER	RER	01/01/1996	31/12/2014	1	m2	4,4,3,4,4	62.41	13.865	45.612	73%
glazing production, triple, U<0.5 W/m2K RoW	RoW	01/01/1996	31/12/2014	1	m2	4,4,3,5,5	63.88	15.932	46.642	73%
market for glazing, double, U<1.1 W/m2K GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	39.98	10.025	29.076	73%
market for glazing, triple, U<0.5 W/m2K GLO	GLO	01/01/2011	31/12/2014	1	m2	4,4,3,5,5	65.90	16.469	48.425	73%
market for natural stone plate, cut GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.55	0.139	0.44012	80%
market for natural stone plate, grounded GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.84	0.210	0.66039	79%
market for natural stone plate, polished GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.08	0.270	0.85054	79%
natural stone plate production, cut CH	CH	01/01/2000	31/12/2014	1	kg	4,4,3,4,3	0.18	0.041	0.15197	82%
natural stone plate production, cut RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	0.54	0.137	0.43469	80%
natural stone plate production, grounded CH	CH	01/01/2000	31/12/2014	1	kg	4,4,3,4,3	0.66	0.147	0.53244	81%
natural stone plate production, grounded RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	0.81	0.206	0.43469	53%
natural stone plate production, polished CH	CH	01/01/2000	31/12/2014	1	kg	4,4,3,4,3	0.92	0.200	0.72259	78%
natural stone plate production, polished RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	1.08	0.268	0.84375	78%
fibreboard production, hard RER	RER	01/01/2012	31/12/2014	1	m3	4,4,3,4,4	1544.07	265.545	883.77	57%
fibreboard production, hard RoW	RoW	01/01/2012	31/12/2014	1	m3	5,5,3,5,5	2093.33	457.459	1286.9	61%
market for fibreboard, hard GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	1998.81	426.799	1225.5	61%
market for medium density fibreboard GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	1308.81	271.555	656.63	50%
medium density fibre board production, uncoated RER	RER	01/01/2012	31/12/2014	1	m3	1,1,3,4,4	1170.79	202.308	572.11	49%
medium density fibre board production, uncoated RoW	RoW	01/01/2012	31/12/2014	1	m3	1,1,3,5,5	1262.63	260.723	612.14	48%
aluminium alloy production, AlMg3 RER	RER	01/01/1998	31/12/2014	1	kg	4,4,3,4,4	7.00	1.412	5.3697	77%
aluminium alloy production, AlMg3 RoW	RoW	01/01/1998	31/12/2014	1	kg	4,4,3,5,5	8.85	2.077	6.7823	77%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
casting, aluminium, lost-wax RoW	RoW	01/01/2000	31/12/2014	1	kg	2,4,3,5,5	113.25	28.440	91.906	81%
market for aluminium alloy, AlMg3 GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	8.32	1.945	6.3766	77%
steel production, chromium steel 18/8, hot rolled RER	RER	01/01/2000	31/12/2014	1	kg	4,4,3,4,4	5.02	1.098	3.9648	79%
steel production, chromium steel 18/8, hot rolled RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	5.02	1.236	3.9648	79%
market for steel, chromium steel 18/8, hot rolled GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	5.02	1.236	3.9648	79%
casting, steel, lost-wax RoW	RoW	01/01/2000	31/12/2014	1	kg	3,4,3,5,5	30.74	7.290	24.055	78%
alkyd paint production, white, solvent-based, product in 60% solution state RER	RER	01/01/1995	31/12/2014	1	kg	4,4,3,4,4	5.74	1.075	4.3643	76%
alkyd paint production, white, solvent-based, product in 60% solution state RoW	RoW	01/01/1995	31/12/2014	1	kg	4,4,3,5,5	6.23	1.370	5.0043	80%
alkyd paint production, white, water-based, product in 60% solution state RER	RER	01/01/1995	31/12/2014	1	kg	4,4,3,4,4	6.00	1.182	4.559	76%
alkyd paint production, white, water-based, product in 60% solution state RoW	RoW	01/01/1995	31/12/2014	1	kg	4,4,3,5,5	6.42	1.453	5.0655	79%
market for alkyd paint, white, without solvent, in 60% solution state GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	6.38	1.448	4.8732	76%
market for alkyd paint, white, without water, in 60% solution state GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	6.16	1.357	4.9786	81%
base plaster production CH	CH	01/01/1995	31/12/2014	1	kg	4,4,3,4,3	0.26	0.057	0.2261	86%
base plaster production RoW	RoW	01/01/1995	31/12/2014	1	kg	4,4,3,5,5	0.34	0.085	0.28969	86%
cement cast plaster floor production CH	CH	01/01/1997	31/12/2014	1	kg	4,4,3,4,3	0.20	0.043	0.16992	87%
cement cast plaster floor production RoW	RoW	01/01/1997	31/12/2014	1	kg	4,4,3,5,5	0.25	0.062	0.21592	87%
gypsum plasterboard production CH	CH	01/01/1997	31/12/2014	1	kg	4,4,3,4,3	0.33	0.057	0.18463	56%
gypsum plasterboard production RoW	RoW	01/01/1997	31/12/2014	1	kg	4,4,3,5,5	0.44	0.104	0.32259	74%
stucco production CH	CH	01/01/1997	31/12/2014	1	kg	4,4,3,4,3	0.07	0.013	0.050423	75%
stucco production RoW	RoW	01/01/1997	31/12/2014	1	kg	4,4,3,5,5	0.09	0.024	0.077653	82%
thermal plaster production, outdoor CH	CH	01/01/1995	31/12/2014	1	kg	4,4,3,4,3	0.83	0.185	0.76228	92%
thermal plaster production, outdoor RoW	RoW	01/01/1995	31/12/2014	1	kg	4,4,3,5,5	0.99	0.252	0.90276	91%
market for base plaster GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.33	0.085	0.28916	86%
market for cement cast plaster floor GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.26	0.066	0.22623	87%
market for gypsum plasterboard GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.45	0.109	0.33428	73%
market for thermal plaster, outdoor GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.02	0.259	0.92331	91%
market for stucco GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.11	0.028	0.090276	81%
market for polyethylene, high density, granulate GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.07	0.502	1.9586	95%
market for polyethylene, low density, granulate GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.25	0.543	2.0867	93%
polyethylene production, high density, granulate RER	RER	01/01/1999	31/12/2014	1	kg	2,3,3,4,4	1.98	0.424	1.8898	95%
polyethylene production, high density, granulate RoW	RoW	01/01/1999	31/12/2014	1	kg	2,3,3,5,5	1.98	0.480	1.89	95%
polyethylene production, low density, granulate RER	RER	01/01/1999	31/12/2014	1	kg	2,3,3,4,4	2.16	0.460	2.0179	93%
polyethylene production, low density, granulate RoW	RoW	01/01/1999	31/12/2014	1	kg	4,4,3,5,5	2.16	0.522	2.018	93%
market for polystyrene foam slab GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	4.15	0.991	3.8187	92%
market for polystyrene foam slab for perimeter insulation GLO	GLO	01/01/2009	31/12/2014	1	kg	4,4,3,5,5	4.69	1.117	4.3024	92%
market for polystyrene, general purpose GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	3.70	0.886	3.5283	95%
polystyrene foam slab for perimeter insulation CH	CH	01/01/2009	31/12/2014	1	kg	4,4,3,4,3	4.16	0.824	3.7857	91%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
polystyrene foam slab production RER	RER	01/01/2003	31/12/2014	1	kg	4,4,3,4,4	4.64	0.973	4.2702	92%
polystyrene foam slab for perimeter insulation RoW	RoW	01/01/2009	31/12/2014	1	kg	4,4,3,5,5	4.64	1.106	4.2629	92%
polystyrene foam slab production RoW	RoW	01/01/2003	31/12/2014	1	kg	4,4,3,5,5	4.64	1.106	4.2702	92%
polystyrene foam slab production, 100% recycled CH	CH	01/01/2009	31/12/2014	1	kg	2,3,3,4,3	0.38	0.082	0.35075	93%
polystyrene foam slab production, 100% recycled RoW	RoW	01/01/2009	31/12/2014	1	kg	2,3,3,5,5	0.62	0.158	0.52739	85%
polystyrene foam slab production, 45% recycled CH	CH	01/01/2009	31/12/2014	1	kg	2,3,3,4,3	2.36	0.489	2.2623	96%
polystyrene foam slab production, 45% recycled RoW	RoW	01/01/2009	31/12/2014	1	kg	4,4,3,5,5	2.49	0.598	2.3492	94%
polystyrene production, general purpose RER	RER	01/01/2001	31/12/2014	1	kg	2,3,3,4,4	3.61	0.762	3.4577	96%
polystyrene production, general purpose RoW	RoW	01/01/2001	31/12/2014	1	kg	2,3,3,5,5	3.61	0.865	3.4602	96%
market for polyvinylchloride, bulk polymerised GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.17	0.566	2.019	93%
market for polyvinylchloride, emulsion polymerised GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.61	0.682	2.4563	94%
market for polyvinylchloride, suspension polymerised GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.01	0.524	1.8762	94%
polyvinylchloride production, bulk polymerisation RER	RER	01/01/1998	31/12/2014	1	kg	4,4,3,4,4	2.08	0.490	1.9503	94%
polyvinylchloride production, bulk polymerisation RoW	RoW	01/01/1998	31/12/2014	1	kg	4,4,3,5,5	2.08	0.544	1.9503	94%
polyvinylchloride production, emulsion polymerisation RER	RER	01/01/1998	31/12/2014	1	kg	4,4,3,4,4	2.53	0.594	2.3873	94%
polyvinylchloride production, emulsion polymerisation RoW	RoW	01/01/1998	31/12/2014	1	kg	4,4,3,5,5	2.53	0.660	2.3878	94%
polyvinylchloride production, suspension polymerisation RER	RER	01/01/1998	31/12/2014	1	kg	2,3,3,4,4	1.92	0.452	1.807	94%
polyvinylchloride production, suspension polymerisation RoW	RoW	01/01/1998	31/12/2014	1	kg	2,3,3,5,5	1.92	0.501	1.8079	94%
injection moulding RER	RER	01/01/2001	31/12/2014	1	kg	4,4,3,4,4	1.24	0.279	1.0787	87%
injection moulding RoW	RoW	01/01/2001	31/12/2014	1	kg	4,4,3,5,5	1.54	0.384	1.2271	80%
market for injection moulding GLO	GLO	01/01/2001	31/12/2014	1	kg	4,4,3,5,5	1.44	0.359	1.1747	82%
fibre cement roof slate production CH	CH	01/01/1991	31/12/2014	1	kg	4,4,3,4,3	0.47	0.080	0.27269	59%
fibre cement roof slate production RoW	RoW	01/01/1991	31/12/2014	1	kg	4,4,3,5,5	0.42	0.094	0.27667	65%
market for fibre cement roof slate GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.44	0.097	0.28734	66%
fibre cement facing tile production CH	CH	01/01/2007	31/12/2014	1	kg	4,4,3,4,3	1.61	0.354	1.3808	86%
fibre cement facing tile production RoW	RoW	01/01/2007	31/12/2014	1	kg	4,4,3,5,5	1.61	0.403	1.3808	86%
market for fibre cement facing tile GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.62	0.406	1.3915	86%
beam, softwood, raw, air drying CH	CH	01/01/2011	31/12/2014	1	m3	4,4,3,4,3	67.48	15.466	57.242	85%
beam, softwood, raw, air drying RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	67.48	17.449	57.242	85%
beam, softwood, raw, kiln drying CH	CH	01/01/2011	31/12/2014	1	m3	2,1,3,4,3	157.11	29.639	38.499	25%
beam, softwood, raw, kiln drying RoW	RoW	01/01/2011	31/12/2014	1	m3	2,1,3,5,5	186.29	39.473	61.016	33%
board, softwood, raw, air drying CH	CH	01/01/2011	31/12/2014	1	m3	4,4,3,4,3	37.59	8.342	33.579	89%
board, softwood, raw, air drying RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	67.67	17.498	57.4	85%
board, softwood, raw, kiln drying CH	CH	01/01/2011	31/12/2014	1	m3	2,1,3,4,3	135.73	24.886	37.823	28%
board, softwood, raw, kiln drying RoW	RoW	01/01/2011	31/12/2014	1	m3	2,1,3,5,5	161.47	33.865	57.625	36%
lath, softwood, raw, air drying CH	CH	01/01/2011	31/12/2014	1	m3	4,4,3,4,3	37.59	8.342	33.579	89%
lath, softwood, raw, air drying RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	67.67	17.498	57.4	85%
lath, softwood, raw, kiln drying CH	CH	01/01/2011	31/12/2014	1	m3	2,1,3,4,3	135.73	24.886	37.823	28%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
market for sawnwood, beam, softwood, raw, air dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	89.97	23.403	76.273	85%
lath, softwood, raw, kiln drying RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	161.47	33.891	57.625	36%
market for sawnwood, beam, softwood, raw, kiln dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	206.90	43.208	78.461	38%
market for sawnwood, board, softwood, raw, air dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	90.16	23.451	76.431	85%
market for sawnwood, board, softwood, raw, kiln dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	182.09	37.814	75.07	41%
market for sawnwood, lath, softwood, raw, air dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	90.16	23.451	76.431	85%
market for sawnwood, lath, softwood, raw, kiln dried GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	182.09	37.814	75.07	41%
planing, beam, softwood, air dried CH	CH	01/01/2011	31/12/2014	1	m3	4,4,3,4,3	76.18	17.327	64.389	85%
planing, beam, softwood, air dried RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	106.51	27.543	89.692	84%
market for sawnwood, beam, softwood, air dried, planed GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	129.00	33.496	108.72	84%
planing, beam, softwood, kiln dried CH	CH	01/01/2011	31/12/2014	1	m3	2,2,3,4,3	169.98	31.545	44.774	26%
planing, beam, softwood, kiln dried RoW	RoW	01/01/2011	31/12/2014	1	m3	2,2,3,5,5	229.21	47.575	91.988	40%
market for sawnwood, beam, softwood, kiln dried, planed GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	249.82	51.789	109.43	44%
planing, board, softwood, air dried CH	CH	01/01/2011	31/12/2014	1	m3	4,4,3,4,3	47.94	10.506	42.201	88%
planing, board, softwood, air dried RoW	RoW	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	118.61	30.597	99.486	84%
market for sawnwood, board, softwood, air dried, planed GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	141.10	36.550	118.52	84%
planing, board, softwood, kiln dried CH	CH	01/01/2011	31/12/2014	1	m3	2,2,3,4,3	153.93	27.659	46.786	30%
planing, board, softwood, kiln dried RoW	RoW	01/01/2011	31/12/2014	1	m3	2,2,3,5,5	218.15	45.087	98.013	45%
market for sawnwood, board, softwood, kiln dried, planed GLO	GLO	01/01/2011	31/12/2014	1	m3	4,4,3,5,5	238.77	49.593	115.46	48%
chromium steel pipe production GLO	GLO	01/01/2008	31/12/2014	1	kg	5,5,3,5,5	5.25	1.310	4.1739	79%
forging, steel, large open die CA-QC	CA-QC	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.20	0.304	1.0729	89%
forging, steel, large open die RoW	RoW	01/01/2011	31/12/2014	1	kg	3,1,3,5,5	0.99	0.252	0.85977	87%
hot rolling, steel RER	RER	01/01/1997	31/12/2014	1	kg	4,4,3,4,4	0.31	0.071	0.28191	92%
hot rolling, steel RoW	RoW	01/01/1997	31/12/2014	1	kg	2,3,3,5,5	0.29	0.075	0.25388	86%
market for chromium steel pipe GLO	GLO	01/01/2012	31/12/2014	1	kg	4,4,3,5,5	5.30	1.305	4.2097	79%
market for forging, steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.00	0.253	0.86336	87%
market for hot rolling, steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.30	0.076	0.26147	88%
market for metal working, average for chromium steel product manufacturing GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.88	0.691	2.2819	79%
market for metal working, average for steel product manufacturing GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.23	0.536	1.8188	81%
market for reinforcing steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.43	0.624	2.2055	91%
market for section bar rolling, steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.24	0.060	0.21388	90%
market for sheet rolling, chromium steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.68	0.166	0.53958	80%
market for sheet rolling, steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.43	0.108	0.36813	86%
market for steel, low-alloyed GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	1.89	0.480	1.6629	88%
market for steel, low-alloyed, hot rolled GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.18	0.556	1.9244	88%
market for steel, unalloyed GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	2.21	0.570	2.0524	93%
market for wire drawing, steel GLO	GLO	01/01/2011	31/12/2014	1	kg	4,4,3,5,5	0.48	0.121	0.42776	90%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
reinforcing steel production RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	2.39	0.613	2.1697	91%
reinforcing steel production RER	RER	01/01/2000	31/12/2014	1	kg	4,4,3,4,4	2.39	0.550	2.1697	91%
section bar rolling, steel RER	RER	01/01/1997	31/12/2014	1	kg	4,4,3,4,4	0.24	0.054	0.21388	90%
section bar rolling, steel RoW	RoW	01/01/1997	31/12/2014	1	kg	4,4,3,5,5	0.24	0.060	0.21388	90%
sheet rolling, chromium steel RER	RER	01/01/1997	31/12/2014	1	kg	4,4,3,4,4	0.59	0.127	0.47856	81%
sheet rolling, chromium steel RoW	RoW	01/01/1997	31/12/2014	1	kg	4,4,3,5,5	0.72	0.177	0.56972	79%
sheet rolling, steel RER	RER	01/01/1997	31/12/2014	1	kg	4,4,3,4,4	0.40	0.092	0.36176	90%
sheet rolling, steel RoW	RoW	01/01/1997	31/12/2014	1	kg	2,3,3,5,5	0.43	0.110	0.37044	85%
steel production, low-alloyed, hot rolled RER	RER	01/01/2000	31/12/2014	1	kg	4,4,3,4,4	2.18	0.498	1.9244	88%
steel production, low-alloyed, hot rolled RoW	RoW	01/01/2000	31/12/2014	1	kg	4,4,3,5,5	2.18	0.556	1.9244	88%
wire drawing, steel RER	RER	01/01/1997	31/12/2014	1	kg	4,4,3,4,4	0.44	0.100	0.40596	92%
wire drawing, steel RoW	RoW	01/01/1997	31/12/2014	1	kg	2,3,3,5,5	0.49	0.123	0.43371	89%
metal working, average for chromium steel product manufacturing RER	RER	01/01/2006	31/12/2014	1	kg	4,4,3,4,4	2.88	0.609	2.2819	79%
metal working, average for chromium steel product manufacturing RoW	RoW	01/01/2006	31/12/2014	1	kg	4,4,3,5,5	2.88	0.691	2.2819	79%
metal working, average for steel product manufacturing RER	RER	01/01/2006	31/12/2014	1	kg	4,4,3,4,4	2.23	0.473	1.8188	81%
metal working, average for steel product manufacturing RoW	RoW	01/01/2006	31/12/2014	1	kg	4,4,3,5,5	2.23	0.536	1.8188	81%
steel production, converter, low-alloyed RER	RER	01/01/2001	31/12/2014	1	kg	2,3,3,4,4	2.62	0.598	2.3566	90%
steel production, converter, low-alloyed RoW	RoW	01/01/2001	31/12/2014	1	kg	4,4,3,5,5	2.64	0.674	2.3725	90%
steel production, converter, unalloyed RER	RER	01/01/2001	31/12/2014	1	kg	2,3,3,4,4	2.14	0.497	2.0028	94%
steel production, converter, unalloyed RoW	RoW	01/01/2001	31/12/2014	1	kg	4,4,3,5,5	2.17	0.559	2.0187	93%
market for transport, freight, light commercial vehicle GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	1.97	0.521	1.7518	89%
market for transport, freight, lorry >32 metric ton, EURO3 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.09	0.023	0.074463	87%
market for transport, freight, lorry >32 metric ton, EURO4 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.09	0.023	0.075868	89%
market for transport, freight, lorry 16-32 metric ton, EURO3 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.17	0.046	0.14996	87%
market for transport, freight, lorry 16-32 metric ton, EURO4 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.17	0.046	0.15307	90%
market for transport, freight, lorry 3.5-7.5 metric ton, EURO3 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.53	0.142	0.46714	88%
market for transport, freight, lorry 3.5-7.5 metric ton, EURO4 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.53	0.140	0.47393	90%
market for transport, freight, lorry 7.5-16 metric ton, EURO3 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.22	0.060	0.19502	87%
market for transport, freight, lorry 7.5-16 metric ton, EURO4 GLO	GLO	01/01/2011	31/12/2014	1	tonne*km	4,4,3,5,5	0.22	0.059	0.19826	90%
transport, freight, light commercial vehicle CH	CH	01/01/2005	31/12/2014	1	tonne*km	4,4,3,4,3	1.54	0.364	1.3997	91%
transport, freight, light commercial vehicle Europe without Switzerland	Europe without Switzerland	01/01/2005	31/12/2014	1	tonne*km	4,4,3,4,4	1.97	0.471	1.7543	89%
transport, freight, lorry >32 metric ton, EURO3 RER	RER	01/01/2009	31/12/2014	1	tonne*km	3,1,3,4,4	0.09	0.021	0.074332	87%
transport, freight, lorry >32 metric ton, EURO3 RoW	RoW	01/01/2009	31/12/2014	1	tonne*km	3,3,3,5,5	0.09	0.023	0.074516	87%
transport, freight, lorry >32 metric ton, EURO4 RER	RER	01/01/2009	31/12/2014	1	tonne*km	3,1,3,4,4	0.08	0.020	0.075739	89%
transport, freight, lorry >32 metric ton, EURO4 RoW	RoW	01/01/2009	31/12/2014	1	tonne*km	3,3,3,5,5	0.09	0.023	0.07592	89%

Ecoinvent Dataset Name	Geography	Start Date	End Date	Functional Unit		DQI Score	Calculated LCIA (A)	Uncertainty A	Ecoinvent LCIA (B)	B/A (%)
transport, freight, lorry 16-32 metric ton, EURO3 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.17	0.046	0.15008	87%
transport, freight, lorry 16-32 metric ton, EURO3 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.17	0.042	0.14968	87%
transport, freight, lorry 16-32 metric ton, EURO4 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.17	0.041	0.15279	90%
transport, freight, lorry 16-32 metric ton, EURO4 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.17	0.046	0.15319	90%
transport, freight, lorry 3.5-7.5 metric ton, EURO3 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.53	0.128	0.4663	88%
transport, freight, lorry 3.5-7.5 metric ton, EURO3 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.53	0.142	0.46748	87%
transport, freight, lorry 3.5-7.5 metric ton, EURO4 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.53	0.127	0.4731	90%
transport, freight, lorry 3.5-7.5 metric ton, EURO4 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.53	0.141	0.47427	90%
transport, freight, lorry 7.5-16 metric ton, EURO3 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.22	0.054	0.19465	88%
transport, freight, lorry 7.5-16 metric ton, EURO3 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.22	0.060	0.19517	87%
transport, freight, lorry 7.5-16 metric ton, EURO4 RER	RER	01/01/2009	31/12/2014	1	tonne* km	3,1,3,4,4	0.22	0.053	0.1979	90%
transport, freight, lorry 7.5-16 metric ton, EURO4 RoW	RoW	01/01/2009	31/12/2014	1	tonne* km	3,3,3,5,5	0.22	0.059	0.19841	90%
door production, inner, glass-wood RoW	RoW	01/01/1997	31/12/2014	1	m2	4,4,3,5,5	95.46	21.358	62.732	66%

Appendix V. R Code for Case Study Analysis

Extracting LCI data from Ecoinvent datasets

The downloaded datasets from Ecoinvent were first converted to ‘.xml’ files and then saved in ‘.xlsx’ format before applying this code.

```
library(readxl)

library(dplyr)

RER_3 <- GHG_list[ ,c("Chemical_Name","CAS.Number")]

number_DS <- length(excel_sheets("C:/Users/deidre.wolff/XL_workbook.xlsx"))

sheetname_DS <- excel_sheets("C:/Users/deidre.wolff/XL_workbook.xlsx")

for (i in 1:number_DS){

  RER <- read_excel("C:/Users/deidre.wolff/XL_workbook.xlsx", sheet = i)

  RER_2 <- RER %>%

     select("ns1:name333", "casNumber", "amount344") %>%

     filter(!(is.na(RER$`ns1:name333`)))

  RER_2 <- filter(RER_2, casNumber == "000124-38-9" | casNumber == "000067-66-3" | casNumber ==
   "010024-97-2" | casNumber == "000811-97-2" | casNumber == "000071-55-6" | casNumber == "00007
   6-13-1" | casNumber == "000075-37-6" | casNumber == "000076-14-2" | casNumber == "002837-89-0"
   | casNumber == "000076-16-4" | casNumber == "000074-83-9" | casNumber == "000353-59-3" | casNu
   mber == "000075-63-8" | casNumber == "000075-45-6" | casNumber == "000075-09-2" | casNumber =
   = "000075-71-8" | casNumber == "000075-43-4" | casNumber == "000074-82-8" | casNumber == "000
   074-87-3" | casNumber == "000056-23-5" | casNumber == "000075-73-0" | casNumber == "000075-69-
   4" | casNumber == "000075-46-7" | casNumber == "007783-54-2" | casNumber == "002551-62-4" | cas
   Number == "000678-26-2")

sheetname_DS_I <- sheetname_DS[i]

colnames(RER_2) <- c("Chemical_Name", "CAS.Number", sheetname_DS_I)

RER_2 <- aggregate(. ~  Chemical_Name + CAS.Number, data = RER_2, sum)

Senarios_kg_per_GHG <- left_join(RER_3, RER_2, by = c("CAS.Number", "Chemical_Name"))
```

Calculating LCIA from extracted LCI data

The extracted LCI data from the code above was multiplied by the IPCC GWPs for each dataset to convert the LCI to LCIA. The resulting LCIA data is summed to give the overall kg CO_2-equivalents for each dataset. The uncertainty in the LCI data and the IPCC GWPs has been propagated. The result is a table with dataset name, mean (kg CO_2-equivalents) and standard deviation.

```
library(readxl)
library(dplyr)
LCIA_Materials <- read_excel("C:/Users/deidre.wolff/XL_workbook.xlsx", sheet = 1)
LCIA_Materials<-LCIA_Materials[1,c(1:3)]
colnames(LCIA_Materials)[1:3]<- c("EcoInvent Material","Mean","Standard Deviation")
LCIA_Materials[1:3] <- ""
IPCC_GWP <- read_excel("C:/Users/deidre.wolff/XL_workbook.xlsx", sheet = 2)
IPCC_GWP <- IPCC_GWP[, c(1,2,4,5,6,7,8)]
sheetnames <- excel_sheets("C:/Users/deidre.wolff/XL_workbook.xlsx")
List_sheetnames_mean <- sheetnames[c(4,9)]
List_sheetnames_SD <- sheetnames[c(5,10)]
#OPEN LOOP 1
for (n in 1:2){
  Material_mean <-  read_excel("C:/Users/deidre.wolff/XL_workbook.xlsx", sheet = List_sheetnames_mean[n])
  Material_SD <-   read_excel("C:/Users/deidre.wolff/XL_workbook.xlsx", sheet = List_sheetnames_SD[n])
    LCIA_6 <- 1:10000
    Number_Datasets <- ncol(Material_mean)-2
    Number_Datasets2 <- 1:Number_Datasets
    Number_GHG <- nrow(Material_mean)
    Number_GHG2 <- 1:Number_GHG
    Names <- colnames(Material_SD[,3:(Number_Datasets+2)])
    Material_SD[3:(Number_Datasets+2)]<- lapply(Material_SD[3:(Number_Datasets+2)], function(x) as.numeric(as.character(x)))
    Y <- matrix(ncol = 1, nrow = 10000)
    Z <- matrix(ncol = 2, nrow = Number_Datasets)
#OPEN LOOP 2
    for (c in Number_Datasets2) {
      LCIA_4 <- 1:10000
      Material1 <- Material_mean[, c(1,2,(c+2))]
      Material2 <- Material_SD[, c(1,2,(c+2))]
```

```
    Material <- left_join(Material1, Material2, by = c("Chemical_Name", "CAS.Number"))
    Material <- left_join(Material, IPCC_GWP, by = c("Chemical_Name", "CAS.Number"))
#OPEN LOOP 3
    for (g in Number_GHG2) {
      LCIA <- Material[g,]
      colnames(LCIA)[3:4] <- c("m", "SD")
#OPEN LOOP 4
      for (l in 1:10000){
        LCIA_1 <- rlnorm(1, log(LCIA$m), log(LCIA$SD))
        LCIA_2 <- runif(1, LCIA$minimum, LCIA$maximum)
        LCIA_3 <- LCIA_1 * LCIA_2
        Y[l] <- LCIA_3
      } #CLOSE LOOP 4
      LCIA_4 <- cbind(LCIA_4, Y)
    } #CLOSE LOOP 3
    LCIA_5 <- rowSums(LCIA_4[,c(2:(Number_GHG+1))])
    LCIA_6 <- cbind(LCIA_6, LCIA_5)
  } #CLOSE LOOP 2
#OPEN LOOP 5
  for (r in Number_Datasets2){
    DSM <- data.frame(LCIA_6[,c(r+1)])
    colnames(DSM) <- "mean"
    DSM <- mutate(DSM, SD = ((mean)^2))
    DSM1 <- (sum(DSM$mean))/10000
    DSM2 <- sqrt(((10000*(sum(DSM$SD)))-((sum(DSM$mean))^2))/((10000)*(10000-1)))
    Z[r,] <- c(DSM1, DSM2)
  } #CLOSE LOOP 5
  Z <- cbind(Names, Z)
  colnames(Z)[1:3] <- c("EcoInvent Material","Mean","Standard Deviation")
  LCIA_Materials <- rbind(LCIA_Materials, Z)
} #CLOSE LOOP 1
```

Generate input distributions for each building material

These distributions were used as inputs to the process system to represent the parameter and scenario uncertainty for each material.

```
library(readxl)

library(dplyr)

LCIA_Materials_2 <-  LCIA_Materials[-1,]

LCIA_Materials_2[, c(2:3)]<- lapply(LCIA_Materials_2[, c(2:3)], function(x) as.numeric (as.character(x)
))

uptake1 <- 1:10000

XX <- matrix(ncol = 1, nrow = 10000)

Scenario_name <- read_excel("C:/Users/deidre.wolff/Material_Category.xlsx")

M_Scenarios<- Scenario_name[, c(1:2)]

M_Scenarios <- left_join(LCIA_Materials_2, M_Scenarios, by = "EcoInvent Material")

M_Scenarios<- M_Scenarios[, c(4,1:3)]

M_Scenarios2 <- M_Scenarios[3:4]

colnames(M_Scenarios2)[1:2] <- c("meanln","sdln")

colnames(M_Scenarios)[3:4] <- c("Mean", "Standard Deviation")

M_Scenarios2 <- mutate(M_Scenarios2, EX = ((log(meanln))-(0.5*(log(((sdln/meanln)^2)+1)))))

M_Scenarios2 <- mutate(M_Scenarios2, SDX = (sqrt(log(((sdln/meanln)^2)+1))))

M_Scenarios3 <- left_join(M_Scenarios, M_Scenarios2, by = c("Mean"="meanln", "Standard Deviation"
="sdln"))

M_BOQ_Result <- read_excel("C:/Users/deidre.wolff/BOQ_result.xlsx")

M_BOQ_Result <- M_BOQ_Result[, (1:6)]

M_BOQ_Result[, c(3,5)]<- lapply(M_BOQ_Result[, c(3,5)], function(x) as.numeric(as.character(x)))

M_material <- M_BOQ_Result$`Material Assignment for database application/ Sector CODE for assump
tion of sector`

#OPEN LOOP 1

for (m in M_material) {

  uptake2 <- filter(M_BOQ_Result, `Material Assignment for database application/ Sector CODE for assu
mption of sector`== m)

   uptake <- filter(M_Scenarios3, `Material`== m)

  dataset_length = nrow(uptake)

    #OPEN LOOP 2

    for (i in 1:10000) {

      random_number = sample(1:dataset_length, 1)

      dataset_row = uptake[random_number,]

      uptake3 <- rlnorm(1, (dataset_row$EX), (dataset_row$SDX))
```

```
      uptake4 <- runif(1, (uptake2$`Activity Data in units of EcoInvent Dataset FU`- uptake2$`95% Unform Distribution`), (uptake2$`Activity Data in units of EcoInvent Dataset FU`+ uptake2$`95% Unform Distribution`))

      uptake5 <- uptake3 * uptake4

      XX[i] <- uptake5

    } #CLOSE LOOP 1

      uptake1 <- cbind(uptake1, XX)

} #CLOSE LOOP 2

colnames(uptake1)[2:4]<- M_material

M_Scenario_Results <- data.frame(uptake1)

M_Scenario_Results <- M_Scenario_Results[,c(2:4)]

Number_Materials <- length(M_material)

#OPEN LOOP 3

for (i in 1:Number_Materials) {

  Material_name <- M_material[i]

  hist(M_Scenario_Results[,i], prob = TRUE, breaks = 60, ylim = c(0,0.00001), main= Material_name, xlab="kg CO2-equivalents")

lines(density(M_Scenario_Results[,i]), # density plot

 lwd = 2, # thickness of line

 col = "red")

} #CLOSE LOOP 3
```

Generate Input Distributions for Direct and Indirect Construction Emissions

```
library(readxl)

library(dplyr)

IO_DIST_CONST <- read_excel("C:/Users/deidre.wolff/BOQ_Result.xlsx")

IO_DIST_CONST_2<-IO_DIST_CONST[c(43,50:52),]

colnames(IO_DIST_CONST_2)<-IO_DIST_CONST_2[1,]

IO_DIST_CONST_2<- IO_DIST_CONST_2[c(2:4),1:8]

IO_DIST_CONST_2[, c(3,5,7:8)]<- lapply(IO_DIST_CONST_2[, c(3,5,7:8)], function(x) as.numeric(as.
character(x)))

uptake1 <- 1:10000

XX <- matrix(ncol = 1, nrow = 10000)

colnames(IO_DIST_CONST_2)[c(3,5)] <- c("meanln","sdln")

colnames(IO_DIST_CONST_2)[7:8] <- c("meanln2", "sdln2")

IO_DIST_CONST_2 <- mutate(IO_DIST_CONST_2, EX = log(meanln2))

IO_DIST_CONST_2 <- mutate(IO_DIST_CONST_2, SDX = sdln2)

IO_sect <- IO_DIST_CONST_2$`Material Assignment for database application/ Sector CODE for assum
ption of sector`

for (s in IO_sect) {

  uptake2 <- filter(IO_DIST_CONST_2, `Material Assignment for database application/ Sector CODE for
assumption of sector`== s)

    for (i in 1:10000) {

      uptake3 <- rlnorm(1, (uptake2$EX), (uptake2$SDX))

      uptake4 <- runif(1, (uptake2$meanln- uptake2$sdln), (uptake2$meanln + uptake2$sdln))

      uptake5 <- uptake3 * uptake4

      XX[i] <- uptake5

    }

      uptake1 <- cbind(uptake1, XX)

}

colnames(uptake1)[2:4]<- IO_sect

IO_Dist_Results <- data.frame(uptake1)

IO_Dist_Results <- IO_Dist_Results[,c(2:4)]

IO_Dist_Results <- mutate(IO_Dist_Results, direct_uncorr_t = Construction..direct_uncorr./1000)

IO_Dist_Results <- mutate(IO_Dist_Results, indirect_uncorr_t = Construction..indirect_Uncorr./1000)

IO_Dist_Results <- mutate(IO_Dist_Results, direct_corr_t = Construction..direct_corr./1000)

IO_Dist_Results_tn <- IO_Dist_Results[,4:6]

Number_sect <- length(IO_sect)
```

```
IO_sect_2 <- c("Construction (direct) per building (Input-Output System)", "Construction (indirect) per b
uilding (Input-Output System)", "Construction (direct) per building (Process System)")

for (i in 1:Number_sect) {

  IO_name <- IO_sect_2[i]

  hist(IO_Dist_Results_tn[,i], prob = TRUE, breaks = 60, ylim = c(0,0.0012), xlim = c(0, 15000), main= I
O_name, xlab="tonnes CO2-equivalents")

lines(density(IO_Dist_Results_tn[,i]), # density plot

 lwd = 2, # thickness of line

 col = "red")

}
```

Generate parameters for distributions

```
library(readxl)
library(dplyr)
uptake1<- c("mean","SD","cov","cos","cok")
uptake1<- data.frame(uptake1)
for (i in 1:B_Number_Materials){
  Material_name <- Material_name_B[i]
  uptake <- B_Scenario_Results_2[,i]
  uptake<- data.frame(uptake)
  uptake<- mutate(uptake, lnX = log(uptake))
  ustar_P <- (1/10000)*(sum(uptake$lnX))
  uptake <- mutate(uptake, ustar = ustar_P)
  uptake <- mutate(uptake, lnx_minus_ustar = (lnX - ustar)^2)
  osquared_P <- (1/10000)*(sum(uptake$lnx_minus_ustar))
  w_P <- exp(osquared_P)
  mean_P <- exp(ustar_P + (osquared_P/2))
  variance_P <- w_P*(w_P - 1)*(exp(2*ustar_P))
  SD_P <- sqrt(variance_P)
  cov_P <- SD_P / mean_P
  skew_y1_P <- (sqrt(w_P - 1))*(w_P +2)
  kurt_y2_P <- (w_P)^4 +(2*((w_P)^3))+(2*((w_P)^2))-3
  uptake2<- c(mean_P,SD_P,cov_P,skew_y1_P,kurt_y2_P)
  uptake1 <- cbind(uptake1, uptake2)
  colnames(uptake1)[i+1]<-Material_name
}
write.csv(uptake1, "C:/Users/deidre.wolff/distribution parameters.csv")
```

Uncertainty Contribution Ranking

```
library(readxl)
library(dplyr)
XX <- matrix(ncol = 1, nrow = 26)
for (r in 1:26){
contribution <- final_result[,r]
contribution<- data.frame(contribution)
contribution <- mutate(contribution, y_result = contribution + sum(mean_process$mean) - as.numeric(me
an_process[r,2]) + (mean_direct_IO*1000)+ (mean_direct_P*1000)+(mean_indirect_IO*1000))
x <- as.numeric(mean_process[r,2])
contribution<- mutate(contribution, xminusmean = contribution-x)
contribution<-  mutate(contribution, yminusmean = y_result - (mean_final*1000))
contribution<- mutate(contribution, ytimesx = xminusmean * yminusmean)
contribution<- mutate(contribution, xsquared = xminusmean^2)
contribution<- mutate(contribution, ysquared = yminusmean^2)
sumA <- (sum(contribution$ytimesx))
sumB <- sum(contribution$xsquared)
sumC <- sum(contribution$ysquared)
corr <- sumA / ((sumB * sumC)^0.5)
XX[r] <- corr
}
final_contri <- data.frame(XX)
```

LIST OF PUBLICATIONS

Publications *in press*:

[1] Wolff D, Duffy A (2021) Development and Demonstration of an Uncertainty Management Methodology for Life Cycle Assessment in a Tiered-hybrid Case Study of an Irish Apartment Development. *The International Journal of Life Cycle Assessment* (**in press**).

Other publications related to LCA, but outside of the work presented in this thesis:

[1] Saouter E, Wolff D, Biganzoli F, Versteeg D (2019) Comparing options for deriving chemical ecotoxicity hazard values for the EU Environmental Footprint (part II). *Integrated Environmental Assessment and Management;* doi: 10.1002/ieam.4169.

[2] Wolff D, Canals Casals L, Benveniste G, Corchero C, Trilla L (2019) The Effects of Lithium Sulfur Battery Ageing on Second-Life Possibilities and Environmental Life Cycle Assessment Studies. *Energies* 12 (12), 2440; doi: 10.3390/en12122440.

[3] Ferreira V, Wolff D, Corchero C (2019). On Life Cycle Assessment to Quantify the Environmental Impact of Lighting Products. *LED Professional Review (LpR)*, 75:44-56.

[4] Wolff D, Benveniste G, Ferreira V, Corchero C (2020). When Circular Economy Meets the Lighting Industry. *LED Professional Review (LpR)*, 80:66-73.

LIST OF EMPLOYABILITY SKILLS AND DISCIPLINE SPECIFIC SKILLS TRAINING

Description	Rationale
MSc in Quantity Surveying Course – *Building Measurement I* (September – December 2012)	This course provided the basic knowledge for preparing a bill of quantities for a building following the regulations for Ireland presented in the Agreed Rules for Measurement (The Joint Committee, 2009).
International Life Cycle Academy Course – *Practical Uncertainty Analysis in Life Cycle Assessment* (March 6 – 8, 2013)	This course provided the most up-to-date information on incorporating uncertainty analysis in LCA studies, including identification, quantification and qualification methods.
Volunteer position at Renewable World in Kenya (June 1 – August 31, 2016)	Renewable World's work in Kenya includes installing off-grid solar-PV hubs in rural fishing communities around Lake Victoria that are not connected to the national grid. The volunteer position involved analysing the supply and demand profiles for the community owned solar-PV hubs, visiting the communities and meeting with members to discuss their needs in terms of the solar hubs, and presenting educational information on energy efficiency and solar energy.
Traineeship at the European Commission's Joint Research Centre (JRC) (March 1 – July 15, 2018)	The traineeship involved the assessment of data and models used to derive the USEtox™ Characterization Factors for aquatic and human toxicity.
Work experience as an LCA Project Engineer at the Catalonia Institute for Energy Research (July 23, 2018 – September 30, 2019)	This position involved conducting LCA studies of innovative products in the energy sector, including 3D-printed Solid Oxide Fuel Cells, Lithium Sulfur batteries for electric vehicles, and modular luminaires. GaBi software and Ecoinvent datasets were used for the LCA studies. Multiple impact categories were assessed.