A multicriteria analytical framework for quantifying the sustainability of concrete materials under methodological uncertainties

コンクリート材料の持続可能性の定量化に向けた方法論的不確実性を考慮した多基準分析の枠組みの構築

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October 2019

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ABSTRACT

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Joel Galupo OPON

Concrete is the most widely used construction material that is recognized to have many implications on sustainable development – the equity of the three pillars: environment, economy, and society. On one hand, concrete is an integral part of infrastructures that support socio-economic development. On the other hand, concrete consumes billions of tons of materials and releases huge amounts of environmentally injurious substances. Making the material sustainable, therefore, is of paramount importance to the concrete sector in particular and to the construction industry in general. Sustainable concrete, however, remains elusive due to the difficulty of conceptualizing concrete from the viewpoint of sustainable development. This necessitates the need of an actionable paradigm that would clarify: 1) What constitutes sustainable concrete? and 2) How to evaluate concrete material sustainability to support decision and policy-making processes? These are the questions resolved in this research work.

The first question requires the building of an indicator framework that distils the conceptual nature of sustainability into measurable components. This framework is developed in this research through the identification of potential sustainability indicators from various literature. A total of 65 quantitative indicators were gathered, most of which describe the environmental character of concrete material. This is evidenced by the abundance of indicators related to environmental measurements, e.g., CO_2 emissions, NOx emissions, SOx emissions, particulate matter emissions, and many others. Several economic indicators were also identified such as the unit cost of raw materials, cost of recycled materials, and unit production cost of concrete to mention a few. A number of social indicators were also found such as structural safety, designed service life, and human toxicity potential, among others. In-depth analyses of the indicators revealed an inherent causal relationship between them, which was used to create the causal network of sustainable concrete material indicators (SCMI).

The identification of these sustainability indicators provides a general overview of what constitutes sustainable concrete, which is essential to perform sustainability evaluation, thus operationally answering the first question. To make the indicator framework a robust construct for sustainability evaluation applications, the indicators relationship to the two global perspectives of sustainable development (the three pillars of sustainability and the Sustainable Development Goals (SDGs)) were also clarified. This clarification provides a governing context for concrete material sustainability evaluation work, which is significant to stakeholders so that they can directly evaluate if their strategies, proposed solutions, and decisions would support the global sustainability agenda.

Answering the second question involved creating an analytical structure so that the indicator framework can be utilized to make quantitative evaluations of the sustainability performance of concrete materials. The architecture of the multicriteria decision analysis (MCDA) – henceforth MA – was used as the primary structure to create the analytical framework. MA is considered to be the most suitable analytical tool for this purpose due to the strong similarity of the sustainable concrete problem with the multicriteria analytical set-up. The steps of MA are comprised of the selection of indicators, data treatment, normalization, weighting, and aggregation. The selection of indicators defines the extent of the analysis. Data treatment assures the suitability of the data for the analysis. Normalization transforms disparate indicators into a comparable unit and scale. Weighting is the assignment of importance to indicators. Aggregation combines the indicators to a composite value.

MA, however, is not unique as many approaches could be used to perform each step. This multiplicity is recognized as a source of *methodological uncertainty* in MA as depending on the method used for the evaluation, different conclusions and decisions could result, leading to output uncertainty. In order to create a robust evaluation method, the *methodological uncertainties* must be managed operationally. In this research a modified MA structure was developed by integrating of uncertainty analysis (UA) and sensitivity analysis (SA). UA propagates the input uncertainties to the output, while SA measures the magnitude of influence of the sources of uncertainties to the output. UA and SA are beneficial for the management of *methodological uncertainties* and to assess whether some sources of uncertainties can be systematically eliminated, as the reduction of uncertainty would increase the robustness of the whole evaluation process.

The reduction of *methodological uncertainty* in MA is governed by a set of statistical rules, which are also part of the analytical framework, i.e., the Kolmogorov-Smirnov D-statistic was used to measure the effect of eliminating a source of uncertainty. In addition, the Dvoretzky-Kiefer-Wolfowitz inequality bound was also utilized to corroborate the result of uncertainty reduction. The decision component of the sustainability evaluation paradigm is characterized by the development and inclusion of a probabilistic hierarchical ordering method into MA. This ordering method assigns relative probability values to each alternative while preserving the output uncertainty. This is practical for comparing sustainability performances when the result is affected by uncertainties, supporting decisions, e.g., the identification of the "best" sustainable option. The combination of MA, UA, SA, and other statistical tools including the probabilistic ordering method create a robust sustainability evaluation analytical framework for concrete material, which operationally answers the second question.

The practical implementation of the indicator framework and the sustainability evaluation analytical framework was demonstrated by comparing the sustainability performance of various concrete materials. Both frameworks were used in various examined scenarios, which considers the effect of the environment on the durability performance of concrete materials and the issues on missing data. In all scenarios, the influences of the uncertainties to the output of the analysis were quantitatively measured. The utilization of the probabilistic ordering of the alternatives was also able to identify the "best" sustainable option under the presence of uncertainties.

Over the course of the research, many other areas were explored relevant to the analytical structure and applicability of MA for sustainability quantification. One of which is on the use of double weighting to account for data variation as weights from stakeholders in conventional MA completely neglects the structure of the data. The research also explored the application of other advanced modelling tools, such as the use of response surface methodology, desirability analysis, and the combination of other statistical tools to create an exploratory sustainability evaluation system for concrete dealing with continuous variables for the purpose of material design. Another exploratory work is the use of a trilateral viewpoint (durability, cost, and environmental performance) as a way to evaluate the sustainability of concrete materials, which also utilize aspects of MA under *methodological uncertainties*.

The development of the indicator framework, the creation of the multicriteria analytical framework for sustainability evaluation under uncertainties, and the rich plethora of analytics devised in this research transform in a robust way the concept of sustainable concrete into terms that are actionable for various decision- and policy-makers. These outputs are expected to advance the innovations in sustainable concrete material research and design, lead to the development of industry standards and specifications, and ultimately assist the industry stakeholders in reaching critical decisions for the sustainability of concrete material. In a much wider perspective, however, the analytical framework for sustainability evaluation under *methodological uncertainties* developed in this research is not only specific to concrete problem. It could also be applied to other sustainable development problems of similar structure, making it a general tool to support with scientific rigor, various sustainability-related decision-making processes and policy implementations.

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ACKNOWLEDGEMENTS

My sincere thanks to the following:

To my advisor and dear friend, Assoc. Prof. Michael Henry, for taking the risk on me. His unparalleled enthusiasm inspired most of this work. For his tireless efforts in critiquing my work and for exposing me to the best opportunities, I will be forever grateful. Thanks also for being my trusted friend and for saving me when I overestimate my limits.

To all Michael Gumi members (Ryosuke, Chris, Chika, Gen, Amy, Boss Farng, Kota, Tojo, Yoshida my brother, Enami, Nicole, Dianne, Yamauchi, Haru, Anna, Bear, Agi, Jun, Min, Carl), you guys will always be my family. Thank you for making my years in Hokkaido University a great and wonderful experience. Thanks for your friendship and love, and for keeping me alive.

To Mariko and Hunter-kun, thanks for making me smile. To my adopted cousins Cee and Jurgen for the encouragement, and for the unforgettable and lovely experiences. To my dear neighbor Wang-san, and to all the countless friends I met, thank you for your encouragement and for keeping me sane always. To my Bisaya in Hokudai group, thanks for the friendship.

To my supervisory committee members, Prof. Takafumi Sugiyama, Prof. Hiroshi Yokota, and Assoc. Prof. Satoshi Nishimura, thank you for the guidance and support.

To Japan International Cooperation Agency (JICA) and to AUN/Seed-Net Program, thank you for providing the scholarship which made this study possible, I am forever grateful.

To all those who I forgot to mention, thank you for the job well done!

And finally, to my family (especially to Mama Inday, and my siblings Melcris and Keith) and to my friends (especially to Te Rich) back home, thank you for the unconditional love and unwavering support.

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LIST OF CORRESPONDING PUBLICATIONS

Bulk of the contents of Chapter 3 have been published in a journal:

Opon, J., Henry, M., An indicator framework for quantifying the sustainability of concrete materials from the perspectives of global sustainable development, Journal of Cleaner Production 218, pp. 718-737, 2019. https://doi.org/10.1016/j.clepro.2019.01.220

Bulk of the contents of Chapter 7 have been published in a technical and conference proceedings:

Opon, J., Henry, M., Use of double weighting to compensate for data variation in multicriteria sustainability evaluation, Japan Society of Civil Engineers Annual Conference, Takamatsu, September, 2019.

Opon, J., Henry, M., Application of response surface methodology and uncertainty analysis for exploratory analysis of concrete material sustainability, Annual Proceedings of the Japan Concrete Institute, Vol. 41, No. 1, pp. 1559-1564, 2019.

Opon, J., Henry M., Utilization of uncertainty and desirability analyses for the trilateral evaluation of concrete sustainability, 3rd Asian Concrete Federation Symposium, September, 2019.

Chapter 1
Introduction

1.1 Background

Concrete is the lifeblood of the construction industry, which nurtures the vibrant worldwide socioeconomic development activities. Much of the advancements of the global society can be attributed to concrete. Concrete, for example, is the primary material used to build essential facilities for human habitation and protection. High-rise buildings, offices, apartments, and even most small dwellings rely on the stability provided by concrete to be a safe haven for human activities. Concrete also connects societies so that socioeconomic activities can be performed more efficiently. Our road infrastructures, railways, port systems, airports and even telecommunications systems wouldn't be possible without concrete. It is hard to imagine the modern society and the direction it is heading without concrete performing its expected task. Concrete is complexly amalgamated within the human society that it could almost be perceived as equivalent to nature.

Concrete, however, is not a flawless material. Tagged as the second most widely used substance next to water, concrete is a voracious consumer of raw materials. Billions of tons of aggregates, limestones, and water are extracted annually to support the growing need of societies for concrete-based infrastructure systems. The processing and production of concrete releases huge amounts of environmentally injurious substances, e.g., CO_2 and other greenhouse gases. The economic vitality created by the immense size of the concrete and construction industry may also encourage corruption and abuse in regard to the use of the material. Concrete is relatively a cheap and easily accessible construction material and thus its massive utilization is almost unregulated. This promotes the building of projects with dubious socioeconomic significance which drains the wealth of the society, affecting the poor and the vulnerable. Concrete with all its good benefits to the society must not continue to be a vehicle of the environmental degradation and socioeconomic decline. Therefore, as a way forward, the concrete industry must embrace sustainable decision-making practices so that concrete could continue to support socioeconomic activities, whilst being sensitive to environmental rehabilitation and preservation.

Sustainable decision-making is the consequence of the practice of sustainability. Sustainability is an innovative idea of the modern age, strongly advocated by the United Nations, which promotes the concept of continued development while assuring the balance between economy, society and the environment – the pillars of sustainable development. In other words, any development activity must not be singly motivated by any of the pillars, but they must be harmoniously considered. Sustainability has recently been conceptualized as a set of 17 Sustainable Development Goals (SDGs) with specific and measurable targets. The SDGs span a wide range of priority areas to sustainability where various industries could participate in. However, there remains significant amount of uncertainty regarding the practice of sustainability, as it is still difficult for many industries to view their commercial constructs either within the paradigm of the pillars or the SDGs. This difficulty can be attributed to the serious lack of sustainability evaluation paradigm for most industries that would support decision-making and progress assessments in regard to sustainable development. In concrete industry, for example, no such paradigm exists. Therefore, developing a sustainability evaluation paradigm is a necessary requirement for concrete industry (or any industry in general) to contribute to the goals of sustainable development.

Sustainability evaluation paradigm generally requires two complementary frameworks: conceptual framework and analytical framework. The conceptual framework aims to distil the abstract nature of sustainability into components that are actionable for stakeholders. This framework is commonly presented as an indicator framework, which defines what constitute sustainable development in the context of the participating industry. Identifying and validating the relevant indicators through a development strategy is necessary to build the indicator framework. In the concrete sector, however, the building of the conceptual framework is challenging due to the lack of indicators development due to the conflict surrounding what constitute sustainable concrete. Therefore, for the concrete industry to be a participant to the international sustainability agenda, an indicator framework for sustainable concrete material needs to be developed.

On the other hand, the purpose of the analytical framework is to quantify and contrast the performance of various sustainability decision alternatives from a product to policy level using various indicators so that decisions can be taken. In the context of the concrete industry, for example, the analytical framework would enable the selection of concrete materials that closely represents sustainability. The analytical framework is often built by following the architecture of multicriteria analysis (MA), which is comprised of a set of methodological steps. However, there remains significant debates about the certainty of the approaches of MA for sustainability evaluation due to the differing perspective on sustainable development. This encourages various non-equivalent analytical approaches to perform sustainability evaluation, making the analytical framework by MA methodologically uncertain (*methodological uncertainty*). Because of *methodological uncertainty*, divergent and sometimes contrasting conclusions and decisions could result. Quantitative sustainability evaluation, however, is still desirable to warrant the objectivity in selecting decisions and policy implementations. While there are available analytical frameworks applicable for concrete sustainability evaluation (or any sustainability problem in general), none have the typical structure for the consideration of *methodological uncertainty*. Therefore, creating a sustainability evaluation analytical framework sensitive to the uncertainties relevant to sustainability is essential to make robust and defensible decisions and conclusions.

1.2 Research objectives and scope

Considering the arguments presented in the previous Section concerning concrete and the requirements for sustainability evaluation, the following research objectives are devised:

1) To develop an indicator-based sustainability framework able to define the constituency of sustainable concrete material that could be used to perform quantitative sustainability evaluations.
2) To develop a sustainability evaluation analytical framework following the architecture of a multicriteria analysis that is able to consider the *methodological uncertainties* in sustainability quantification.
3) To demonstrate the practical implementation of the indicator-based framework for sustainable concrete and the sustainability evaluation analytical framework in concrete decision-making processes.

The scope of concrete and sustainability is very wide, which would overwhelm this research if all is considered. Therefore, concerning the topic on concrete, this work is limited only on the study of concrete material sustainability. The sustainable attributes of concrete presented herein are specifically identified for concrete materials only; although, they may be used for other purposes, this work is not claiming about their validity for such applications unless it is independently verified. In the aspect of sustainability, on the other hand, this work focuses only on quantitative assessment methodologies. The uncertainties considered are the methodological and stochastic forms, and the other forms of uncertainties (e.g., Knightian) are not discussed in this work.

1.3 Significance

The research touches on two of the most significant areas for the practices of sustainability in the concrete industry. First is the need of a holistic indicator framework for concrete sustainability that anatomizes its conceptual structure to an analytical model. The development of the indicator framework for sustainable concrete material formalizes the constituency of concrete material sustainability and provides mechanisms on how the concept of sustainable development can be integrated into concrete. Aggregating potential sustainability indicators into a unified framework will provide a relatively comprehensive outlook and evaluation structure for sustainable concrete. This makes concrete stakeholders aware of the diversity of indicators available and their inherent relationship. The indicator framework will also illuminate and validate the contributions of the concrete sector towards the realization of the international agenda for a sustainable future.

Second is the need of an analytical framework for sustainability evaluation that would accommodate various considerations in sustainability quantification (i.e., *methodological uncertainties*). This is a significant output because a robust quantitative analytical framework will support critical sustainability-related decision-making processes, and thus encourage the practice of sustainable development within the industry in particular and several other industries in general. The analytical framework provides a tangible value to a so general and pluralistic idea as sustainable development that different stakeholders can work on and use in various decision-making activities. The combination of the indicator framework for sustainable concrete and the evaluation analytical framework for sustainability will together create a single paradigm that would facilitate the development of sustainable concrete from conceptualization to design, and would generally support a wider scope of sustainability decision-making processes and policy implementations.

1.4 Structure of the dissertation

This dissertation is comprised of 9 chapters. The organization and structure of the chapters is as shown in Figure 1.1. This Chapter – Chapter 1 – provides a quick background about the motivations of this work and outlines the objectives and scope. The first part of Chapter 2 details the concept of sustainable development and two of its global perspectives: The Pillars of sustainability and The Sustainable Development Goals (SDGs). The discussion on sustainable development is used as a launching point of the second part which discusses about the general concept of concrete sustainability. The 2nd part of Chapter 2, on one hand, discusses how concrete can be in conflict with the concept of sustainable development, and on the other hand, how concrete can support sustainability and be made sustainable.

Chapter 3 formalizes the concept of sustainable concrete material by developing a relatively comprehensive sustainable concrete material indicators framework that can be used for a holistic sustainability evaluation. The connection of these indicators with the pillars of sustainability and the SDGs is also discussed. The end part of Chapter 3 shows a simple demonstration about the applicability of the indicators framework for concrete material sustainability evaluations.

Chapter 4 introduces the general outline of the methodological approach for performing sustainability evaluations by multicriteria analysis (MA). MA is considered as the most appropriate method for making sustainability quantifications, which is comprised of: indicator selection, normalization, weighting and aggregation. Each of these steps serves different functions to support various considerations (analytical and otherwise) about sustainability evaluations. Chapter 4 also introduces the concept of *methodological uncertainties* due to the multiplicity of approaches applicable to perform the steps of MA. Chapter 4 further argues that the *methodological uncertainties* would cause and place significant uncertainties on the result of the evaluation, and continues by providing demonstration calculations using concrete materials to illustrate the effect of *methodological uncertainties*.

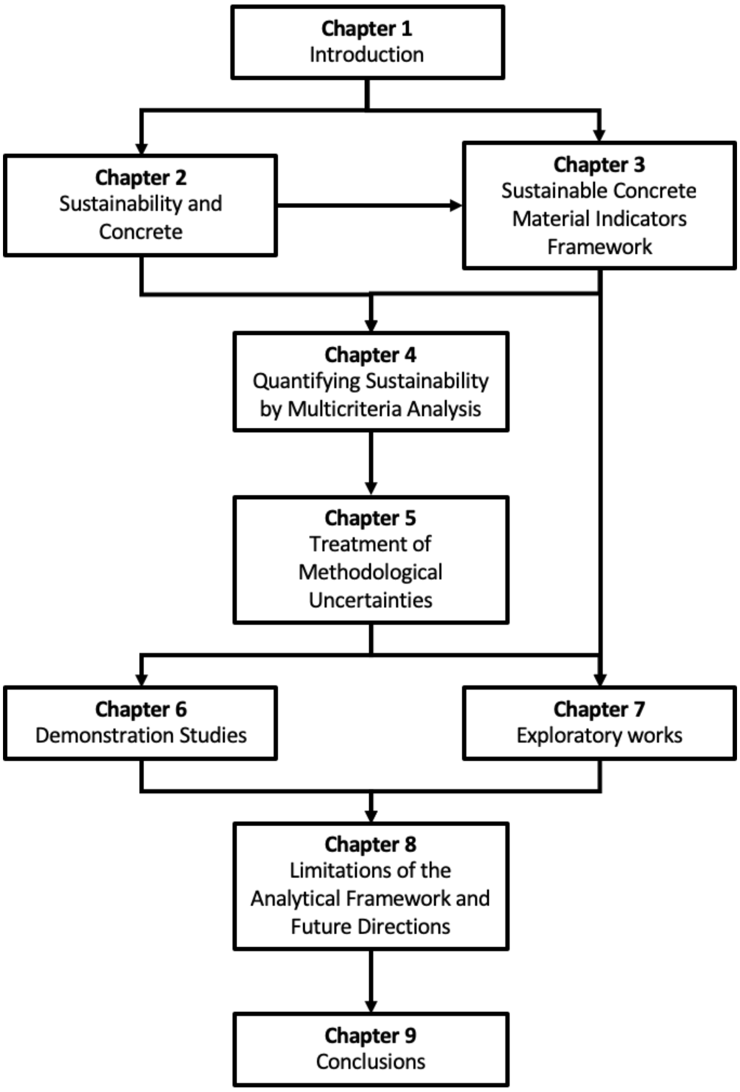

Figure 1.1 Structure of the dissertation

Chapter 5 introduces a modified multicriteria framework by incorporating uncertainty and sensitivity analyses for the management of *methodological uncertainties*. Uncertainty analysis maps how uncertainties propagate through the structure. Sensitivity analysis, on the other hand, measures the influence of the input uncertainties to the output, which provides quantitative basis for the management of the uncertainties. Bulk of the chapter is dedicated to the mathematical structure of the framework.

Chapter 6 demonstrates using ready-mix concretes the practical implementation of the multicriteria sustainability evaluation framework under uncertainties introduced in Chapter 5 and utilizes the indicator framework from Chapter 3. Three scenarios were demonstrated accounting for the different considerations in concrete sustainability evaluation work such as the effect of environmental condition and the issue on missing indicator data. Chapter 7 introduces and demonstrates the other analytical works explored relevant to sustainability evaluation, which are directly relevant to the framework in Chapter 5.

Chapter 8 provides the structural limitations of the framework and other considerations about its use. It also discusses some future directions for the continuance of the research on sustainable concrete material and the quantitative evaluations of sustainability. Finally, Chapter 9, summarizes the work and provides the conclusions generated from this research activity.

Chapter 2
Sustainability and concrete

2.1 Sustainability and sustainable development

The concept of sustainable development has a long history of evolution. The early resemblance of the concept can be traced back to the German forestry in the late Middle Ages where the principle about equity between the quantity of trees harvested and grown was explored (Schmuck and Schultz, 2002). Several other events can be attributed to the development of the concept, e.g., the formulation of the idea of maximum sustainable yield, and ecological carrying capacity, among others. The original form of sustainable development was closely associated with maintenance of environmental quality (Bell and Morse, 2008), until it was rationalized by the Brundtland Report in 1987. That report defined sustainable development as the development that "meets the needs of the present without compromising the ability of the future generations to meet their own needs" (UN General Assembly, 1987).

The term Sustainability, on the other hand, is a derivative of sustainable development. Sustainability and sustainable development are used interchangeably (Purvis et al., 2019) by many proponents of the concept – as is also being done in this manuscript. Distinctively, however, sustainable development could be taken as the process or journey, while sustainability is the aim or destination (Georgopoulos and Minson, 2014). The concept of sustainable development has increasingly becoming even more relevant over time specially in this era of rapid industrialization as more complex environmental issues resulting from human-made developments emerged – the most prominent of which is climate change. There is also the accelerated depletion of non-renewable resources (e.g., oil), creating greater market instability, affecting various social infrastructures – the poor in particular.

While the purpose of sustainable development is for the wellbeing of the human-environmental systems, it is not without criticism as the definition by the United Nations is relatively vague. One criticism, for example, points to the lack of boundaries on what constitutes a sustainable state. Another criticism is on the ambiguity associated with the word "need" in the definition by the Brundtland Report that must be met in both present and future generations. The lack of specificity of the concept of sustainable development leads to various uncertainties in its operationalization, making it difficult for many industries and businesses to participate in the process of sustainability. Sharpening, therefore, of this vague concept could be beneficial to delineate the borderline region in which the concept of sustainability neither truly applies nor truly does not apply (Regan et al., 2002).

The vagueness of the definition of sustainability makes it difficult to detail its theoretical underpinnings as it allows for a variety of interpretations depending on which area of concern is being considered (Bell and Morse, 2008) by different parties. This situation is particularly challenging when doing evaluations about the progress of societies towards sustainable development – to clarify in what way actions or decisions will contribute to sustainable development and what does not. Formalizing the contextual nature of sustainable development in the form of frameworks, therefore, is necessary to reduce it into an intelligible form, facilitating sustainability evaluation work. This requires understanding and defining the system to be measured, as well as its contributing categories (Burgass et al., 2017), which depend ultimately on how sustainable development is conceptualized.

Sustainable development could be conceptualized in various ways depending on the organizing perspective. However, to promote a uniform framing on sustainable development, the governing perspective advocated by the United Nations (UN) is usually followed. Currently, there are two global perspectives of sustainable development: the three pillars of sustainability and the sustainable development goals (SDGs). Adopting these perspectives will provide a homogenized outlook about the whole sustainability evaluation process and institutionalizing the concept of sustainable development. Both the Pillars and the SDGs perspectives are beneficial to sustainability evaluation works because: (1) both are equally recognized globally, (2) they have differing conceptual paradigms and scope – with the pillars being more general and largely familiar to stakeholders, while the SDGs are relatively new concept that aim for specific targets. The following subsections provide further detail about the structure of the two perspectives.

2.1.1 The three pillars of sustainable development

The conventional concept of sustainable development is popularized by the Brundtland Report "Our Common Future," which sparked debates among different sectors. That report characterized sustainable development as the interconnection of the three pillars: the environment, economy, and society as graphically illustrated in Figure 2.1 – one of many alternative manifestations (Purvis et al., 2019). Achieving sustainability requires the synchronized operationalization of the concept of sustainable development in the sphere of these three pillars. However, the conceptual origins of the pillars as they relate to sustainable development remain unclear and that if they would translate into a more comprehensive understanding about the concept of sustainability (Purvis et al., 2019; Thomson, 2017). Nevertheless, the concept of the pillars of sustainability is still dominantly viewed to capture the essential elements of sustainability (Wu, 2013), making it a common authority among sustainability evaluation tools (see e.g., Mayer, 2008).

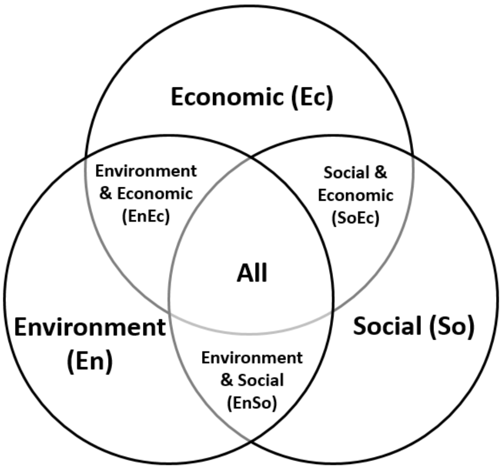

Figure 2.1. The three pillars of sustainability

Concerns have been put forward regarding the vagueness of the pillars concept and their applicability for sustainability evaluation work as it is difficult to define the assessment boundaries. There is a lack of both science-based and policy-based boundaries able to define the threshold between what contributes to sustainable development and what does not (European Commission, 2012). Defining the environmental part, for example, involves many issues, and none are truly adequate to gauge the total environmental sustainability. Some environmental concerns, for example, tackle only limited issues such as those relevant to biodiversity, global warming, ozone destruction, and resource depletion (Sakai and Noguchi, 2013). The three pillars are also inherently intertwined as one argument relevant to the issue of economic sustainability points that improvements in economic pillar cannot occur unless the strategies which are being formulated and implemented are ecologically sustainable over the long term (Barbier, 1987), suggesting causal – either reinforcing or competing – relationships that may exist between the pillars themselves. Nonetheless, in the absence of a more comprehensive representation of sustainability, the pillars of sustainability offer a temporary universal viewpoint with which to make general assessments of sustainable development activities.

2.1.2 The Sustainable Development Goals

The other worldview of sustainability is in the form of the SDGs introduced by the United Nations is 2015. The SDGs paradigm is composed of 17 goals (as in Figure 2.2) with 169 targets, to be achieved by 2030. These targets were agreed upon by members of the United Nations (UN). The SDGs are the new plan of the UN for a sustainable future, with ambitious and transformational vision, particularly to free the world from poverty, hunger, and disease (UN, 2015). The SDGs' targets are designed so that each government can set their own priorities and level of ambition in terms of the scale and pace of transformation (Allen et al., 2016).

Figure 2.2 The sustainable development goals (adopted from United Nations)

The core structure of the SDGs is the identification of various priority areas relevant to sustainability. While contemporary sustainability literatures may center around these SDGs, the three pillars themselves were explicitly embedded in their formulation (Purvis et al, 2019; United Nations, 2012), thus the SDGs and the pillars are inherently related. The goals are presented independently (Singh et al., 2017), encompassing a variety of issues such as poverty, health, climate action, sustainable cities and communities, peace, sanitation and many others. The goals, however, are sometimes mutually reinforcing or conflicting in nature (Fu et al., 2019) as dependencies may arise between the targets of each goal (see e.g., Singh et al., 2017).

Specific examples of activities that directly and indirectly support the delivery of the SDGs remain unclear, suggesting a need for research that demonstrates how businesses can support these sustainability targets within the context of their commercial priorities and activities (Sullivan et al., 2018). This is important in promoting the theoretical innovation to tackle the criticisms about the subjectivity about the SDGs framework (Fu et al., 2017), since adopting SDGs in national policies requires objective evidence (Fu and Wei, 2018). The SDGs structure, therefore, could be viewed as a new opportunity for different industry (i.e., concrete industry) to examine how their strategies and decisions could lead to the attainment of the goals of this new sustainable development paradigm.

2.2 Sustainability and concrete

It is clear that sustainability affects every industry and that it requires a concerted effort from everyone involved to participate in the operationalization of its targets be it from the pillars or the SDGs perspective. The focus, however, of this work is on concrete materials and its relation to sustainability, as more than any other industry, the construction sector is largely affected by the ongoing sustainability debate (Muller et al., 2014), requiring the sustainability of concrete material be examined comprehensively.

Traditional concrete is a composite of cement, sand, gravel, and water, and is used primarily for construction (Kisku et al., 2017). Concrete is the second most consumed material worldwide next to water (Watts, 2019), and entails a variety of social, economic and environmental sustainability issues. The statistics of concrete consumption globally are not particularly impressive when it comes to the topic of sustainable development. In this section, relevant views about the conflicts of the concept of sustainable development and the use of concrete are discussed which centers around the three pillars of sustainability only because of generality, as pillars were explicitly embedded in SDGs perspective (Purvis et al., 2019). Additionally, the SDGs are relatively new, thus the relationship of concrete and the SDGs is still largely unclear.

2.2.1 Conflicts between sustainability and concrete materials

(1) Environmental aspect

The environmental aspect of concrete sustainability is very wide and complex. This subsection, therefore, focused only on three important issues surrounding the sustainable use and production of concrete materials: resource depletion, environmental emissions and waste generation. It is estimated that concrete uses about 20 billion tonnes of raw materials every year (The Fredonia Group, 2011). This amount is expected to continue to rise for decades into the future (Mehta, 2002) if developing countries are to expand their infrastructure development to the current global average (Watts, 2019). According to an OECD report (2016), construction materials – particularly sand, gravel and crushed rock – dominate the worldwide resource consumption and this amount could double in the 2060, which has the potential to deplete natural resources. In Vietnam, for example, it is estimated that the domestic demand for sand may exceed the country's total reserve (Torres et al., 2017). The demand for raw construction materials also requires massive extraction of sand and gravel that are destroying rivers, lakes and ocean ecosystem (Weyler, 2018). In Poyang Lake, China, for example, where the largest sand mining operation in the world happens, the rich biodiversity of the lake is threatened due to the rate of extraction of 236 million m^3 sand per year in 2005-2006 (de Leeuw et al., 2010). Indiscriminate mining of sand in southwestern coast of India also affected floodplain areas, leading to severe damages to the river basin (Sreebha & Padmalal, 2011).

In terms of environmental emissions, it is estimated that about 4-8% of the world's CO_2 emissions can be attributed to concrete production (Baumert et al., 2005; Hooton and Bickley, 2014; Rogers, 2018). CO_2 is the primary greenhouse gas that is directly linked to the global warming impact. Much of the CO_2 emissions from concrete can be attributed to cement production as a result of a chemical process of limestone calcination at high temperatures (Katawiec et al., 2018). This CO_2 emissions is expected to increase in the future as a direct consequence of the rise in cement production (Imbabi et al., 2012) needed for concrete-based infrastructure developments (Watts, 2019). In turn, this would affect several environmental and social issues, as global warming impact could transcend across different contextual systems and barriers.

The wastes generated from cement production and use is also substantial. It is estimated that about 30% of the total weight of building materials delivered on site could become construction wastes (Osmani, 2011). Recent issues have focused on the large quantities of wastewater from concrete plants (Klus et al., 2017), and another is on the waste materials in the form of returned fresh concrete mix due overproduction and to poor quality (Abelleira, 2019; Vieira et al., 2019). Concrete production is responsible for the huge amount freshwater consumed annually (see e.g., Miller et al., 2018), and much are not directly used for the mixing process, but are utilized for cleaning equipment and delivery trucks, which would constitute the bulk amount of wastewater from concrete production. The amount of waste generated from concrete production and use could encourage various environmental and social issues especially when regulations are weak or absent.

(2) Economic aspect

Concrete is essentially cheap, and its constituent materials are readily accessible in most parts of the world. This is the reason why concrete remains a popular choice of building material amongst construction stakeholders and owners. Because of its unique economic quality, concrete becomes one of the primary drivers of the construction industry's economic activities. This, however, encourages many economic sustainability issues. On one hand, this would drive the over extraction of raw constituent materials to support the building of various socio-economic infrastructures, such as the building of roads and bridges. On the other hand, this would also lead to social issues such as labor exploitations in order to allow the continuance of the economic activities relevant to the high demand for concrete production.

The massive use of concrete as a cheap construction material could also become a source of abuse and corruptions. One of the flaws is the overused of concrete for dubious construction projects at staggering costs that are constructed without proper evaluations whether this would benefit the economy or the local community. In China, for example, the National Bureau of Statistics found 450 km^2 of unsold residential floor space, which is the result of excessive developments (Watts, 2019). Illegal sand mining is also pervasive in the industry due to high demands, affecting the environment, ecosystem dynamics, and the social stability in areas where regulations are weak.

(3) Social aspect

Concrete could introduce various social related impacts particularly on the health and wellbeing. Unfavorable impacts include the disturbance of landscape, dust and noise and the disruption of the local biodiversity from quarrying limestones (Narayanan, 2016). Operators in concrete production plants that come into contact with substances could face a significant health issue (Moretti et al., 2017). The cement causes many health issues as it is highly toxic, which can prompt several allergic reactions (Beech, 2019). The silica in the form of respirable crystalline silica, for example, could pose a problem as this can lead to asthma and other pulmonary disorders (Beech, 2019).

The impact on wellbeing, on the other hand, may be difficult to directly relate to concrete use as wellbeing is associated with many other environmental stimuli. Nevertheless, it is suspected that concrete use could also impact human wellbeing. The massive use of concrete, for example, has transformed substantially the landscape of cities which contributes directly to heat island effect and flood risks. Heat island effect affect communities by increasing summertime peak energy demand, air conditioning costs, air pollution and greenhouse gas emissions, heat-related illness and mortality, and water pollution (EPA, 2019). Flooding in urban areas, on the other hand, is due to the reduction of natural drainage and water storage as most areas are covered with concrete. All these issues are contributory to the deterioration of the wellbeing of the people, which are indirectly caused by massive concrete consumption.

2.2.2 The sustainability credentials of concrete materials

(1) Environmental aspect

The previous subsection has casted doubts about the environmental sustainability of concrete material. Contemporary researches, however, provide alternative insights on how concrete material could actually contribute to achieve the sustainable development goals. In terms of the environmental impact, the areas on resource depletion, environmental emissions and waste generation correspondent to the previous section are also examined. To become sensitive to resource depletion, the industry is setting new standards to counteract the excessive use of natural resources and the extraction thereof. For example, the use of recycled aggregates such as those coming from precast sector or other secondary sources (Georgopoulos and Minson, 2014) are now being used in low-grade and are being considered in high grade infrastructure applications. In addition, some construction standards require suppliers to submit environmental product declaration (EPD) or a certification that their material is responsibly sourced (e.g., the BES 6001 or the Framework Standard for the Responsible Sourcing of Construction Products) to discourage excessive and unregulated raw material extraction.

In terms of environmental emissions, particularly CO_2, the concrete sector permits the use of alternative supplementary cementitious materials (SCMs) and admixtures which would substantially reduce the amount of cement in the concrete matrix. For example, the use of blended cements such as fly ash and blast slag cements allows reduction by up to 50% of CO_2 emissions compared to the traditional Portland Cement (MPA, 2017). Some statistics shows that CO_2 emissions level have already been reduced by up to 44.8% since the 1990 absolute terms (Georgopoulos and Minson, 2014) as a result of the changes implemented in the industry. Aside from the benefit of CO_2 emission reduction, the use of by products from other industries in a form of cement combinations has reduced the need for raw materials and minimizes the waste generated by the source industry (MPA, 2017).

The flexibility of concrete material allows the use of recycled materials generated by construction activities, e.g., waste water and demolition wastes, making concrete a circular industry. In addition, the cement sector is a net user of waste from other industries (Georgopoulos and Minson, 2014). Some are used as direct cement replacements, and some are used as fuels, which significantly reduces the demand for raw and fossil fuel for cement production. Another example waste utilization in concrete production is the use of recycled water as some concrete plants are improving their process efficiency by using as much grey water as possible (CCAA, 2012). Several other techniques such as improving the durability of material and using less water-to-cement ratio (Aitciin and Mindess, 2011) reduces the wastes generated by concrete production.

(2) Economic aspect

The most relevant economic aspect of concrete to sustainability is its cheap cost and durability compared to other construction materials. Concrete allows the building of essential infrastructures without having to burden the economy and cause excessive tax on the people. Concrete also allows worldwide economic activities to exists and has the capability to mandate sustainable practices across other industries and services. For example, it could affect mining and resource extraction, which would lead to innovations in these areas. Concrete is also a very stable and durable material with extremely long life, which would only require minimal life cycle cost if properly designed and constructed (MPA, 2010).

Concrete is the primary driver of economic growth that affects job creation. Many industries depend on the economic activities created by the concrete industry. For example, the construction industry is the largest single economic activity and the greatest industrial employer in Europe with some 20 million jobs (The Concrete Initiative, 2019). Concrete industry also generates billions of taxation revenue and is a primary vehicle for wealth generation (CCAA, 2012). As such, concrete play a significant role in various economic sustainability aspects in both the local and global arena.

(3) Social aspect

The sustainability credentials of concrete in the social aspect are also varied and complex. In the area of health and safety, for example, the concrete industry is increasingly creating a safe environment for people to work. In pre-cast concrete industry, the use of self-compacting concrete technology reduces the exposure of workers to noise from vibration, providing a quieter working environment (Georgeopoulos and Minson, 2014). The setting of standards in aggregate extraction, is another example, making the sector an increasingly safe industry (Georgeopoulos and Minson, 2014).

The varied characteristics of concrete make it possible to create a variety of concrete structures corresponding to differing social needs (Sakai and Noguchi, 2013). Infrastructures are responsible for the delivery of various services such as energy, water, waste management, transport and telecommunication systems (Thacker et al., 2019), which indirectly affect the wellbeing of the people. For example, concrete allows the construction of agricultural facilities such as irrigation systems and dams to support food production and security. The construction of roads would allow people to have access to essential services such as hospitalization and other government-related services. Concrete is also resilient to damages and limits the potential for loss of lives and livelihood due to natural hazards and disasters. In short, concrete promotes the wellbeing by creating a safe environment for human habitation.

2.3 Techniques for developing sustainable concrete materials

The previous Section compared and contrasted how the production and use of concrete could, on one hand, be in conflict with the concept of sustainability, and on the other hand, how it could support sustainable development strategies. It is clear that there are many courses of action available for the industry to promote the production and use of concrete in a sustainable way. Amongst many strategies, this Section focused on the primary roles of constituent materials including the relevant codes and specifications for the development of sustainable concrete.

2.3.1 The role of constituent materials

(1) Cements and combinations

The cementitious component of concrete represents the majority of associated CO_2 emissions (MPA, 2017). Therefore, cements and its combinations with other cementitious materials have a vital role in improving the sustainability of concrete. Cement is primarily produced from the calcination of limestone with clay at approximately 1400 C (Georgopoulos and Minson, 2014). This process of cement production requires huge energy and produces large quantities of CO_2. In Japan, for example, about 766.6 kg-CO_2 is emitted resulting from the production of 1 ton of ordinary Portland cement

(JSCE, 2006). This amount, however, varies widely regionally. To reduce the associated emissions, the use of alternative fuels and cementitious additions is practiced industrywide.

The use of alternative fuels diverts wastes from landfill and reduces the need for fossil fuel, while cementitious additions not only improve the performance of concrete but also increase the recycled content and reduce the CO_2 emissions (MPA, 2017). These strategies in regard to cement production are ideal for sustainability efforts. The most effective means of decreasing both energy and consumption and the production of greenhouse gases is to substitute Portland cement by supplementary cementitious materials (SCMs) (Aitciin and Mindess, 2011). Conservative estimates, for example, point that each kilogram of substitution by SCM reduces by about 1 kg the emission of CO_2 (Aitcin and Mindess, 2011). These SCMs are often the by-product of other industry processes that are commonly landfilled. Examples of these SCMs include fly ash, ground granulated blast furnace slag, silica fume, rice hush ask, and calcined clay, among others. Few are described in the following articles.

Fly ash is the most widely used SCM that is substituted at varying levels for cement. Fly ash is a by-product from the burning of pulverized coal to generate electricity at power stations (MPA, 2017). The pozzolanic property of fly ash is initiated by the alkaline environment created by Portland cement (MPA, 2014). Aside from environmental impact reduction due to fly ash substitution, this SCM also improves some concrete quality. For example, fly ash improves the workability and pumpability, improve long-term strength and durability, and improve the resistance to Alkali Silica Reaction (Georgopoulos and Minson, 2014). Ground granulated blast furnace slag (GGBS), on the other hand, is a by-product of the production of pig iron (Aitcin and Mindess, 2011) and is also used at varying replacement ratios to cement. One estimate suggests that it is substituted to about 50% by mass of the total cementitious content (MPA, 2014). It is the most reactive of the pozzolanic materials specially when placed in the alkaline environment created by Portland cement (Aitcin and Mindes, 2011; MPA, 2017). Its use in concrete could also improve the workability of concrete, reduce the risk of thermal cracking, and improves the resistance to chloride ingress, among others (Georgopoulos and Minson, 2014).

Silica fume is another popular SCM, which is a by-product of silicon and ferrosilicon industries (Aitcin and Mindess, 2011). Its application is mostly limited to high strength concretes or concretes in aggressive environmental conditions (MPA, 2017). Rice husk ash is obtained from burning the siliceous skeleton of rice grain composed of vitreous silica that is highly pozzolanic (Aitcin and Mindes, 2011). The calcined clay, however, is not a by-product of any other industrial processes. It is produced by heating kaolin clay to temperatures about 750°C and 850°C, producing metakaolin that is highly pozzolanic (Aitcin and Mindess, 2011). The benefit from using calcined clay is that it requires lesser fuel and energy in the calcination process, thereby effectively reducing the environmental impact of concrete.

The use of SCMs is beneficial for the sustainability credential of concrete as by-products from other industrial processes are consumed in the production of cements. This also affects the resource depletion as every tonne of additional cementitious material used in concrete mixes saves about 1.4 tonnes of raw materials (MPA, 2010). SCMs also lead to better economic outcomes for construction as they can be procured at a lower cost than that of manufactured cement.

(2) Natural and recycled aggregates

Aggregates are the major component of concrete by volume and are inherently a low-carbon product (MPA, 2017). Aggregates are mined by a variety of means, including ripping, blasting and dredging (CCAA, 2010), which may cause sustainability issues. The restrictions on the expansion of existing quarry sites also have a major impact on the reliable and cost-effective supply of aggregates (CCAA, 2010). Although bulk of the aggregates used in concrete are sourced naturally, aggregates for concrete can also come from recycled and manufactured sources (MPA, 2017). Concrete reclaimed from the demolition of old concrete structures, for example, may be processed to produce aggregates suitable for use in new concrete (Aitcin and Mindess, 2011). Another example is the secondary or manufactured aggregates that are by-products from other industries (e.g., ceramics) not previously used in construction (MPA, 2017).

The use of recycled concrete aggregate, however, may result in concrete that is generally weaker compared to their natural aggregate counterpart at the same water-to-cement ratio, limiting their use to low-grade applications. Various strategies, however, have been proposed to improve the properties of recycled concrete aggregate to make them suitable for high-grade applications. For example, recycled aggregates are sometimes combined with SCMs to produce a good quality concrete (Kisku et al., 2017). Another is pretreating recycled concrete aggregate by carbonation to improve its property. Treatment of recycle aggregate not only benefits the property of the recycled concrete aggregate but also improves the CO_2 rating of concrete.

The use of by-product from other processes besides construction include aggregates in the form of steel slag, copper slag and molten stag (Sakai and Noguchi, 2013), among others. The utilization of these by-products in concrete may have varying grades application. It is important, therefore, to ensure the conformance of these aggregate types to the requirements of the specification and the intended used of the concrete materials (MPA, 2017). Nevertheless, their incorporation into concrete can have a profound contribution to resource and energy conservation (Sakai and Noguchi, 2013) which is beneficial for the sustainable development agenda.

(3) Water and recycled water

Over 1 trillion liters of fresh water are used annually in the production of concrete (Aitcin and Mindess, 2011), therefore water is equivalently vital to sustainability as the other constituent materials. Water play a special role in concrete as it is related to the amount of cement needed in the matrix and the resulting strength and quality of the material. Recent water shortages and global climate change effects have led to some regulations regarding water use for concrete construction. Therefore, as a way to improve the sustainability of concrete material, the amount of water in the matrix must be reduced, thereby significantly saving huge volumes of fresh water (Aitcin and Mindess, 2011). This is also beneficial to concrete quality as the strength of concrete is inversely proportional to the water-cement ratio of the concrete mix; i.e., low water-cement ratio may lead to higher strength (AACC, 2010).

Another way of reducing water demand for concrete is to recycle water, e.g., the runoff or slurry from concrete production operations (AACC, 2010). Recovered water from operations may include water from surplus concrete, water used to clean the stationary and truck mixers and concrete pumps (Georgopoulos and Minson, 2014). However, the use of recovered water as mixing water for concrete must also conform to the specifications for water in concrete as it may have significant impact on the quality of the resulting concrete material. Nevertheless, recycling water as concrete mixing water is not only important from the environmental perspective (Sakay and Noguchi, 2013) but also from the economic standpoint, which overall supports the sustainability of concrete material.

(4) Novel constituents

New innovations aiming to extend the sustainability credentials of concrete should focus on constituent materials such as the manufacture of new cements or the discovery of novel aggregates. These are the areas that could pose greater impacts on sustainability particularly in CO_2 emissions reduction and on the depletion and destruction of natural habitats due to the extraction of raw materials. Examples of these material as listed by Georgopoulus and Minson (2014) are: alkali-activated cements and geopolymer cements, belite cements, magnesium oxide cements from magnesium carbonates, magnesium oxide cements from magnesium silicate, and C-fixed cements.

The innovations in cement production technologies mostly centers on finding ways of reducing the associated CO_2 emissions (Sakai and Noguchi, 2013). In belite cement, for example, where the temperature for calcination is reduce by about 100°C, which translates to 20% less energy consumption and 10% less CO_2 emission. This is particularly important not only from the environmental point of view but also from the economic standpoint as environmental impacts are slowly being considered in monetary terms, therefore there is a commercial gain in developing such materials in the future (Georgopoulus and Minson, 2014).

Novel aggregates, on the other hand, centers around finding new purpose of materials that would otherwise be considered as waste from other industries. Although the innovations in this area is limited, new materials are being investigated. For example, as listed in Aitcin and Mindess (2011) materials such as mineral wastes, blast furnace slag, building rubble, metallurgical slags, bottom ash, municipal wastes, incinerator residues, and granulated rubber are some waste/by-products being considered in concrete as new aggregates. Recycled tires are of particular interests as billions of scrap tire are stockpiled annually, which poses considerable environmental problem. Many other materials can be accommodated into concrete to further improve its sustainability credential that could affect the three dimensions of sustainable development.

2.3.2 New technologies

Technological advancements could lead to new innovations in concrete production and construction. These technologies sometime work beyond the normal substitution of the conventional constituent materials, which target the functionality of concrete under environmental stresses. The effect of environment, for example, can manifest in the form of expansion and cracking of concrete (Huseien et al., 2019), which could lead to the deterioration of the functionality of structures. Therefore, new innovative solutions that would improve resiliency of concrete under the action of aggressive environmental conditions will have great impact on the sustainability performance of the material. Here, two new technologies most relevant to concrete material's durability under the action of environment are presented: on the self-healing concrete and on the use of graphene-based nanosheets.

(1) Self-healing concretes

Self-healing is beneficial for the materials' durability (Huseien et al., 2019), affecting its sustainability. Self-healing contributes directly to enhance the environment credential of concrete and on pollution reduction by increasing concrete structure's life-span. It also affects the demand for cements, which directly affects the energy requirements and thus increasing the sustainability performance of concrete (Huseien et al., 2019). Self-healing concrete could be dealt with in 4 general strategies: use of hollow fibers, encapsulations, mineral admixtures and use of bacteria.

Hollow fibers store healing agent inside its tube-like structures that are released once the crack is formed in concrete, initiating the healing process. The mechanism for microencapsulation involves the use of synthetic encapsulation device that are ruptured when cracks are formed in concrete, releasing the healing agent and initiating the crack healing process. Mineral admixtures are expansive agents added to the concrete mix that rehydrates when exposed to moisture reintroduced into the cracks in concrete. The use of bacteria is a rather complex process. One method used is the introduction of ureolytic bacteria to accelerate the precipitation of $CaCO_3$ in the microcrack areas in concrete (Husseien et al., 2019).

Self-healing technology has many advantages relevant to sustainable development. First, it conserves raw materials that are otherwise used to replace the damaged structural elements. Second, it extends the life of the structure which would also reduce the materials needed for reconstruction. This translates to significant environmental and economic benefits as the burden over material extraction is lessened and the cost for repair and reconstruction will be substantially minimized. This also involves social benefits, as it would allow almost zero recovery time due to repairing damaged structural elements.

(2) New material: Graphene

Graphene-based nanosheets (GNS) have exhibited potential to enhance crucial properties of construction materials such as mechanical strength and durability (Shamsaei et al., 2018). Its basic structural unit is graphene that are packed together closely into a two-dimensional honeycomb structure (Novoselov et al., 2004). The incorporation of GNS could modify the microstructure of the cementitious matrix. The strength enhancement is achieved due to the strong interfacial adhesion of the nanosheets with the cement matrix. On the other hand, the durability performance could be improved due to the nanostructure modification of the cement matrix by the incorporation of the GNS (Shamsaei et al., 2018)

The application of GNS to large scale infrastructure projects is yet to be materialized. However, researches at the macro and nanoscale have proven the potential of this material to significantly affect the quality of concrete that are vital for sustainable development. There are still challenges preventing its widespread application including the development of an efficient and environmentally sustainable production process (Shamsaei et al., 2018) and the lack of researches about its effect on the large scale structural elements. Nevertheless, GNS offers a promising idea for the enhancement of the sustainability of concrete materials.

2.3.3 The role of specifications and standards

Specification and standards have very delicate functions to play for the enhancement of the sustainability of concrete material. The functions can be outlined along the axis of regulatory, instructional and precautionary roles. Specifications and standards act as a regulatory measure to ensure the quality of the produced concrete materials. Recycled and secondary sourced aggregates for concrete, as an example, need to pass certain measures and limits such as the BS EN 12620:2013, which specifies the properties of aggregates and filler aggregates obtained by natural, manufactured and recycled processes. The regulatory role extends well to the extraction and preparation of the constituent materials of concrete. For example, the BES 6001 ensures that constituent materials have been sourced responsibly. The regulatory roles of standards and specifications help promote sustainability by assuring that different actors are working within the standards of the industry.

The instructional role of specifications and standards informs actors about the state of the art. It presents well-structured and corroborated frameworks about the various practices of the industry so that comparative evaluations can be done. It also allows the homogenization of complex processes so that standards are developed, maintained or refined. In the assessment method for the potential environmental impacts of constructed assets, as an example, ISO/TC59 (building construction)/SC14 (design life) developed the ISO 2004 or the environmental standards for buildings (Sakai and Noguchi, 2013). ISO also provides various life cycle analysis (LCA) tools to help in the quantification processes (e.g., ISO 21930 – Sustainability in building construction). Another example is the Recommendation for Environmental Performance Verification for Concrete Structures (draft) by the JSCE, which guides the quantification of environmental impacts of structures. Without these specifications and standards, it would be difficult to make clear assessments about the directions of sustainable development that the industry is traversing.

Lastly, specifications and standards also play precautionary role in the practice of sustainability. This is often manifested by the absence of specifications and standards itself for new materials and processes, which prevents their immediate assimilation into the wider market until these innovations are independently validated and corroborated by research and demonstrative applications. However, this also discourage and may delay important actions and decisions that may be vital for the advancement of sustainable development. In the sustainability of concrete materials, for example, specific and stand-alone codes defining the constituency of sustainable concrete are still nonexistent, despite the urgency to have one. Nevertheless, precautionary measures also support sustainable development so that inadvertent applications of new technologies are prevented that would otherwise lead to a more unsustainable situation.

2.4 Summary

The general concept of sustainable development and an overview of the sustainability of concrete materials is introduced in this Chapter. The concept of sustainable development has been formalized by the United Nations through the Brundtland Report “Our Common Future” which refers continuance over many generations of its three interconnected components: the environment, economy, and society – the pillars of sustainable development. The pillars remained the commonly accepted conceptualization of sustainability, as it allows a manageable approach on assessing the progress of societies in operationalizing sustainability. The pillars, however, are still vague as it remains difficult to solidly define from the sphere of environment, economy and society where the assessment boundaries may lie. The current marketed viewpoint of sustainability is expressed as the Sustainable Development Goals. This paradigm is composed of 17 goals and 169 targets, accounting for different specific areas of concerns relevant to sustainable development. The SDGs, however, remained incomprehensible for many industries as the goals are not conceptualized comprehensively. Nevertheless, the lack of an overarching concept for sustainable development, both the pillars and the SDGs provide a homogenized viewpoint, which is beneficial for sustainability evaluation.

The rest of the section discussed about the sustainability of concrete materials and how it could support the concept of sustainable development both in the general and specific sense. On one hand, the conflicts between sustainability and concrete production and use is examined under the lens of the 3 pillars. Concrete affects the environment in the form of resource depletion, environmental emissions and waste generation. The conflict on the economic pillar relates to the abuses in in the use of concrete which inspires the building of infrastructures of dubious significance, which would burden the economy and misuse the tax of the people. Concrete also affect the social aspect of sustainable development, as its use could be injurious to the health and wellbeing of humans. In contrast, the Chapter also discussed the sustainability credentials of concrete material in the perspective of the pillars. In regard to the environment, the concrete industry is actually a heavy consumer of recycled materials from its own and from other industries. Concrete is also the primary driver of economic activities, generating wealth and providing jobs to billions of people engaged in the industry worldwide. Health and wellbeing are also improved through concrete utilization by providing safe environment for workers and access for people to vital services.

Finally, the Chapter also introduce concepts on how sustainability of concrete can be improved at the material level by looking at the various roles played by the constituent materials themselves, the development of new technologies, and the specifications and standards. Various material manipulations can be done to raise the sustainability of concrete. Cements, for example, can be substituted and combined with by-products from other industries with pozzolanic properties, which will affect resource consumption and environmental emissions. New material innovation is also a promising area where concrete could extend its sustainability credentials. Inventions such as self-healing concretes and the use of innovative material like graphene promote safer infrastructure system, directly affects raw material consumption and maintenance cost. The specifications and standards also contribute to the sustainability of concrete material by way of regulation, instruction and precaution to ensure the quality of concrete material and the adherence of major industry players to accepted practices and standards. In summary, the concept of sustainable development and concrete material are both conflicting and reinforcing, suggesting the need to develop sustainability evaluation methodologies to find a balanced state between the goals of sustainable development and the aims of the concrete industry.

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Chapter 3
The sustainable concrete material indicators framework

3.1 Introduction

Sustainability was introduced to concrete and reinforced concrete beginning in the 2000s. However, in addressing concrete sustainability, the industry still faces various challenges. Contemporary practice on concrete sustainability relies on the policies and technical standards developed by professional organizations and government agencies. Some methods for assessing and certifying the sustainability of buildings have become mainstream, including the Building Research Establishment Environmental Assessment Method (BREEAM) and the Leadership in Energy and Environmental Design (LEED). These certification systems, however, are too general, they emanate from differing national contexts (Chandratilake, 2013), and they lack the conceptual framework to resolve concrete sustainability at the material level.

Various organizations, on the other hand, join the conversation on concrete sustainability by introducing assessment standards. ISO/TC71/SC8, for example, published the ISO 13315 series, the environmental standards for concrete and reinforced concrete structures. The Japan Society of Civil Engineers (JSCE) offers the Recommendation of Environmental Performance Verification for Concrete Structures (draft), serving as a guide to quantify the environmental impacts of concrete structures. While these standards provide a definite picture of the environmental character of concrete, they lack the basic framework with which sustainability can be considered (Sakai, 2013), and they focus primarily on environmental impacts (Henry and Kato, 2010). The *fib* Model Code 2010 interim framework for concrete sustainability, similarly, does not consider the cost and risks as part of the performance requirements (Sakai, 2013). In other words, these guidelines fail to reflect a holistic view on concrete sustainability. The American Concrete Institute (ACI), through Committee 130, aims to publish in 2018 their version of concrete sustainability standards. Nevertheless, from the viewpoint of standardization, concrete sustainability still requires huge investment.

In research, sustainable concrete evaluation methods also exist. These methods provide a platform that could harmonize the different aspects of sustainability and may supplement the lack of comprehensiveness in the policies and standards. Central to these methods are the utilization of indicators, defined as figures or other measures that enable the information on a complex phenomenon, like environmental impact, to be simplified into a form that is relatively easy to use and understand (ISO 13315-1, 2012). In literature, indicators operationalized for this purpose are increasing. The indicators in their current structure, however, are diverse, unstructured, and lack focus due to the differing conceptualization process from which they were developed. An indicators-based assessment, for instance, may only contain indicators that describe the environmental character of the concrete, while others may focus on mechanical properties and durability. The absence of a governing context for indicators development breeds uncertainty and complexity in selecting appropriate indicators from a myriad of disorganized indicators to represent the sustainability of concrete, thereby confusing designers and specifiers.

Developing sustainable concrete remains a challenge to many concrete engineers and designers, necessitating the need for a concrete sustainability framework that will address the gaps in the current practice and research. This Chapter introduce a holistic concrete sustainability indicator-based framework, consistent with the requirements of the sector to develop sustainable concrete quantitatively. The framework was developed whilst addressing two points: (1) the development of a structured list of indicators, and (2) the inclusion of a governing context using the two perspectives of sustainable development introduced in Chapter 2.

Aggregating potential SCMIs into a unified framework will provide a comprehensive outlook on sustainable concrete, making concrete producers aware of the diversity of indicators available. This would enable sustainability analysis to become more extensive and representative of the different priorities for sustainable concrete. Integrating the pillars of sustainability and the SDGs into the framework will illuminate the contributions of the concrete sector toward the international sustainability agenda.

3.2 The concept of sustainability indicators

Indicators have been extensively used to operationalize the conceptual nature of sustainability. Although biologist originally used them for many years to gauge ecosystem health (European Commission, 2012), the use of indicators was popularized when the concept of sustainable development was introduced by the United Nations (UN). Indicators became the core measurement system for the UN to gauge every member nation's contribution to international sustainability agenda. Indicators, however, are also applied to many areas such as sustainable forest management (United Nations, 2015), infrastructure projects (Allen et al., 2016), sustainable manufacturing (Rametsteiner, 2011), and many others involving to multicriteria analysis.

Indicators function to simplify a complex system. They reduce a large quantity of data to its simplest form, retaining essential meaning for the questions that are being asked (Sullivan et al., 2018;

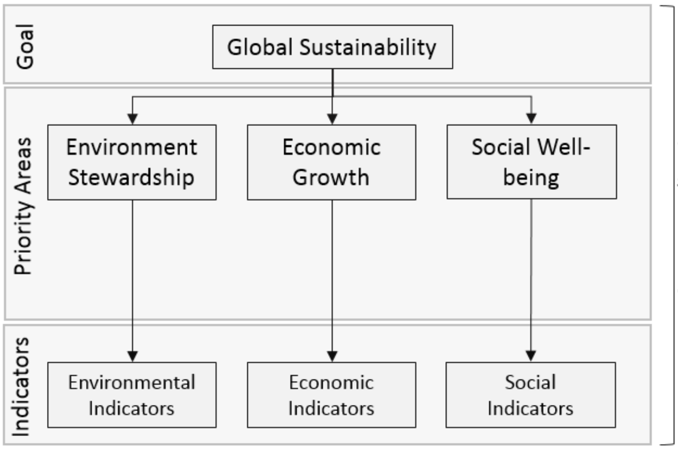
Rametsteiner et al, 2011). Therefore, indicators development is a fundamental step of an indicator-based sustainability evaluation system, described later in Chapters 4 and 5, which ultimately revolves on the indicator's potential to be quantified and eventually accepted. A set of indicators can be adopted by: (1) top-down approach, and (2) participatory (bottom-up) approach. A top-down approach is an imposition of decisions and actions (Bell and Morse, 2008), where a prepared set of indicators is introduced to the affected users or stakeholders. On the contrary, the participatory approach is a systematic identification of relevant indicators that are generally agreed on by the stakeholders.

Additionally, in indicator framework development, two things are necessary: one is conceptualization process, and the other is operationalization (Gough, et al., 2008). Conceptualization frames what is to be measured, while operationalization defines how to measure and interpret it. While conceptualization and operationalization seem to support the validity of the resulting indicator set, the abstract nature of sustainability itself makes indicator confirmation a formidable task, in the sense that they cannot "be proven true" (Saltelli et al., 2008). Therefore, it can only be said that the indicators are extensively corroborated (Michael, et al., 2014). Moreover, conventional practice requires that indicators should exhibit three functions: simplification, quantification and communication (ISO 21929-1, 2011).

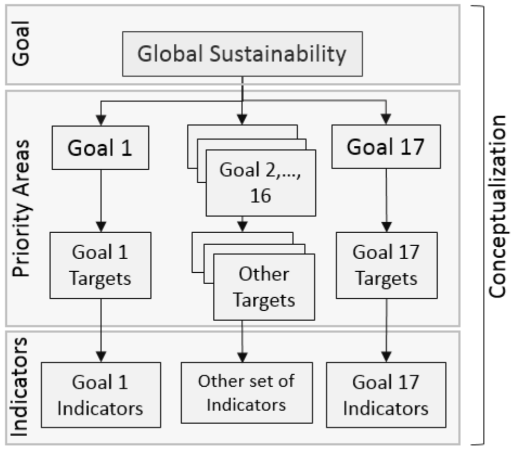
3.2.1 Conceptualization

Conceptualization is the systematic decomposition of a system into representative priority areas, creating a structure that connects the goal towards the indicators. The principle is to reduce the system into manageable components through the use of indicators without losing representativeness. When it comes to sustainability, however, representativeness is difficult to define due to the apparent lack of an assessment boundaries defining what constitute a sustainable system. What can be done is to individuate sustainable development through conceptualization, capturing relevant components using indicators.

One generic example of conceptualization is the use of three pillars to represent the idea of sustainable development, as shown in Figure 3.1a. The pillars in this case could be regarded as the primary indicators of sustainability. However, because the scope of each pillar is still too wide they can still be further conceptualized and reduced to representative specific indicators that are easy to measure, as reflected in Figure 3.1a. Using the pillars directly for indicator development, however, may present some degree of ambiguity because of the huge scope, which could result to an overlap of the function of some indicators. Elaborate conceptualization, therefore, is sometimes more appropriate for a complex system such as sustainability; for instance, using the SDGs as in Figure 3.1b. In this conceptualization, global sustainability is represented by a more defined priority areas, representing the primary indicators. The SDGs are then further conceptualized into a goal-target-indicator structure, wherein each goal is simplified into targets, and, from these targets, the specific indicators are determined. This structure is more illustrative of the priority areas of sustainable development and far less ambiguous.



(a) The pillars of sustainable development



(b) SDGs

Figure 3.1 Example conceptualization of global sustainable development perspectives

3.2.2 Operationalization

Operationalization is the process of employing indicators to quantify the state of a system and communicate the meanings of these measurements. Indicators became the most commonly accepted approach in evaluating sustainable development as they bring a different meaning to different levels (Michael et al., 2014), and indicators help identify focus areas for improvement in regard to sustainability (Joung et al, 2012). To understand the state of sustainability of a system, the indicators are interpreted individually or collectively. Individual interpretation is useful to get an idea of a specific behavior. On the other hand, collective analysis summarizes various indicators into a composite value that are easier to communicate – such as the Environmental Sustainability Index (ESI) and Environmental Performance Index (EPI), among others (Pakzad and Osmond, 2016). Composite indicators have the ability to represent various priority areas and their interrelationships. Interpretability with indicator sets, however, remains key issue in operationalization as the complexity of the interrelationships of indicators causes a number of contrary conclusions about the level of sustainability and what can be done to improve it (Joung et al., 2012).

3.3 Indicator-based sustainability evaluation

Indicator-based methodologies has become the standard for sustainability evaluation because the use of indicators allow more flexibility in the analysis and in monitoring of the state of a system

(Mascarenhas et al., 2015). In indicator-based sustainability evaluation, the number of indicators is often combined through mathematical manipulations to produce indices that reflect the overall performance of a system (Wu and Wu, 2012). Examples of these indicator-based approach are: (1) the Human Development Index developed by the United Nations, (2) Sustainability Performance Index by Narodoslawsly and Krotscheck, and (3) Urban Sustainability Index by Zhang (Singh et al., 2012), among others. These indices rely on their indicator set regarding their applicability over various systemic conditions. Therefore, careful attention is given to the identification of these indicators so that they can ideally and reliably represent the sustainability of the system of interest.

Despite the popularity of indicator-based approach to gage system sustainability, some distaste their use due to some limitations. One criticism regarding sustainability indicators is that they attempt to encapsulate complex and diverse process in a relatively simple measures (Bell and Morse, 2008), which could neglect a number of possible interactions among system components. In fact, many indicator-based systems can only reflect certain aspects of a system; however, some are more integrative than others (Wu and Wu, 2012). This is not a new problem, as, in science, complex systems such as in weather forecasting are often reduced to a number of variables in a meteorological model. The same simplification problems occur when using indicators to gauge system sustainability. The challenge, therefore, for an indicator-based sustainability evaluation is to cover various dimensions relevant to sustainability and capture their inherent interactions as holistic as possible.

3.4 Identification of sustainable concrete material indicators (SCMIs)

Indicators play a central role in capturing the sustainability of a system. Therefore, the sustainability of concrete materials could likely be captured quantitatively by identifying the relevant indicators. This section is dedicated for the developing and identifying the sustainable concrete material indicators (SCMI). The development of the indicator framework presented in the following articles, however, did not follow the typical conceptualization process. This is because, there is still considerable debate about the priority areas about concrete sustainability. What was instead executed is the reverse, in which the indicators were identified first from various literature discussing the topic of sustainable concrete. The SCMIs are the metrics considered by different parties (academics and professional organizations such as the JSCE) to ascertain the sustainability of concrete materials. It is presumed, however, that these SCMIs underwent the respective conceptualization process programmed by the proposing entity and are also independently corroborated. While it is the intent of this research to aggregate all possible indicators, a comprehensive SCMI framework is still difficult to establish due to the limitations of indicator identification from of the literature review, the anticipated limited number of indicators available, and the lack of consensus within the industry on what bounds sustainable concrete.

3.4.1 Literature review

Exhaustive literature review (from Google Scholar and Science Direct repository) on the theme of sustainable concrete was done to identify the indicators. To be more inclusive, the proceedings of two conferences on the subject of sustainable concrete were also reviewed: (1) International Conference on Concrete Sustainability (ICCS), and (2) International Conference on Sustainable Construction Materials and Technologies (SCMT). Using these sources, a systematic methodology was followed to identify the papers for review. First, search keywords (see Table 3.1) were used to identify potential papers. Second, the abstract and conclusion of these papers were read, taking into further consideration if the context of sustainability measurement using indicators or other indices is emphasized. The last step was the full paper review to identify all proposed indicators, and they were pooled with indicators from other literatures. The following metadata, whenever available, were also collected: (1) indicator name; (2) indicator description; (3) the method of measurement; (4) information on the necessity of inventory data; and (5) expected indicator behavior.

Table 3.1 Keywords used to search potential articles.

Main keywords	Derivatives
Sustainable Concrete	Green Concrete Eco Concrete Sustainable Concrete Development Sustainable Development - Concrete
Concrete Sustainability Indicator	Sustainability Indicator Indicators Performance Indicator Environmental Indicator Social Indicator Economic Indicator
Supplementary Cementitious Materials Recycle Aggregates	Cement Replacement Aggregate Replacement Recycle Concrete Aggregate Recycle Materials Waste Materials
Material Performance	Behavior of Sustainable Materials Performance of Concrete

3.4.2 Criteria for selection

The pooled indicators were tagged and then accepted if the following criteria are met, benchmarked from (Joung et al., 2012; Sustainable Measures, 2010). This is done to control the quality of the selected indicators and to assure that they can be used for quantitative sustainability evaluation.

a. Measurable: The indicator value can be obtained by experimentation; can be calculated from the values of related indicators; or can be calculated using inventory data.
b. Relevant: The indicator is relevant to the theme of concrete material sustainability.

c. Understandable: The indicator can be easily communicated and understood by different stakeholders with varying technical backgrounds.
d. Reliable/Usable: The indicator definition is not arbitrary, and its value can be obtained from a reliable methodology.
e. Data Accessible: The data should be accessible or can be made available for indicators that need inventory data to derive their values.
f. Long-term Oriented: The indicator stays relevant for future applications.

From the above criteria, measurability was the primary standard used for an indicator to be accepted. This is important so that an indicator could be easily analyzed and combined with others when creating a composite index. Related to the criterion of measurability are the indicator's reliability and accessible data. Both criteria support the potential of an indicator to be measured. It is necessary that the value of an indicator is obtained by a reliable methodology or the data needed for the computation of the value is accessible to facilitate for an easy analysis. The other criteria such as the relevance, understandable and long-term oriented help assure that the indicator properly represent the concept of sustainable concrete material.

3.4.3 Thematic combination and decomposition

The pooled indicators from literature review revealed that some of the indicators have synonymous meanings and these indicators were combined to a single thematic indicator. The purpose is to represent unanimously their collective meaning to minimize the complexity of the indicator list. For example, the indicators carbon dioxide (CO_2) (Thomas, 2010), carbon footprint (Saadee et al., 2013), CO_2 intensity (Noel et al., 2016), and carbon dioxide emissions (Bloom and Edil, 2016), all of which aim to measure the associated carbon dioxide emissions from concrete production and use, were all combined to 'Carbon Dioxide emissions.' The recycled aggregate content (Aguado et al., 2016), recycled materials (Kumar and Naik, 2010), use of recycled resources (Imoto et al., 2013), and reused material indicators (Fernandez et al., 2016) were all combined to 'Recovered, Recycled or Waste Material Content' (Arturo et al., 2010). Several other indicators underwent thematic combination, including 'Mechanical Properties,' 'Durability' (Morbi et al., 2010), 'Consumption of Primary Raw Materials' (Stepanek et al., 2013), and 'Water Consumption' (Fernandez et al., 2016). On the other hand, a few papers also introduce indicators in the form of a composite index – the combination of two or more sub-indicators into a single-variable indicator. One example is by normalizing global warming potential (GWP) by compressive strength (Muller et al., 2014), another is using a weighted strength (i.e., compressive strength) with respect to the volume of raw materials (Henry et al., 2011). These types of composites were decomposed and only their component variables are listed and accepted as indicators. The reason for this is twofold: (1) to represent uniformly the indicators in their elementary state, and (2) to not complicate the other steps of sustainability evaluation (presented in Chapter 4) process such as the importance assignment in the form of weights.

3.4.4 The list of SCMIs

In total, 92 papers were read with the following composition: 34 from SCMT, 32 from ICCS, and 26 papers from the general repositories. The limited number of papers implies that the topic of sustainable concrete is still an emerging concept in the concrete field. Much is still needed to raise the value of sustainability in the concrete industry by creating standards and specifications to facilitate its integration. Nevertheless, the literature review has provided some evidence that the area of sustainability is now being examined by other researchers through the use of indicators to describe what for them constitute sustainable concrete.

Most environmental impact indicators found from literature review originates from an established Life Cycle Impact Analysis (LCIA) guidelines (e.g., Life Cycle Assessment Operational Guide – Center for Environmental Science, Leiden University (CML) (CML, 2001)). Notably, however, only a limited number of emission indicators were found that account for the contribution of the numerous types of environmental emissions, neglecting the other associated emissions, especially those coming from the unconventional materials mixed into the concrete. For example, there are not many greenhouse gasses used as potential environmental indicators, and the focus was almost placed on carbon dioxide emissions. This operationally neglects the contribution of other greenhouse gas to define the environmental character of concrete materials. Therefore, to account the other emissions, the following placeholder indicators were included to describe the environmental character of concrete in its entirety: (1) other greenhouse gas emissions; (2) other acidifying agent emissions; (3) other photochemical ozone creation chemicals emissions; (4) other eutrophication substances emissions; and (5) other ozone depleting substances emissions.

As a result, 65 SCMIs, including the placeholder indicators, were aggregated, and are listed in Table A.1 in Appendix A. Within this list, some indicators are disaggregated to represent various areas of interest under one theme. 'Carbon Dioxide Emissions,' for example, is disaggregated into emissions from production (SCMI 5.01) and transportation (SCMI 5.02) (Morbi et al., 2010), which are helpful in identifying point and other emissions sources. The 'Durability' (SCMI 20) is disaggregated into 11 types of measurements, which generally describe how the deterioration of concrete material will progress due to varying environmental conditions. The 'Mechanical Properties' (SCMI 17) is also disaggregated into four measurements, which represents the basic mechanical performances relevant to the design of concrete structures. The SCMI list further reveals the high disaggregation in environmental indicators due to differing environmental exposures. The 'Ecotoxicity Potential' (SCMI

33), for instance, is disaggregated into three domains: freshwater, marine, and terrestrial (Habert et al., 2010).

Because of the pre-defined criteria used for indicator selection described in Section 3.4.2, all SCMIs are quantitative. This means that the values of the indicators can be obtained by either experimentation or analytical computations. Quantitative SCMIs could reduce the arbitrariness of the analysis and are easier to communicate to different stakeholders. This will also allow the indicators to be aggregated into composite indices, making the comparison of various sustainable concrete mixes straightforward and unambiguous. It is also apparent from the indicator's description that some indicators are somehow interrelated. The indicators describing the environmental emissions (e.g., CO_2 emissions), for example, are highly associated to the amount of constituent materials used in concrete production, suggesting a natural causality between them. Other indicators show the same level of causality; for example, the CO_2 emissions indicator is also highly associated with the global warming potential (GWP) indicator.

Although the conceptualization process was not performed, it is still noticeable from the list that different priority areas are covered, representing the evolution of concrete from its constituent materials, to its behavior as a single unit, including its implications to structural safety, production cost, and environmental degradation. This supports the presumption that the SCMIs already underwent individual conceptualization by the proposing entity. This evolution is analogous to the "cradle-to-gate" portion of a Life Cycle Assessment (LCA); however, in some cases, the SCMI list cover areas that are external to this limit including those describing the designed service life, structural safety, and maintenance cost. The SCMI list contains a mixture of indicators representing the environmental, economic, and social aspects of sustainability, implying that this list is holistic enough to describe the sustainability of concrete from the perspective of the pillars of sustainable development. Additional indicators, however, may be included in the future to account for new materials and applications that could enhance the comprehensiveness of this list.

3.5 Characterization of the SCMIs

The list of SCMIs introduced in the previous section needs further characterization to describe how the indicators behave relevant to sustainability. It is apparent from the list that the indicators are expressed in disparate units and scales, and thus these differences could have great implications on sustainability quantification. For example, some indicators may have opposing behaviors or time-dependent values. Therefore, when utilizing the indicators to quantify the sustainable performance of concrete materials, one should be cautious about these behaviors. In this section, some relevant metadata for indicator measurement are described so that they can be used properly in the analysis.

3.5.1 Indicator behaviors relevant to sustainability quantification

The SCMI in Table A.1 further reveal what indicator behavior will result in a more desirable concrete from the viewpoint of sustainability. In most cases, an increase in raw indicator value does not necessarily mean sustainability is improved. The increase in the associated CO_2 emissions, for instance, would negatively influence the sustainability. On the other hand, a high compressive strength is desirable for sustainability. It is important, therefore, to distinguish whether an indicator's value causes the sustainability of concrete material to improve or not.

The apparent bidirectional behavior of the indicator list is similar to the conflictual situation studied in multi-criteria decision theory (Munda, 2005), which can be resolved by some analytical processes such as normalization and aggregation techniques that as described in Chapter 4. In order to distinguish what indicator behavior is desirable to improve the sustainability performance of concrete materials the SCMIs in Table A.1 are marked with '+' meaning an increase in indicator value contributes positively to the sustainability of concrete. Those indicators marked with '–' means a decrease in value will positively contribute to sustainability. The identification of this desirable behavior as it relates to sustainability is important as it may confuse the analyst and could be a critical source of error in the analysis.

3.5.2 SCMIs needing inventory data

While the value of some indicators in the list could be obtained easily by experimentation or analytical computation, for some, however, determining their value may be challenging. Thirty-eight (38) indicators in Table A.1 require inventory data to derive their value and are marked accordingly. Inventory data, also known as 'characterization factor' are standardized quantities of inputs and outputs of a product system or inventory item including its processes (Kawai et al., 2005). It is applied to convert an assigned life cycle inventory analysis result to a common unit of the category indicator (ISO 14040, 2006). For example, in converting CO_2 emissions to global warming potential. Without these inventory data, it would be close to impossible to determine the value of some indicators.

Inventory data are geographically and temporally sensitive (CML, 2001), which limits their use and functionality. In Japan, for example, the unit CO_2 footprint of normal Portland cement is 766.6 kg-CO_2 equivalent per ton of clinker-derived cement (JSCE, 2006), while in Thailand it is 862 kg CO_2 equivalent per ton of clinker-derived cement (ACF, 2014). The cost inventory data are the most sensitive to regional boundaries and time dimension due to technological improvements. This implies a great variation in some inventory data, which should caution the user about their appropriateness.

The variation is influenced by several factors including material sources, the types of technology, and the process of concrete production. Using inventory data, however, without regard to their appropriateness could mislead the analysis, and cripple the solutions and decisions that could be derived from them.

Some inventory data, on the other hand, are standardized globally. For example, the inventory data for environmental emissions. Therefore, to distinguish which inventory data is appropriate for some indicators in Table A.1 in Appendix A they are further mark as region-specific (marked ‘Y-R’) or standardized globally (marked as ‘Y-S’). Fifteen SCMIs can be computed readily by using globally standardized values. While the remaining may depend on the availability of the regional variation of the data. Standard inventory data, however are also periodically updated, so their reliability should be checked prior to using them to avoid misleading results, misjudgments, and biased decisions.

3.5.3 Time-dependent SCMIs

Some SCMIs in Table A.1 may also have time-dependent values. The ‘Mechanical Properties’ (SCMI 17) and ‘Durability’ (SCMI 20), for example, vary as the curing time progresses. This variation is due to the continued hydration of cement or the pozzolanic reaction of supplementary cementing materials (SCM) in the matrix. Therefore, the value of these indicators should be adopted fastidiously, depending on the goal of the evaluation or on applicable standards. For concrete structures, as an example, the 28-day mechanical performance is commonly specified as predictors of concrete quality. This standard, however, is restrictive for mixtures with SCMs that require longer time to chemically react to develop strength and durability (e.g., fly ash and blast slag). There is still a considerable debate in standards and specifications whether to allow a 56-day or longer curing period when specifying concrete quality. The time dependency of some indicators may ultimately affect the results of the sustainability analysis.

3.6 The SCMI framework

Selecting indicators for analysis directly from the SCMI list (Table A.1) is still unwieldy because the indicators are still isolated from each other. In this section, a framework that would not only assist in indicator selection, but also shows the interrelationships between indicators is presented. This is done by transforming the list in Table A.1 into a causal network (CN). CN is a combination of a series of causal loops and feedback loops, such as the pressure-state-response framework and its transformations (Pakzad and Osmond, 2016) that reveal the indicators’ dependency and interrelatedness. Causal network is a common framework of choice for indicator selection by various organizations such as the OECD (Pakzad and Osmond, 2016), which also supports result interpretation.

The fundamental step in transforming the list to a causal SCMI framework is to establish the relationships between indicators. These inherent relationships have been previously hinted by the strong affinity between some of the indicators description as describe in Section 3.4.3. Finding these relationships was accomplished by using the models from civil engineering principles, material flow, and cost analysis. The models from civil engineering principles help connect the material usage to the fresh and hardened properties of concrete; for example, the dependency of concrete's mechanical properties (i.e., compressive strength – SCMI 17.01 and durability – SCMI 20) on the amount of water (SCMI 3) and cement (SCMI 2) in the mix (or the water-binder ratio) (Aitciin and Mindess, 2011). The material flow concept establishes the causality between constituent materials, their associated emissions, and the environmental impacts of those emissions. The equivalent carbon dioxide emissions, as an example, can be calculated using inventory data for constituent materials. Cost analysis, similarly, links material usage to its economic equivalent such as the cost of raw materials (SCMI 23), cost of waste materials (SCMI 25), and unit production cost of concrete (SCMI 40).

The established relationships between the indicators also reveal that some indicators are dependent on multiple indicators. CO_2 emission, for instance, is dependent on SCMI 1, 2, 3, and 4. This multi-dependency adds complexity to the causal network, thus, to simplify the SCMI framework, the levels of causality was limited to three using the driving force (D), state (S), and impact (I) levels, forming the D-S-I causal network. The combination of these relationships forms the causal SCMI framework, shown in Figure 3.2.

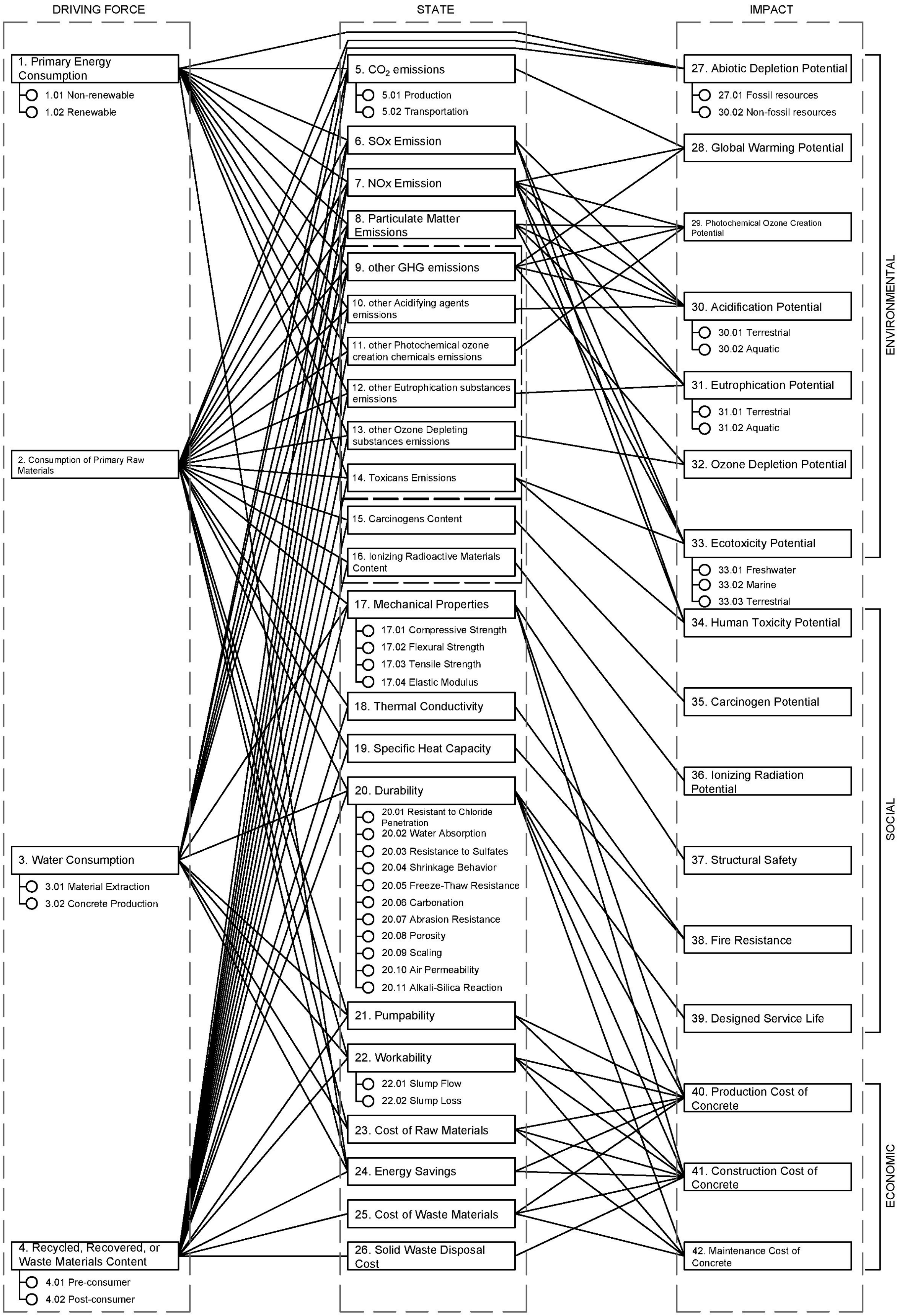


Figure 3.2 Sustainable concrete material indicators framework

3.6.1 Causal SCMI relationships

The transformation of the list of indicators into a causal network elicits more meaning to the aggregated indicators, making them easier to communicate to stakeholders, whilst also assisting the subsequent indicator selection process. Driving force indicators (or pressure indicators) underlie the causes (Pakzad and Osmond, 2016) that influence the state indicators (Bell and Morse, 2008). The state indicators, on the other hand, describe the state of a variable (Bell and Morse, 2008) (e.g., quantity of associated CO_2 emissions, SCMI 5). Finally, the impact indicators translate state indicators into outcomes/impacts or possible scenarios; for example, global warming potential (SCMI 28).

In the SCMI framework (see Figure 3.2), four driving force indicators are identified (i.e., SCMI 1, 2, 3, and 4), characterizing the use of constituent materials, except for the 'Primary Energy Consumption.' This implies that material consumption is the predominant issue in concrete sustainability that affects every other priority area. This mirrors the fact the concrete is a voracious industry when it comes to material consumption, affecting several environmental issues. The lines connecting the driving force indicators and state indicators show the pre-established causality, suggesting that the changes in the driving force indicators will propagate to the state indicators they connect to.

On the other hand, there are 37 state indicators identified that are also shown in Figure 3.2. Among them, the state indicators CO_2, SOx, NOx, and PM emissions were treated as separate from the placeholder indicators (see Section 3.4.3), since these emission indicators are the commonly considered environmental metrics in literature, which might be due to the availability of inventory data that focuses primarily on these types of emissions. The state indicators also include the mechanical performances of concrete and the durability measurements, which assures the quality of concrete for a desired application. Some elementary cost indicators are also within the state indicator group.

The impact indicators, analogously, elucidate the practical implications of the state indicators. There are three impact indicator groups distinguishable in this framework that represent the pillars of sustainability (see Figure 3.2): one contains the indicators describing the potential to degrade the environment (e.g. SCMI 27-33); another group relates to social aspects including structural safety and the designed service life of the structure (e.g. SCMI 40-42); the other deals with the economic dimension, encompassing production, construction, and maintenance costs (SCMI 34-38). The lines connecting the state and impact indicators show which state indicators contribute to an impact indicator. The SCMI framework also shows that a state indicator can influence several impact indicators. SOx emissions, for instance, influence both acidification potential and toxicity potential, giving rise to the dilemma of dividing the quantity of SOx into both impacts. This is termed as 'classification,' which is recognized in some LCIA standards (e.g., ISO 14040 series).

3.6.2 Implications to indicator selection, traceability, and focus areas

In the SCMI causal framework, important changes can be observed and traced, which are useful when selecting indicators for sustainability evaluation from any causality levels. The most linear way of selecting indicators using this framework is to begin with indicators in the driving force group, then tracing the relationship lines to determine the relevant state indicators and working towards the impact indicators. For example, selecting the Primary Energy Consumption (SCMI 1) automatically prompts that the 11 state indicators it is connected to (see Figure 3.2) are also essential to the analysis. By extension, the impact indicators connected to these state indicators become necessary, eliminating irrationality in indicator selection. The selection could also start from the impact indicator group and by tracing the dependencies, both the relevant state and driving force indicators can be identified. This indicator selection process, however, do not necessarily guarantee the inclusion of the indicators to the analysis as it may ultimately depend on the availability of the data (e.g., inventory data) and other structural factors (e.g., multi-collinearity).

The traceability feature, on the other hand, of the SCMI causal framework is advantageous in identifying focus areas. Because the indicators are connected, it becomes easily verifiable what causes a certain indicator's value to change. The GWP (SCMI 28), for example, can be controlled by making changes in the three indicators on which it is dependent (i.e., SCMI 5, 7 and 9). As a result, solutions can be formulated targeting the indicators that can be easily manipulated. The SCMI framework, therefore, makes it easier to affect the desired changes to improve the sustainability of concrete material, thereby, supporting the efficient development of sustainable concrete and the eventual decision-making process.

3.7 The SCMI Framework and the Global Perspectives of Sustainable Development

During indicator development, it is important to address the challenge of fully integrating and capturing the interrelationship between the social, economic, and environmental dimensions of sustainability (Michael el al., 2014), and, recently, the SDGs. Incorporating these two perspectives provide the indicator framework with solid contexts in which to examine if the strategies taken and proposed by the stakeholders of the industry to make concrete sustainable truly embodies the essence of sustainable development. As a consequence, each SCMI must reflect these dual perspectives of sustainable development, as illustrated in Figure 3.3. Connecting the SCMIs to the perspectives of sustainable development validates the value of the SCMI framework for sustainability evaluation works.

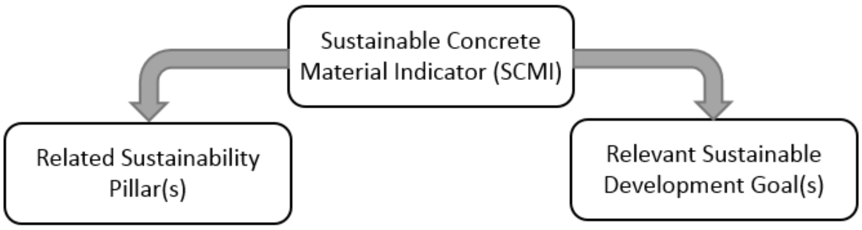


Figure 3.3 The dual character of the SCMIs

3.7.1 The SCMIs and the three pillars of sustainability

There is a considerable interest in indicators that better reflect the linkages between the three pillars of sustainable development (Michael et al., 2014). Such linkages do not only provide context to the SCMI framework for sustainability evaluation but are also favorable in dealing with the challenges in balancing the environmental, economic and social pillars (Michael et al., 2014). To relate the SCMIs to the pillars, the following definitions were used:

a. Environmental Indicators: indicators referring to environmental issues affecting global, regional, local and the built environment, such as biodiversity, global warming, ozone destruction, and resource depletion (Sakai and Noguchi, 2013).
b. Economic Indicators: indicators that translate resource and material consumption, processes, energy, and waste utilization and production into their economic equivalent (Sakai and Noguchi, 2013).
c. Social Indicators: include aspects with relevant social values, such as quality of materials, human health and safety, security, and serviceability.

From the above definitions, the description of each indicator (Table A.1), and on the previously identified impact indicator groups (see Section 3.6.1), SCMIs 27 to 33 are, therefore, classified as environmental indicators (see also Figure 3.2); SCMIs 40, 41 and 42 are classified as economic indicators; and SCMIs 34 to 38 belong to the social pillar. The dependency of the impact indicators to the state indicators was used to assign the indicators in the state group into their respective sustainability dimensions. For instance, PM emissions (SCMI 8) contributes to SCMI 29, 30, 31, and 33, which are all environmental indicators, implying that SCMI 8 belongs to the environmental pillar. The multidimensionality of a state indicator occurs when it contributes to impact indicators belonging to different sustainability pillars. The 'Mechanical Properties' (SCMI 17), for example, contributes to a social indicator SCMI 37, as well as to economic indicators SCMI 40 and SCMI 41, thus SCMI 17 is both Social and Economic (SoEc). The driving force indicators were classified in the same manner; however, all were designated as representative of all sustainability dimensions because the state indicators they contribute to represents all the pillars. The association of the SCMIs to pillars are also summarize in Table A.1 in Appendix A.

The distribution of the SCMIs into their respective sustainability dimensions is reflected in Figure 3.4, showing that 31% of the indicators are purely environmental as a consequence of the high disaggregation of the environmental indicators (see Section 3.4.3). The social indicators, however, including those classified into multiple dimensions (such as EnSo and SoEc), cover about 47% of the distribution – the highest among the dimensions – implying that the social dimension is becoming relevant. This is contrary to the previous conception of concrete sustainability, which focuses on the environmental aspect only of concrete. Nevertheless, the economic dimension arguably is still the governing concern of the construction industry practitioners (Kamali and Hewage, 2007), despite only 11% of the SCMIs are purely economic indicators. The distribution, therefore, implies that there is somewhat an imbalance between the pillars regarding the number of representative indicators. Further, it also reveals the overlap between the pillars as some indicators could represent one or more pillars of sustainability. As one advantage of this relationship, the underperforming pillar can now be easily ameliorated by improving the indicators representing it.

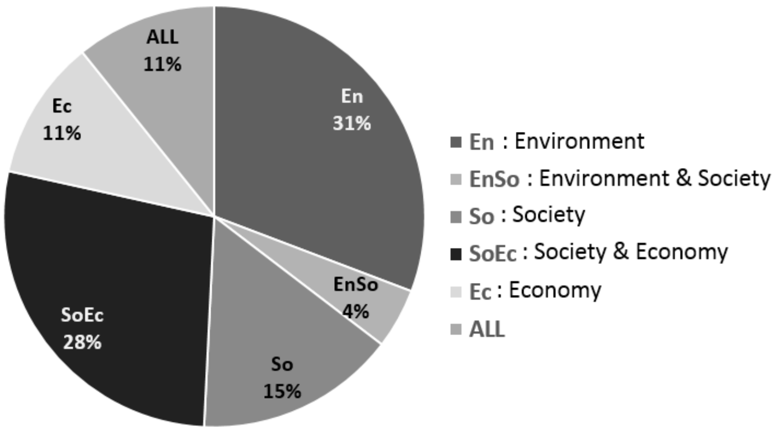


Figure 3.4 Distribution of SCMIs into sustainability dimensions

3.7.2 The SCMIs and the SDGs

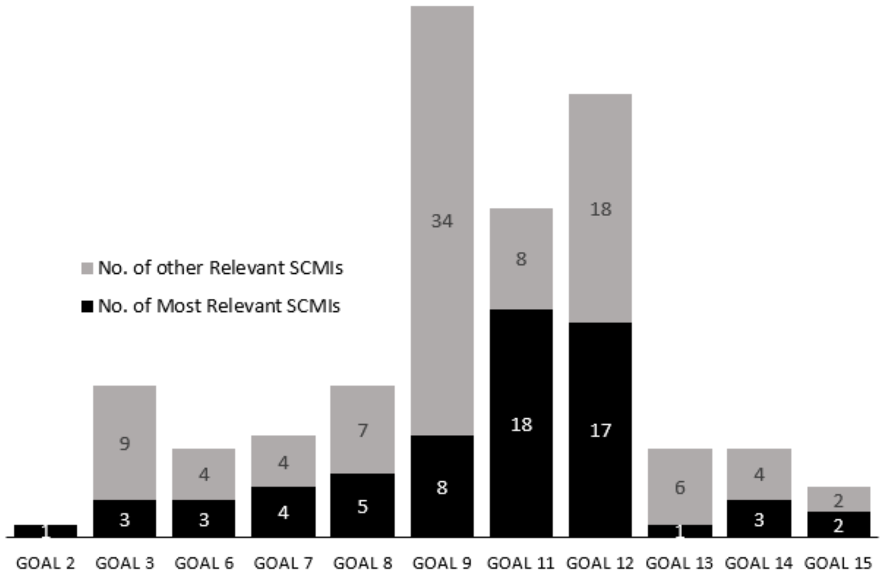
While the SDGs' paradigm is elaborately conceptualized (see Section 3.2.1), it still remains confusing for various sectors using the structure of the SDGs to link their sustainability strategies (e.g., the development of more sustainable concrete) with each goal and its targets. The SDGs paradigm do not provide explicit framework for various sectors to participate in the achievement of its goals. It relies on the vagueness of the statement of its targets (Hak et al., 2016), which in contrast provides an open opportunity for sectors to indirectly link their sustainability strategies to the SDGs. In the Sendai Framework for Disaster Risk Reduction, for example, the parallelism of some SDGs' target statements to the Framework's seven global targets has been used to disclose how it could contribute to the SDGs (UNISDR, 2018).

Along the same vein, the following analysis utilized the SDGs' targets as the natural structural basis to relate the SCMIs to the SDGs. This is done by finding mutual similarity between the indicator's theme and definition, and the SDGs' target statements. For instance, the 'Recycled, Recovered or Waste Materials Content (pre-consumer)' (SCMI 4.01), which is roughly defined as the amount of by-products from industrial processes (e.g., fly ash) in the concrete matrix (see Table A.1), has mutuality with the SDG targets 6.3, 9.4, 11.6, 12.2, and 12.5, as illustrated in Figure 3.5. These targets were identified by exhaustively analyzing the SDG's target statements in the context of waste utilization, recycling, and resource efficiency. This mutuality suggests that SCMI 4.01 is indirectly relevant to more than one target. Additionally, amongst the targets, SCMI 4.01 is determined to be most relevant to target 12.5 due to their strong mutual affinity in the context of recycling and reuse, suggesting this indicator is most relevant to Goal 12 of the SDGs (Responsible consumption and production). Moreover, since SCMI 4.01 is also relevant to targets 6.3, 9.4 and 11.6, this indicator is also somewhat relevant to Goal 6, Goal 9, and Goal 11. The association of the SCMIs to the SDGs is also reflected in Table A.1 in Appendix A, which specifies the most relevant goal and all the relevant SDG targets per indicator.

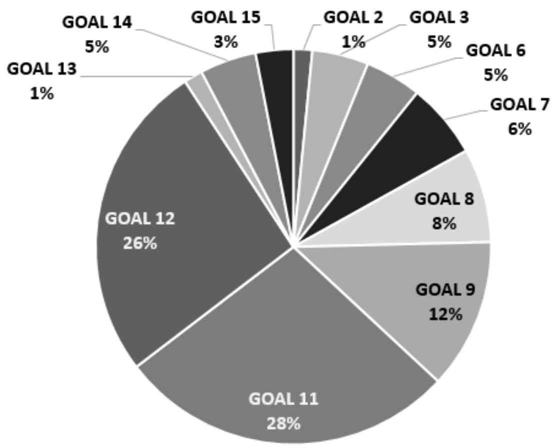
Figure 3.5 Sample indicator matching with the relevant SDG targets

The distribution of the SCMIs into their relevant SDGs after determining which SDG they are most relevant and somewhat relevant to is shown in Figure 3.6. This figure suggests that the indicators are only relevant to 11 of the 17 SDGs. Further, Figure 3.6a shows the number of indicators most relevant to, as well as the number of indicators that are somewhat relevant to, a particular SDG. Figure 3.6b, on the other hand, reflects only the proportion of indicators that are most relevant to a particular SDG, showing that the SCMIs are most relevant to goals 9, 11, and 12. These SDGs are closely related to the civil engineering discipline, with Goal 9 addressing infrastructure resiliency and sustainable industrialization; Goal 11 promoting a safe, resilient, and sustainable human settlements; and Goal 12 aiming at efficiency in material use and recycling, which affects concrete production and consumption.

Figure 3.6 also reveals that there are SDGs that may be perceived as unrelated to concrete because of their thematic descriptions. SDG 2 (Zero Hunger), for instance, is difficult to connect to concrete directly. However, the analysis of SDG 2 reveals that of the targets listed in this goal, such as targets 2.3 and 2.4 which aim to double the agricultural productivity and improve soil quality, respectively, will be affected by NOx, PM and other eutrophication-causing substances associated with concrete use – measured by SCMI 31.01 (Eutrophication Potential – Terrestrial). The linkage between the indicators and SDGs, therefore, elucidates that concrete sustainability is also relevant to areas that are perceived as not directly related to building and construction.



(a) Overall distribution



(b) Most relevant SDGs only

Figure 3.6 Distribution of the SCMIs to their relevant SDGs

3.7.3 Implications for decision-making regarding the development of sustainable concrete

Concrete sustainability remains a challenge for the concrete industry, since it is difficult to picture concrete mix design from the viewpoint of the three pillars of sustainability or the SDGs due to the lack of consensus and specific guidelines. The JSCE Standard Specifications for Concrete Structures, for example, in its current form does not specify any performance requirements regarding the environment, nor does it make any clear statements regarding the reduction of environmental loads (Yokota et al., 2016). Additionally, concrete producers and contractors are often just interested in prequalification and quality control testing, while owners are interested in the performance of the hardened concrete in the structure (Hooton and Bickley, 2014).

It is clear, therefore, that there seems to be a traditional disconnect between concrete material design/specification and the principle of sustainable development. But, over the past decade, the perspective on sustainable concrete has changed, and sustainability is now encouraged industry-wide. This is evidenced by the growing literature about the development of sustainable concrete as reviewed by the author. Decision makers, in turn, require a set of sustainability indicators to know if the sustainability strategies are adhering to those pathways (Vazquez et al., 2015). This has been addressed extensively in this Chapter, which resulted into the aggregation and the creation of an SCMI causal network. Further, the relationship of the SCMIs with the pillars of sustainability and the SDGs, as described previously, provides the initial structure describing how to achieve this purpose by providing solid contextual viewpoints for evaluating and for developing concrete materials from the perspective of sustainable development.

The SCMIs' relationship with the pillars of sustainability also reinforces the identification of focus areas that could be improved to enhance the sustainability of concrete. The SCMI-SDG relation, on the other hand, illuminates how the goals can be affected by the indicator's behavior, exposing the trade-offs that may arise between the goals. Since the trade-offs between different aspects of sustainability are one of the reasons why disagreements between stakeholders exist, it is the ultimate goal of a sustainability framework to clarify these trade-offs to support the decision-making process and infuse consensus to guarantee sustainability. The SCMIs' relationship with the pillars and the SDGs enables the stakeholders to make informed choices and to recognize their contributions to global sustainability agenda, consequently, narrowing the gap between the concerns on material performance and that of sustainability.

3.8 Demonstration of the applicability of the SCMI framework for concrete sustainability evaluations

This section illustrates the applicability of the SCMI framework for the quantitative evaluation of concrete sustainability. The two perspectives of sustainability were also utilized as governing context in the analytical process. In the following sub-sections, various sustainable concrete materials developed by manipulating the constituent materials (e.g., using recycled aggregates) were examined. The analysis used pre-selected indicators which are aggregated by linear sum to contrast the sustainability performance of different concrete mixes in the context of the three pillars and the SDGs.

3.8.1 Selected SCMIs for demonstration

Figure 3.7 shows the hierarchical evaluation paradigm utilizing the pre-selected SCMIs. For the demonstration, all driving force indicators were used except for SCMI 1 due to data limitations. For the same reason and based on causality, only a few state indicators were included. Finally, only SCMI 28 and 40 were selected from the impact indicators due to the limited number of state indicators available to derive the other impact indicators. In total, 11 indicators were used in the analysis, which are then linked to their respective pillars and to the most relevant SDG.

From the pillar's perspective, 5 of the SCMIs represent the environmental pillar, 9 for the economic pillar, and 6 for the social pillar. On the other hand, for Goals 6, 8, 9, 11, 12, and 13, the number of representative SCMIs are 1, 3, 3, 1, 2, and 1, respectively. The multidimensionality of some SCMIs were retained in this structure as shown in Figure 3.7. The contribution, therefore, of an indicator to different pillars are accounted in this analysis. The elementary form of a multicriteria analysis were used in this demonstration wherein the 11 indicators are combined by weighted sum – the most common indicator-based approach to sustainability evaluation.

To reflect the relative importance of each indicator, weights are sometimes applied in a multicriteria analysis. However, the debate on weight assignment is still unresolved due to the plurality of methodological approaches to derive them (e.g., by extracting weights from the stakeholders, i.e. Vazquez et al., 2015). Chapter 4 further elaborates the considerations on weighting. Nonetheless, in this evaluation, equal weights (S_w = 1.000) were assigned at the pillar's and SDG's hierarchical level (see Figure 3.7) for simplicity and to signify dimensional equality. The weights for each SCMI in each perspective were calculated using the following expression:

$$W_i = \frac{S_w}{N} \qquad \text{Eq. 3.1}$$

where: S_w : weight assigned per Sustainability Pillar or per SDG;

N : number of SCMIs contributing to a particular Sustainability Pillar or SDG; and

W_i : the sustainable concrete material indicator weight.

As an example of the weighting process for the environmental pillar, each representative indicator was assigned with $W_i = 0.200$, since $N = 5$ and $S_w = 1$. For multidimensional SCMIs, on the other hand, their value was fully allocated to each pillar they represent. As a result, multidimensional indicators received 3 weights for each pillar. For instance, the En, Ec, and So components of SCMI 4.01 were assigned with different weights equal to 0.200, 0.111, and 0.167, respectively as SCMI 4.01 represents all pillars. Similar weight assignment was followed for the SDGs perspective. Figure 3.8 details the pre-selected SCMIs in their causal form, which also includes the related sustainability pillars, and the most relevant SDG per SCMI with their corresponding weight assignments.

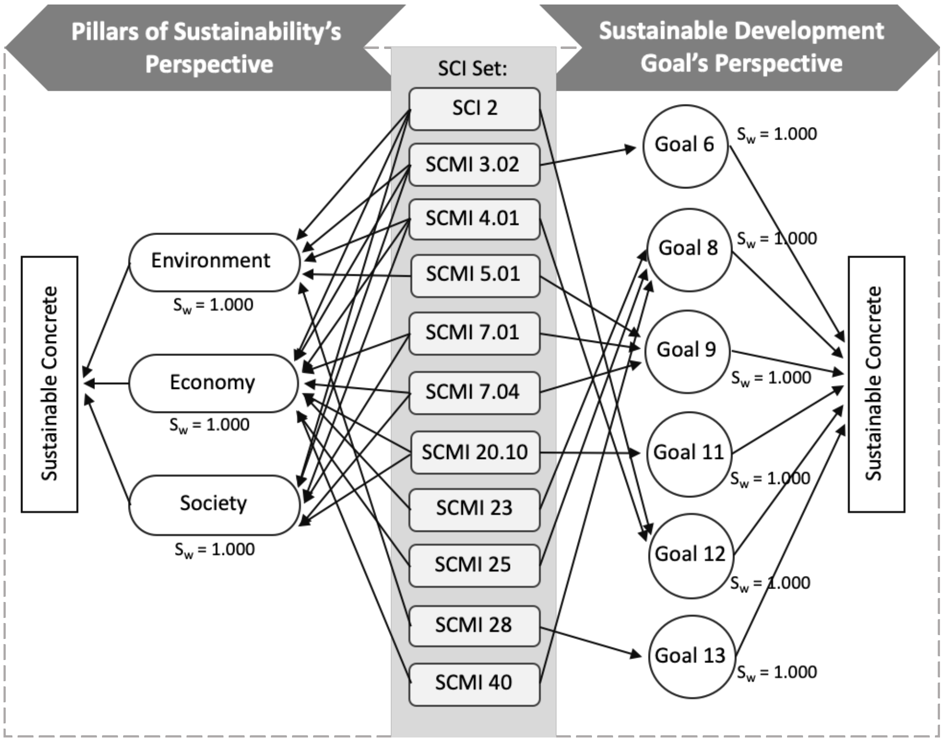


Figure 3.7 Viewpoints in evaluating sustainable concrete through sustainability pillars and SDGs

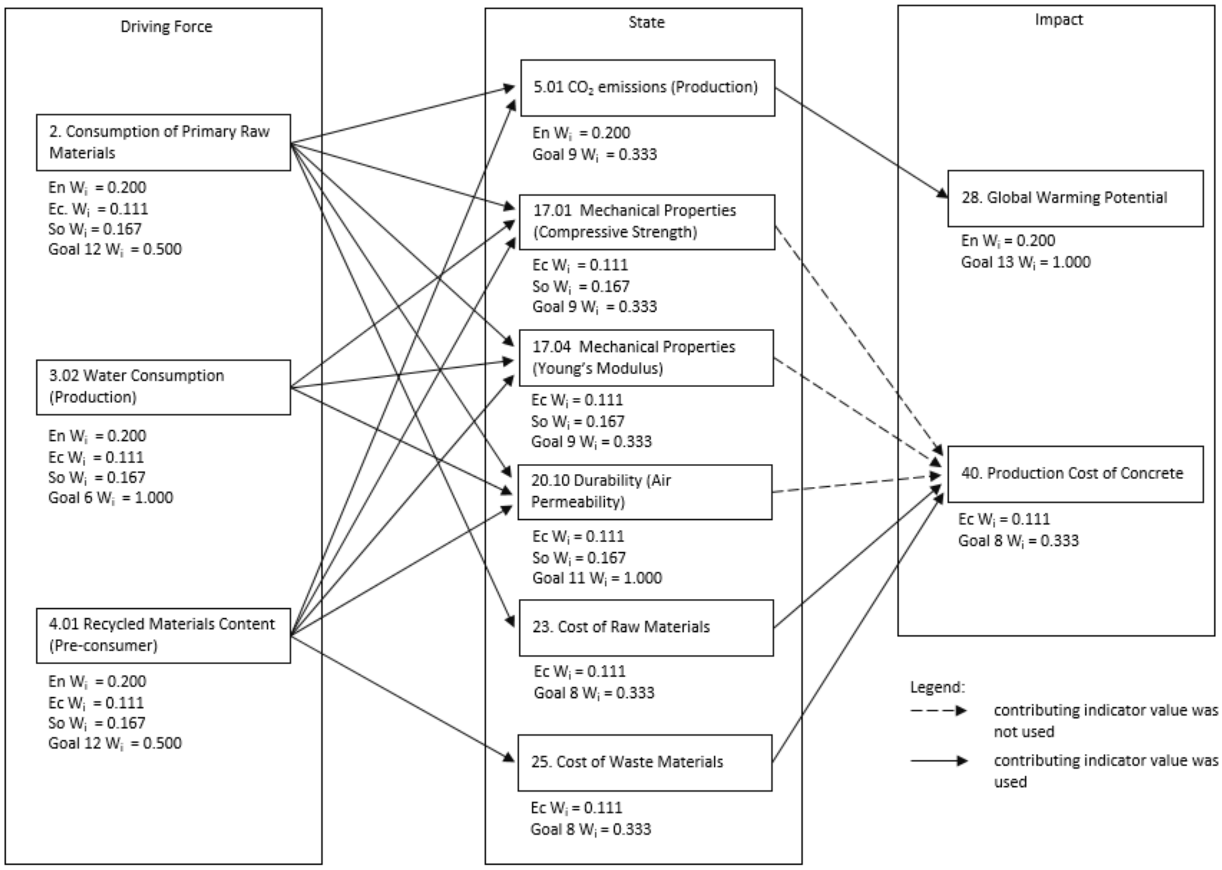


Figure 3.8 Selected SCMIs used for analysis

3.8.2 The data set and analytical scenarios

The data of the different concrete mixes used in this demonstration is from the work of Henry and Kato (2010), with the mix proportions shown in Table 3.2. In this set, the control mix was selected as the reference material for comparison, since, in the concrete field, no standard reference mix exists with which the alternative mixes can be compared to for verification. The experimental factors examined – which also constitute the different scenarios – were: (1) the effect of binder content (Normal Binder – NB and Low Binder – LB); (2) the effect of coarse aggregate type (normal – NA and recycled – RA); (3) the effect of fly ash (FA) replacement (none and 50% replacement of cement); and (4) the effect of combining fly ash and recycled aggregate. Binder content was used instead of the water-cement ratio to represent explicitly the values of SCMI 2 and 3.02.

Table 3.2 Mix proportion and SCMI values per concrete mix

Series	Mix Proportions (kg/m^3)						Mass of Constituent Materials (kg/m^3)		CO_2 emissions	fc' 28-day	Young's Modulus (28-day)	Air Perm. (28-day)	Cost of Constituent Materials (JPY/m^3)			GWP
	W **(SCMI 3.02)**	C	FA	S	NA	RA	Raw Material **(SCMI 2)**	Recycled Material **(SCMI 4.01)**	kg-CO_2/m^3 **(SCMI 5.01)**	MPa **(SCMI 17.01)**	(1x10^4) N/mm^2 **(SCMI 17.04)**	(1x10^{13} * ln) m/s **(SCMI 20.10)**	Raw Material **(SCMI 23)**	Recycled Material **(SCMI 25)**	Total (Production Cost – **SCMI 40**)	**(SCMI 28)**
Control	171	342	0	746	1,015	0	2,103	0	268	43.5	3.54	4.00	5,815.1	0.0	5,815.1	0.27
NB-NA	165	550	0	624	1,009	0	2,183	0	427	75.6	3.94	2.21	7,613.9	0.0	7,613.9	0.43
NB-RA	165	550	0	624	0	905	1,174	905	427	59.5	3.30	3.60	6,272.0	561.1	6,833.1	0.43
LB-NA	135	450	0	687	1,111	0	2,248	0	351	87.1	4.29	2.20	6,882.7	0.0	6,882.7	0.35
LB-RA	135	450	0	687	0	996	1,137	996	351	62.5	3.27	3.27	5,405.1	617.5	6,022.6	0.35
NB-NA-FA50	165	275	275	590	955	0	1,820	275	221	52.9	3.32	2.22	4,849.4	1,100.0	5,949.4	0.22
NB-RA-FA50	165	275	275	590	0	856	865	1,131	221	39.7	2.48	3.36	3,579.3	1,630.7	5,210.0	0.22
LB-NA-FA50	135	225	225	659	1,067	0	1,951	225	182	46.9	3.32	2.41	4,620.8	900.0	5,520.8	0.18
LB-RA-FA50	135	225	225	659	0	957	884	1,182	182	41.3	2.55	3.35	3,201.7	1,493.3	4,695.0	0.18

Note: W – water; C – ordinary Portland cement; FA – fly ash; S – sand; NA – natural aggregate; RA – recycled aggregate.

3.8.3 The SCMIs' raw and normalized values

The values of the pre-selected SCMIs are also shown in Table 3.2. The analysis was based on a 1 cubic meter functional unit of concrete. Functional unit is the quantified performance of a product system for use as a reference unit (ISO 14040, 2006). The calculation of an indicator value depends on its description in Table A.1 in Appendix A. Since the indicators have disparate scale and unit, there values are also obtained by varying strategies. For this demonstration the calculation of the indicators value is described as follows.

The value of SCMI 2 is obtained by summing the masses of cement (C), sand (S), and normal aggregate (NA) in Table 3.2. Cement, sand and normal aggregate represent the generic raw constituent materials of normal concrete. For SCMI 3.02, the unit mass of water from the mix proportion is simply adopted. SCMI 4.01 is the sum of the masses of FA and RA, which represent the by-product and recycled materials used in the concrete matrix, respectively. The CO_2 emissions, compressive strength (SCMI 17.01), and Young's Modulus (SCMI 17.04) are from the source literature. The amount of equivalent CO_2 emissions, however, could be derived using inventory data. This works by multiplying the contributing entity (e.g., the amount of cement) by the appropriate inventory data for CO_2 emissions. For example, the cement in the mix proportion is multiplied by 766.6 kg-CO_2 equivalent per ton of cement used in the case of Japan to get the amount of CO_2 emissions due to cement consumption. The SCMI 17.01 and 17.04, on the other hand, are obtained from experimentation. The air permeability (SCMI 20.10) – regarded as one indicator for durability – from the source, was also obtained through experimentation. Its actual value, however, was converted using natural logarithmic scale in this demonstration since the actual value are too small for comparative analysis.

The values of SCMI 23 and 25 were derived by multiplying each relevant constituent materials with the unit costs shown in Table 3.3, which were the costs of the constituent materials at the time when the original work was performed. It is important to note, however, that these unit costs might change if the analysis is viewed in a different timescale, directly affecting the analysis. The values of SCMI 28 were calculated using the contributions from CO_2 emissions only, as other inputs were unobtainable due to data unavailability. GWP was derived by multiplying the CO_2 emissions with the corresponding characterization factor, equal to 1.0 for CO_2 for a 100-year time horizon. The inventory data for converting other greenhouse gasses to their equivalent GWP are usually standardized globally. SCMI 40 is the sum of the cost of raw and recycled materials. The contributions to SCMI 40 from SCMI 17.01, 17.04, and 20.10 were not considered due to the lack of data, such as the mixing effort for an equivalent compressive strength.

Table 3.3 Unit costs of constituent materials

Item	Unit Cost, JPY/kg (JPY = Japanese Yen)
Cement	9.60
Sand	1.55
Natural Aggregate	1.33
Water	0.15
Recycled Aggregate	0.61
Fly Ash	4.00

The indicator's raw values in Table 3.2 are still expressed in different units and scales, which are unfavorable for cross comparisons. Therefore, to render them comparable and in order for them to work together in a single framework (Burgass et al., 2017), they were normalized. Normalizing the values of the indicators eliminates their dependency on a particular unit and transforms the data structure into a uniform scale. In the case of this demonstration study, the indicator values were normalized using Eq. 3.2a and 3.2b. This normalization technique is analogous to the distance to a reference, which measures the relative position of a given indicator vis-à-vis a reference point (OECD, 2008). This method was chosen because of its applicability for this particular set, since a reference mix exists. However, this may not always be the case for concrete due to the difficulty in setting reference values as a consequence of its wide array of applications. Nevertheless, the literature provides a plethora of normalization methods, including the corresponding issues thereof that can be applied to various situations (see e.g., Saisana and Saltelli, 2011).

$$N_i = \begin{cases} 1 + abs\left[\dfrac{I_i - I_r}{I_r}\right], & \text{indicator has positive expected behavior;} \quad \text{Eq. 3.2a} \\ 1 - abs\left[\dfrac{I_i - I_r}{I_r}\right], & \text{indicator has negative expected behavior;} \quad \text{Eq. 3.2b} \end{cases}$$

where: N_i : normalized indicator value;

I_i : indicator value

I_r : value of the reference correspondent to I_i;

abs : absolute value

The raw indicator data set is still bidirectional, in the sense that it is ideal for some indicator values to increase (e.g., SCMI 17 and 20), while for others a decrease is preferable (e.g., SCMI 5 and 28) (see also Section 3.5.1). Normalization provides one way to transform the data set to a unidirectional behavior, such as "more is better." With regards to the ideal indicator behavior, Eq. 3.2a is used if an indicator's value follows the positive expected behavior described in Section 3.5.1; otherwise, if the behavior is in the opposite trend, Eq. 3.2b applies. The normalized values are shown in Table 3.4. In this particular SCMI set, the I_r used for SCMI 2 and 4 is the sum of the reference values for SCMI 2 and 4. Also the I_r for SCMI 23 and 25 is the sum of the reference value of SCMI 23 and 25. For these pairs of indicators, I_r is the combination of the primary and recycled materials in the control mix, since the recycled materials acted as replacement to the primary raw materials in the original definition of the experimental set-up. The normalized values, N_i, above 1.00 mean that the experimental variables have a positive contribution to the sustainability of concrete; otherwise, if N_i is less than 1.00, the experimental variables negatively affect sustainability. In short, for all SCMIs the higher the N_i the more desirable it is for concrete sustainability.

Table 3.4 Normalized SCMI values relative to the control mix

Series	Normalized indicator values, N_i										
	SCMI 2	SCMI 3.02	SCMI 4.01	SCMI 5.01	SCMI 17.01	SCMI 17.04	SCMI 20.10	SCMI 23	SCMI 25	SCMI 28	SCMI 40
Control	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NB-NA	0.96	1.04	1.00	0.41	1.74	1.11	1.44	0.69	1.00	0.41	0.69
NB-RA	1.44	1.04	1.43	0.41	1.37	0.93	1.10	0.92	0.90	0.41	0.82
LB-NA	0.93	1.21	1.00	0.69	2.00	1.21	1.45	0.82	1.00	0.69	0.82
LB-RA	1.46	1.21	1.47	0.69	1.44	0.92	1.18	1.07	0.89	0.69	0.96
NB-NA-FA50	1.13	1.04	1.13	1.18	1.22	0.94	1.45	1.17	0.81	1.18	0.98
NB-RA-FA50	1.59	1.04	1.54	1.18	0.91	0.70	1.16	1.38	0.72	1.18	1.10
LB-NA-FA50	1.07	1.21	1.11	1.32	1.08	0.94	1.40	1.21	0.85	1.32	1.05
LB-RA-FA50	1.58	1.21	1.56	1.32	0.95	0.72	1.16	1.45	0.74	1.32	1.19

3.8.4 Weighted contributions of the SCMIs to the pillars and the SDGs

The normalized values of indicators representing the pillars or the SDGs were weighted linearly using Eq. 3.3, with the results summarized in Table 3.5. The weighted values, succinctly, explain how the experimental factors considered affect each aspect of sustainability. A weighted value more than the control (set to 1.00) means there is an overall positive impact on a particular pillar or SDG; otherwise, if the weighted value is less than 1.00, the impact is negative. The result of each considered scenarios are described in the following articles.

$$W_h = \sum_{i=1}^{n} N_i \times W_i \qquad \text{Eq. 3.3}$$

where: W_h : total weighted value of a particular pillar or SDG; and

$i,.., n$: is the indicator count.

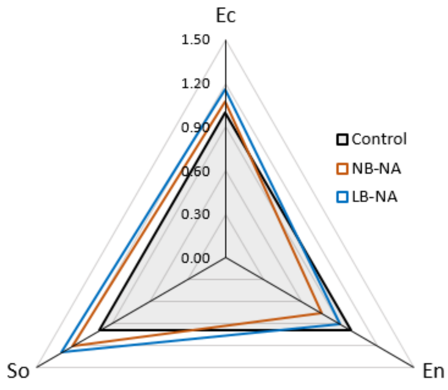
Table 3.5 Weighted change from the sustainability pillars' and SDGs' perspective

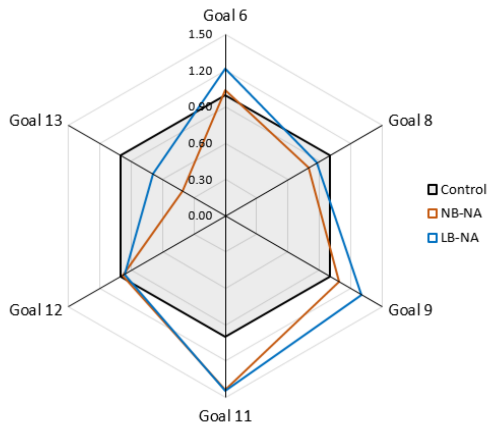
Series	Weighted Value (Sustainability Pillars Perspective)			Weighted Value (SDGs' Perspective)					
	En	Ec	So	6	8	9	11	12	13
Control	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NB-NA	0.76	1.07	1.21	1.04	0.79	1.09	1.44	0.98	0.41
NB-RA	0.94	1.11	1.22	1.04	0.88	0.90	1.10	1.44	0.41
LB-NA	0.90	1.16	1.30	1.21	0.88	1.30	1.45	0.97	0.69
LB-RA	1.10	1.18	1.28	1.21	0.98	1.02	1.18	1.47	0.69
NB-NA-FA50	1.13	1.10	1.15	1.04	0.98	1.11	1.45	1.13	1.18
NB-RA-FA50	1.30	1.13	1.16	1.04	1.07	0.93	1.16	1.56	1.18
LB-NA-FA50	1.21	1.10	1.13	1.21	1.03	1.11	1.40	1.09	1.32
LB-RA-FA50	1.40	1.17	1.20	1.21	1.13	1.16	1.16	1.57	1.32
Standard Deviation	0.191	0.053	0.084	0.091	0.098	0.113	0.164	0.244	0.348

(1) Effect of binder content

NB-NA and LB-NA mixes were used to describe the effect of differing binder contents on the pillars and the SDGs (Figure 3.9). From the viewpoint of the pillars (Figure 3.9.a), both mixes exhibit positive contribution to economic and social aspects, however, both mixes also negatively impact the environmental sustainability, relative to the control. The examination of environmental indicators, i.e., SCMIs 2.0, 5.01 and 28 reveal that they all are less than the reference values, primarily due to the higher cement content of the mixes compared to the control (see Table 3.2)

From the SDGs' perspective (Figure 3.9b), on the other hand, both mixes contribute positively to Goals 6, 9, and 11 due to the reduced water consumption, increased compressive strength, and increased durability (due to reduced air permeability), relative to the control. However, both mixes also negatively affect Goals 8, 12, and 13, because of the increase in costs, cement consumption, CO_2 emissions and GWP. It is evident from these results that the trade-offs between the aspects of sustainability on both perspectives exist. Between the two mixes, however, LB-NA shows better sustainability in most aspects for both sustainability perspectives.



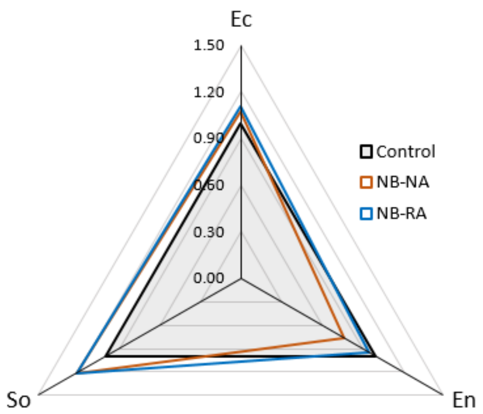


(a) Three Pillars (b) SDGs

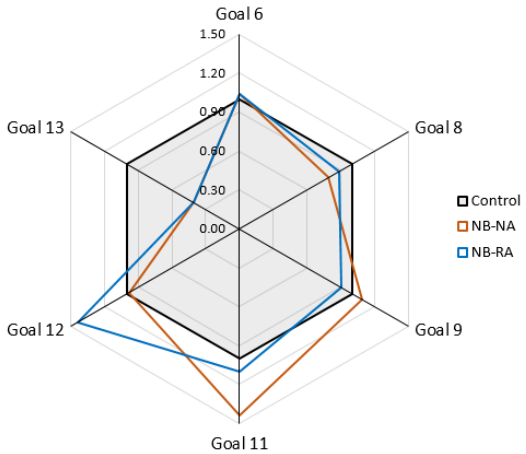
Figure 3.9 Relative weighted beneficial change for concrete mix with different binder content

(2) Effect of aggregate type

NB-NA and NB-RA were used to describe the effect of changing the aggregate type on the pillars and the SDGs, the results are shown in Figure 3.10. Both mixes contribute positively to the economic and social aspects of sustainability (see Figure 3.10a). However, only NB-RA has environmental sustainability comparable to the control (W_h = 0.94) due to the use of recycled aggregate. With respect to the SDGs (Figure 3.10b), NB-NA shows better sustainability rating in Goals 9 and 11, and comparable rating on Goals 6 and 12, with respect to the control, while NB-RA shows better sustainability rating in Goals 11 and 12, and comparable rating on Goal 6, with respect to the control. Both mixes have negative impact on Goal 13, because of the increased CO_2 emissions. These results suggest that NB-RA is relatively more sustainable than NB-NA from the perspective of the pillars; however, it is not easily discernable which between the two mixes is more sustainable from the SDGs' perspective. This further implies that the outcome of sustainability evaluation may also depend on the viewpoint of the analysis.



(a) Three Pillars

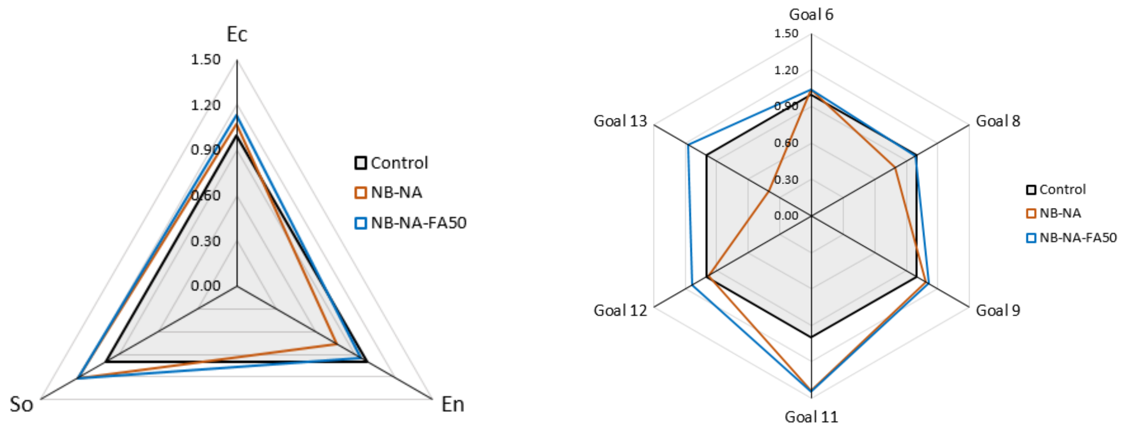


(b) SDGs

Figure 3.10 Relative weighted beneficial change for concrete mix with different aggregate type

(3) Effect of using fly ash

NB-NA and NB-NA-FA50 mixes were used to determine the effect of replacing cement with 50% fly ash on the pillars and the SDGs, as shown in Figure 3.11. From the perspective of the pillars (Figure 3.11a), both mixes show positive contributions to the economic and social pillars, while only NB-NA-FA50 shows comparable environmental rating with respect to the control, due to the reduced associated CO_2 emissions. On the other hand, from the SDGs' perspective (Figure 3.11b), NB-NA-FA50 exhibits better sustainability compared to the control on all goals except for Goal 8, with W_h = 0.98, which is still comparable to the control. NB-NA-FA50 exhibits acceptable sustainability rating on both perspectives, suggesting that replacing cement with 50% fly ash is beneficial for concrete sustainability. The result further implies that a sustainable concrete could be developed that satisfy the differing requirements of various analytical perspectives.

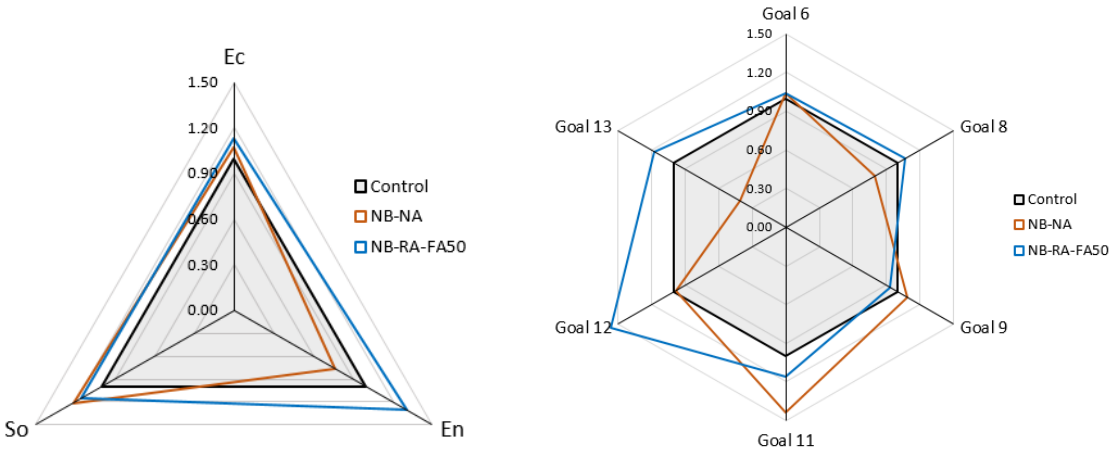


(a) Three Pillars (b) SDGs

Figure 3.11 Relative weighted beneficial change for concrete mix with and without fly ash

(4) Effect of using both RA and FA

NB-NA and NB-RA-FA50 were used to compare the effect of using both RA and 50% FA cement replacement on the pillars and the SDGs, shown in Figure 3.12. From the viewpoint of sustainability pillars (Figure 3.12a), NB-RA-F50 positively contributes to all pillars of sustainability, while NB-NA needs improvement in environmental sustainability, with respect to the control. This implies that a combination of RA and FA improves the sustainability of concrete in the pillar's perspective. However, a close examination of indicators for NB-RA-F50 shows that the compressive strength (SCMI 7.01) and Young's Modulus (SCMI 7.04) is less than the reference (see Table 3.2), which cannot be readily observed with the weighted values, implying that aggregation may obscure negative behavior. On the other hand, from the viewpoint of the SDGs, it is directly evident from Figure 3.12b that NB-RA-F50 positively contributes to all relevant SDGs except for Goal 9, with respect to the control mix. NB-RA-F50 also scores better in most SDGs compared to NB-NA except for Goal 11 and 9. This result suggests that material manipulation, by combining different raw material alternatives, is an effective way to improve the sustainability rating of concrete.



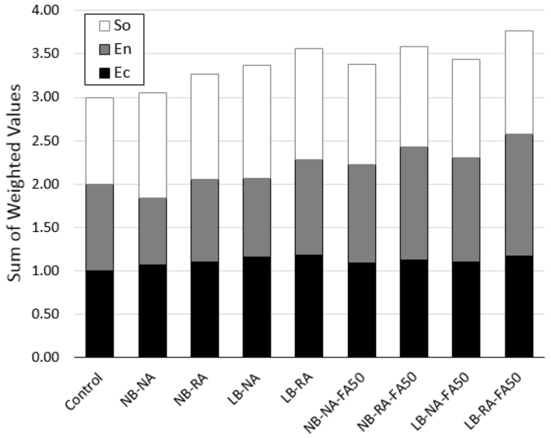
(a) Three Pillars (b) SDGs

Figure 3.12 Relative weighted beneficial change for concrete mix combining recycled aggregate and fly ash

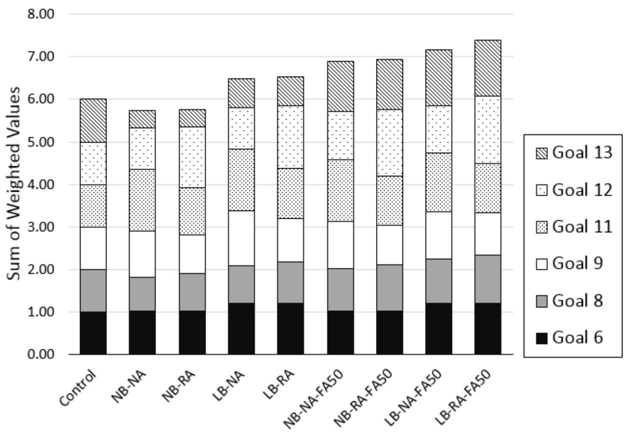
3.8.5 General observations

The preceding demonstration illustrates that the SCMIs' relationship with the pillars of sustainability and the SDGs is quantifiable, allowing trade-offs to be directly compared, as summarized in Figure 3.13. The demonstration further solidifies the importance of using the two sustainability perspectives as the indicator framework's contextual perspective – otherwise, it will be a difficult to elucidate how strategies (i.e., material manipulation) directly contribute to sustainable development.

The various strategies of manipulating the constituent materials show differing effects. Concrete mixes using the combination of recycled concrete aggregate and fly ash replacement have high relative increases in their environmental sustainability scores. With respect to the pillars of sustainability (Figure 3.13a), the environment is the most affected pillar, with standard deviation of En weighted values equal to 0.91 (see Table 3.5). The SDGs show similar variability (Figure 3.13b), with some SDGs exhibiting more sensitivity to the experimental variables than others. In other words, some aspects of sustainability are more sensitive to material manipulation than others. This observation suggests that the behavior of sustainability aspects is a function of the indicators under them. Amongst the mixes analyzed, LB-RA-FA50 proves to be the most sustainable, which coincidentally scores highest for both sustainability perspectives.



(a) Three Pillars



(b) the SDGs

Figure 3.13 Effect of material manipulations on the different aspects of sustainability

3.9 Summary

This Chapter undertakes the growing complexity of concrete material sustainability evaluation by presenting an indicator framework for the quantitative development of sustainable concrete based on two contextual perspectives: the pillars of sustainability and the SDGs. Three primary points were addressed and presented in this Chapter that led to this development. First, is the creation of the SCMI framework, which provides a comprehensive outlook on what concrete sustainability is about. This was achieved by aggregating the multitude of indicators that represent the needs of the concrete sector to ensure both material performance and operationalize sustainability. The SCMI framework reveals the causality that exists between the indicators, which was portrayed in a causal network forming the driving force-state-impact relationship. This causality is useful in selecting the appropriate indicators for sustainability evaluation, in tracing dependencies, and in identifying focus areas necessary to effect changes in order to improve the sustainability of concrete. As a result, the SCMI framework was able to simplify the complex nature of concrete sustainability to a form that is relatively easy to communicate to the stakeholders.

The second point was the establishment of the relationships that link the SCMIs to the pillars of sustainability, as well as to the SDGs, which provided the governing contextual evaluation perspective for the efficient development of sustainable concrete. The use of indicators' descriptions, the definition of each sustainability pillars, and the different targets of the SDGs prove to be useful tools in establishing these relations. Additionally, these linkages will enable the determination of focus areas that are beneficial for the creation of target-based strategies for the improvement of the underperforming sustainability aspects. This ensures the balance between the different aspects of sustainability, which is one primary objective of sustainable development. The relations also illuminate the opportunities for the concrete sector to participate in the global sustainability agenda.

The third point was the demonstration of the practical applicability of the SCMI framework, which illustrated that the relationship between the SCMIs and the pillars of sustainability, as well as the SDGs, could be evaluated quantitatively. Therefore, the trade-offs that exist between the different aspects of sustainability could be compared unambiguously, making it easier to evaluate the feasibility of concrete mix alternatives. Finally, quantification communicates to the stakeholders their contributions toward the achievement of global sustainability, which is a fundamental input to reach robust decision and in expanding the concept of sustainable concrete.

There are, however, important structural issues revealed in the demonstration work regarding the use of the SCMI framework for sustainability evaluation in the aspect of indicator selection, weighting and aggregation. These analytical steps are viewed as uncertain and highly subjective, which only reflects the disparity about the perception of sustainability. This leads to multiple evaluation context, affecting the result of the sustainability evaluation process. The issues about the uncertainty and subjectivity of the analytical steps is further discussed in the next Chapter.

Chapter 4
Quantifying sustainability by multicriteria analysis

4.1 Introduction

Sustainability has become a polysemous word as it has not been used with a precise meaning (Diaz-Balteiro et al., 2017). Since its conception, sustainability gained momentum in both research and practice, particularly in policy and decision-making areas to anticipate the sustainability implications of proposed actions (Pope et.al, 2004; Bond & Morrison-Saunders, 2011). The concrete industry, for example, as discussed in Chapter 2, initiated various actions to participate in the global sustainability agenda. However, it remains a challenge – not only for concrete industry – to explicitly demonstrate the implications of these actions to sustainable development. Therefore, means at elucidating that sustainability is operationalized is of paramount importance for sustainability decision-making processes.

The most common way of demonstrating that sustainability is operationalized is to perform sustainability evaluations. Sustainability evaluations is one of the most complex types of appraisal methodologies (Sala et al, 2015) as it must find a balanced role between scientific process and the purposeful inclusion of subjective values (Martin, 2015). Sustainability evaluation does not only entail multidisciplinary aspects, but also cultural and value-based elements (Sala et al., 2015). Sustainability is a complex topic that encompasses many dimensions, which requires unique analytic tools in order to ensure that the analysis is rigorous and robust (Miller et al., 2017).

The concept of sustainability is often captured in quantitative terms by mathematical models or frameworks that aim to condense its multifaceted and convoluted character to a state that is more palatable to different stakeholders. Sustainability evaluation has a character of a multicriteria decision-making problem (or multicriteria decision analysis (Cinelli et al., 2014)) – henceforth multicriteria analysis (MA) – due to the intrinsic multidimensionality of the concept (Diaz-Balteiro et al., 2017). In Chapter 3, as an example, the multidimensional character of concrete sustainability is introduced through the SCMI framework. The framework – showing the complex interactions of the indicators – justifies that the quantification of the sustainability of concrete material is inherently a multicriteria problem.

Multicriteria analysis is a set of methods that can be used to compare alternatives from a product level to a policy one, by covering one or more sustainability aspect (Cinelli et al, 2014; Munda et al., 2005; EPA, 2006), and is considered as the appropriate tool to perform assessments of sustainability (Cinelli et al., 2014). The basic form of sustainability evaluation utilizing multicriteria analysis is to calculate the total value score of indicators as a linear weighted sum of its scores across several criteria (Huang et al., 2011), which was simplistically demonstrated in Chapter 3. There are concerns, however on whether these methods/models are really comprehensive and able to judge in a robust and reliable way that sustainable development is achieved (Ciuffo et al., 2012). These concerns can be grounded on both the conceptual nature of sustainability itself and the technicalities associated with model building.

The intrinsic conceptual vagueness of sustainability (Ciuffo et al., 2012) poses problems for any form of sustainability assessment as there are likely to be differing expectations of the goals of the assessment (Bond & Morrison-Saunders, 2011). Modeling technicalities, on the other hand, contribute to the problem due to the inadequacy of scientific models to mimic the real world (Ciuffo et al., 2012). Accordingly, the portion captured by the model is only an arbitrary enclosure of an otherwise open, interconnected system (Saltelli et al., 2008). These statements suggest that there is an intrinsic degree of unavoidable uncertainty involved in sustainability evaluation that organically corresponds to the two types of uncertainties: aleatoric – refers to uncertainty about an inherent variable phenomenon – and epistemic – refers to the uncertainty arising from lack of knowledge (Sullivan, 2015). Many sources of uncertainties indeed exist in sustainability evaluation, some of them are naturally irreducible, while others are quantifiable.

Uncertainty is an important feature of sustainability evaluation as it represents the condition where unpredictability, incomplete control, and plurality of legitimate perspectives (Funtowicz & Ravetz, 1993) are considered in the analytical structure. Defining sustainability within a multi-criteria framework entails merging multidisciplinary point of views, all equally legitimate opinions of what is sustainability and how it should be measured (Nardo et al., 2005). This is the underlying reason why there is no standard methodology for solving sustainability problems (Dias-Balteriro et al., 2017). Additionally, the methodological aspect is inherently subjective as it depends primarily on the skill level and personal judgments by the analyst or expert (Martin, 2015; Funtowicz & Ravetz, 1993), which subscribes to a specific world view and methodologies to assess sustainability performance (Sala et al., 2015). As a result, *methodological uncertainties* emerge, and depending on the organizing framework or perspective chosen, one may arrive at vastly different conclusions about the sustainability of system of interest (Wu & Wu, 2012).

Focusing attention on the possible sources of uncertainty has been traditionally exploited to delay policies (Sala et al., 2015) or used to hide or neglect a problem (Sala et al., 2015). This has been the motivating factor of this work, which aims to discuss and demonstrate the effects of uncertainties in sustainability evaluation by multicriteria analysis using of concrete material as an example in this Chapter. It is important to resolve the issue on *methodological uncertainties* in the multicriteria analytical structure to dissuade the negative connotations and misuse of their existence in the evaluation line. Uncertainty management in sustainability in the context of decision-making is very important to policy makers (Ciuffo et al., 2012; Sala et al., 2015) because it can confuse them (Sala et al., 2015), affecting sustainable policies that rely on reconciling divergent views (Bond & Morrison-Saunders, 2011).

4.2 State of the art of sustainability evaluation

Evaluating system sustainability is more becoming a common practice in products, policies and institution appraisals (Ciuffo et al., 2012). The purpose is to provide decision-makers with an evaluation of global and local integrated nature-society systems in short- and long-term perspectives in order to assist them to determine which actions should or should not be taken in an attempt to make society sustainable (Singh et al., 2012). This requires an elaborate analytical framework that have the ability to condense the complex nature of sustainable development. Currently, however, there remains no universal standard for sustainability evaluation.

Most evaluation approaches rely on the concept of multicriteria decision analysis as multidimensionality is intrinsic to sustainability (Diaz-Balteriro et al., 2017) The structure takes many forms, but the most popular when it comes to sustainability quantification is the use of indicators and composite index. The use of indicators arises from values (we measure what we care about), and they create values (we care about what we measure) (Meadows, 1998). Multicriteria analysis is initiated by scoping what issues are to be included through the use of indicators such as policy controversies and environmental concerns. Sustainability indicators are used as means to compile and structure knowledge and to express societal and pollical norms and priorities (Rametsteiner et al., 2011). In a multicriteria analysis as with most sustainability evaluations, the indicators are often combined to a single composite value or an “index”.

The methodologies for multicriteria analysis could be viewed in two aggregation perspectives: monetary aggregation and physical aggregation (Singh et al., 2012). Monetary aggregation could be regarded as the basis for life cycle cost assessment methodologies, which is a form of multicriteria analysis. International sustainability assessments rely on this type of aggregations perspective such as the ISO 14042 (Life cycle impact assessment). Other methods rely on the physical aggregation of indicators that are not necessarily transformable to monetary equivalence. Most aggregation methods are not originally developed for sustainability evaluation work, but are only adopted from various decision-making fields such as in the economics and environmental management.

Some examples of multicriteria analysis that are adopted to sustainability evaluations are as follows: Analytic Hierarchy Process (AHP) developed by Saaty (1980) which relies on a pairwise comparison of different alternatives based on several criteria. ELECTRE (Elimination and choice translating algorithm) and PROMETHEE (Preference ranking and Organization Method for Enrichment Evaluations), which are both based on outranking the alternatives. Many other methods and combinations of MCDA for sustainability evaluations are reviewed elsewhere in literature such as the work of Diaz-Balteiro et al. (2017) and Jato-Espino (2014).

The evolution of sustainability evaluation has over the years depended on various fields such as in economy, environmental management and decision analysis. The development of the theories from these fields have led to a combination and modifications of methods so that they can be made fit for sustainability science problems and needs. However, there remains much challenges in sustainability evaluation and quantification such as the need for these multicriteria methodologies to be adaptive and holistic, encourage transdisciplinary approach in their structure, promote learning and mutual feedback and more importantly the consideration and management of uncertainties (Sala et al., 2015).

4.3 The multicriteria analysis and sustainability evaluation

It is mathematically impossible to identify the best solution for a complex nonlinear system that usually has multiple solutions (Wu, 2013). Sustainability is one example of such system due to the lack of consensus on what it is in a quantitative sense (Mayer, 2008) – an organic consequence of the uncertainty over the definition of sustainability as described in Chapter 2. Conflicting views about sustainability is unhelpful in examining whether the proposed solutions and practices are leading to a more sustainable state. In concrete materials, for example, the debate whether the use of recycled materials would lead to a more sustainable concrete is still prevalent. One view suggests that recycled materials could raise the sustainability credential of concrete, while the other view contends because of its negative effect on concrete quality (e.g., the effect on strength and durability) which negatively impact the sustainability of concrete.

On the other hand, conflicting views on sustainability may also encourage the creation of various innovations to examine several legitimate perspectives and to understand competing views (Bell and Morse, 2008). On the example of the use of recycled materials, competing perspectives produced many alternative solutions and actions to make it feasible for recycled materials to be incorporated in the concrete matrix. For example, several solutions have been proposed to produce good quality concrete using recycled materials including pre-treatment process, changing the mixing stages and the inclusion of other supplementary cementitious materials. Nevertheless, a precise quantitative definition of sustainability is yet to be established.

Most sustainability evaluation rely on comparing a set of alternatives or actions, i.e., $x = \{x_a\}$ (where a = 1, 2, 3, …, n are the number of examined alternatives) based on multiple criteria. Therefore, multicriteria analysis is often used in sustainability evaluation work. Multicriteria analysis consists of a group of approaches, which allow to account explicitly for multiple criteria (or indicators), in order to support individuals or groups to rank, select and/or compare different alternatives (Cinelli et al., 2014; Belton & Stewart, 2002). It works as an integrated assessment that try to handle the information from individual indicators in a comprehensive manner, by considering interrelationships and interdependencies among them, accounting for the different importance that they might have and adopting different degrees of aggregation (Cinnelli et al., 2014).

The aim of a multicriteria analysis is to assign either a rank (R_a) or a sustainability score (I) to alternatives so that they can be compared quantitatively. Multi-criteria analysis has been a familiar tool to evaluate system sustainability and is applied to a variety of fields such as waste management (Mulutinovic et al., 2014), construction minerals (Chen et al., 2015), renewable energy (Trolborg et al., 2014), and construction (Jato-Espino et al., 2014), among others. Over the years, new techniques with varying complexities have emerged in literature that are applied to sustainability evaluations. For example, the Analytic Hierarchy Process, developed by Saaty (1980), which is based on a pairwise comparison of weighted criteria with the overall performance of the alternative aggregated in a linear additive model (Saaty, 2005). Another is TOPSIS (The Technique for Order Preferences by Similarity to Ideal Solutions) that proposes minimization of the distance with respect to the ideal and, simultaneously, the maximization of the distance with respect to the anti-ideal (Hwang & Yoon, 1981; Diaz-Balteiro et al., 2017). A sufficient review of various multi-criteria methods can be found in the works of Jato-Espino et al. (2014), Huang et al. (2011), Diaz-Balteiro et al. (2017), Cinelli et al. (2014), and Singh et al. (2012), among others.

The literature on sustainability evaluation (or assessment) utilizing multicriteria analysis is growing (Cinelli et al., 2014), assuming various roles including: (1) integrating sustainability spheres and considering their interrelationships, (2) supporting constructive interaction among stakeholders, (3) accounting for uncertainties, and (4) contributing to monitoring and communication of results (Cinelli et al., 2014; Bockstaller et al., 2008; Gasparatos et al., 2008). The development of quantitative measures of sustainability improve our understanding of the intricate relationships among components of sustainability in practical terms, and this promote the science and practice of sustainable development (Wu & Wu, 2012). Under the wing of multicriteria analysis, the heterogeneous and uncertain information is managed by involving different protocols, algorithms to combine them, and processes to interpret and use formal results in actual advising or decision-making context (Huang et al., 2011).

4.4 The analytical framework of multicriterial analysis and its uncertainties

There is a sense of urgency in developing substantiated – scientifically sound and corroborated – and transparent methodologies to measure sustainability to assist in decision making. This is revealed by the increasing use of sustainability indicators and composite indices built within the architecture of multicriteria analysis. Indices are gaining importance as a powerful tool for policy making and public communication (Singh et al., 2012). Their ability to summarize, focus, and condense enormous and complex information (Godfrey and Todd, 2001; Singh et al., 2012) has been the rationale replicated in the analytical framework presented in this section.

The analytical framework of MA is illustrated in Figure 4.1 comprised of the following stages, which are typical of a multicriteria analysis: (1) indicator identification and selection – the setting of criteria, (2) statistical characterization of the data and treatment of missing data, (3) data normalization, (4) indicator weighting, and (5) data aggregation. The aim of the framework is to assign either a rank (R_a) or a sustainability score (I) to a set of alternatives x. Briefly each step functions as follows:

i. Selection of Indicators (SI): formalizes the evaluation process wherein the issues associated with sustainability are expressed using multiple indicators that are naturally of disparate in terms of scale and dimension (Saisana and Saltelli, 2011; Hak et al., 2016; Opon and Henry, 2019a).
ii. Data Treatment (DT): ensures the appropriateness of the data for decision- and policy-making processes (Martin, 2015), which also appertain to data quality, data structure, and the treatment of missing data (OECD, 2008; Martin, 2015; Saisana and Saltelli, 2011; Mayer, 2008; Dempster and Rubin, 1983).
iii. Data Normalization (N): transforms the scale and unit of disparate indicators into a common measure – usually a dimensionless quantity – so that they can be compared within a single multicriteria framework (Cinelli et al., 2014; Burgass et al., 2017; Opon and Henry, 2018b).
iv. Indicator Weighting (W): functions to reflect the relative importance of indicators based on stakeholder views or on policy priorities (Henry and Kato, 2012; OECD, 2008). In some instances, weights can also be used to deal with data structure and internal correlations between indicators (Paraulo et al., 2013; Opon and Henry, 2019b).

v. Aggregating Indicators (A): summarizes the indicators into a composite value to reduce the complexity of interpretation and for easy communication of the result to stakeholders – the public in particular (Burgass et al., 2017, Sharpe, 2004).

While the analytical stages of MA seem straightforward, they are not without issue, as each stage is not always objective, precise, or certain (Wu and Wu, 2012). There are methodological issues associated with each stage that need to be addressed to avoid data manipulation and misrepresentation (OECD, 2008), and the lack of clarity and guidance on methodological choices can cause model uncertainty (Burgass et al., 2017). Therefore, in the following discussions the uncertainties resulting from methodological multiplicity are examined as to how they affect the rank (R_a) and the sustainability score (I) of the alternatives.

Methodological uncertainties stem from the use of multiple methodological approaches at each stage of the multicriteria analysis. *Methodological uncertainty* is the manifestation of the plurality of ideas on how to capture sustainability quantitatively. Multiple methodologies – each with valid rationale – are the root cause of variable, and sometimes conflicting, outputs or decisions. Indicator weights, for instance, may have non-equivalent values depending on the choice of method to extract them (see Section 4.4.5). Employing different methods, however, has a natural advantage, as it may shed light on the vulnerability of the result due to methodological choices, suggesting that sustainability evaluation may not be a single-valued but, rather, a multi-valued problem.

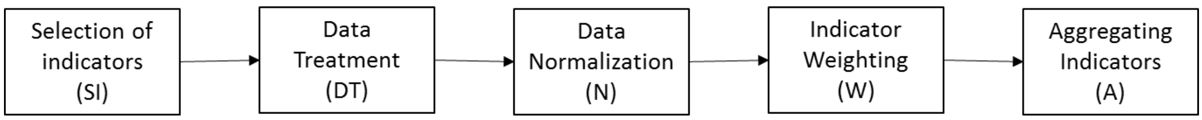


Figure 4.1 Multicriteria analytical framework for sustainability evaluation

4.4.1 The methodological uncertainties

The two main sources of uncertainties in sustainability evaluation are the concept of sustainable development itself, including the definition of boundaries to assess it, and the intrinsic subjectivity of many assessment tools (Ciuffo et al., 2012). The uncertainties stemming from the analytical stages of the framework are derivatives of these two main sources. The first main source of uncertainty refers to the various framings of sustainability, which is very challenging to sustainability evaluations because it is concept-reliant. Essentially, this is a type of linguistic uncertainty, as the scientific vocabulary defining sustainability is under-specific, ambiguous, vague, context-dependent, or exhibiting theoretical indeterminacies (Regan et al, 2002; Burgass et al., 2017). Linguistic uncertainty, however, is a feature of sustainability; because the environmental, social and economic conditions of societies around the globe differ greatly and attempting to apply a single definition across this diversity could be both impractical and dangerous (Bell and Morse, 2008). The concept of sustainability, therefore, essentially propagates the linguistic uncertainty when defining the assessment boundaries and system quality (Bell and Morse, 2008). The assessment boundaries, on the other hand, refer to the scale – the resolution and extent (i.e., temporal and spatial) – at which the system quality is observed (Mayer, 2008; Bell and Morse, 2008), while "sustainable" equates to a situation where quality remains the same or increases (Bell and Morse, 2008). Uncertainty over the definition of assessment boundaries and definition of quality rationalizes the lack of both science-based and policy-based boundaries able to define thresholds between what contributes to sustainable development, and what does not (Ciuffo et al., 2012).

The second main source of uncertainty, unlike the first main source, can be defined and addressed in mathematical terms, and is the main focus of the following sub-sections. This source of uncertainty is the result of the conceptual anatomization of so general an idea as sustainability, wherein there is no principled point at which to draw methodological standards (Wu and Wu, 2012). Formalization of the system generates an image – the theoretical framework – that is valid only within a given information space and reflects only the choices made by the sustainability evaluators (Nardo et al., 2005). The vast choice of analytical methods applicable to every stage of the sustainability evaluation framework creates *methodological uncertainties*, as these methods are mathematically non-equivalent. There is no established dogma, however, on how to combine different methods, creating contradictory results depending on methodological choices.

In a multicriteria setting, the choice of which indicators to use, how those are divided into classes, whether normalization should be carried out (and how), the choice of weighting method, and how indicator data are aggregated are all dependent on the perspective of the problem or system to be modelled (Nardo et al., 2005). Uncertainty is a standard part of decision-making in the assessment of risks (Martin, 2015), and *methodological uncertainties* should not prevent or invalidate the result of any sustainability evaluation, as this only mirrors the human values of sustainable development – the accommodation of legitimate subjective judgements. Following this ideology, it is critical, therefore, for any attempt at the evaluation of some system's sustainability to consider all possible framings, and their ramifications to the result.

4.4.2 Indicator selection and uncertainties

The first stage of MA is the selection of indicators. An indicator is an operational representation of an attribute of a system (Gallopin, 1997; Wu and Wu, 2012), which translate issues, such as sustainability, into quantifiable measures, with the ultimate aim of helping address key concerns (Azapagic, 2004). In other words, the basic purpose of indicators is to represent complex or poorly understood systems with a limited number of variables (McCool and Stankey, 2004). Indicators are developed to provide a solid base for decision making, and to contribute to self-regulatory sustainability of integrated environmental and developmental systems (UN, 1992: Haghshenas and Vaziri, 2012).

The selection of indicators to mathematically underpin the concept of sustainability is determined by numerous factors, including the framework that details what is to be sustained and the data regarding the indicators (McCool and Stankey, 2004). Some guidelines assist in indicator selection, such as the Bellagio Principles, which detail the process of the choice and design of indicators (Hardi and Zdan, 1997). Indicator selection is usually made by experts or through participatory approaches, aiming to resonate stakeholder values to influence the institutionalization of the indicator system so that they are used and maintained (Mascarenhas et al., 2015).

While sustainability indicators are used extensively, it does not necessarily follow that they are scientifically sound or used appropriately, as there is a serious lack of practical guidelines for both indicator developers and users (Hak et al., 2012). As a result, many indicators set reflect only certain aspects of a system, and none are comprehensive enough to gauge the full spectrum of sustainability issues by itself (Wu and Wu, 2012), particularly when the indicator set must scrutinize across different scales (e.g., global and national). In the United Nations (UN) Sustainable Development Goals (SDGs) framework, for example, despite the goal of designing the SDG indicator set to be truly universal, it is envisaged that some indicators may not apply to every country (e.g., tropical diseases), requiring complementary national indicators (Hak et al., 2016). Additionally, it would be impossible, and indeed impractical, to try to translate all the issues into indicators of sustainable development (Azapagic, 2004) because the assessment boundaries are inherently uncertain, and, thus, can be expanded or contracted without restraints.

Reducing the entire system into parts has limits when crucial properties of the entire system are lost, as individual indicators often hide the whole picture (Saisana and Saltelli, 2011). This has been a core argument of the debate over whether sustainability evaluation should tend towards reductionism or holism (Bond and Morrison-Saunders, 2011; Wu, 2013). Reductionism frames systems as being understood by breaking them down into sub-components (i.e., using indicators), while holism frames systems in terms of inherent interactions, which cannot be analyzed through sub-components alone (Bond and Morrison-Saunders, 2011). However, there remains genuine uncertainty over the degree to which sustainability evaluation should be reductionist, and the degree to which it should be holistic (Bell and Morse, 2008; Bond and Morrison-Saunders, 2011), indicating that the debate is far from resolved. Nevertheless, indicators remain instrumental for sustainability evaluation. Uncertainty is an unavoidable component in indicator selection, as the process of system decomposition is seen as highly subjective, given the arguments for including an indicator are driven by logical arguments, historic inclusion of analysis, and normative description of the phenomena (i.e., sustainability) being assessed (Miller et al., 2017).

The inclusion or exclusion of indicators into a set is the main source of *methodological uncertainty* in indicator selection. This is magnified when both type 1 error – the inclusion of irrelevant indicators – and type 2 error – the exclusion of relevant indicators – are committed when defining the extent of system sustainability (Opon and Henry, 2018b; Miller et al., 2017). The subjective choices made by indicator developers are anticipated to produce inconsistent indicator sets, and thus producing inconsistent results. Even with solidly corroborated indicator sets – a product of participatory approach – the problem of internal consistency and data reliability due to multicollinearity could lead to inclusion or exclusion of indicators (Opon and Henry, 2018b).

In Chapter 3, for example, a complex sustainability indicator for concrete material is presented. This framework, however, does not provide solid rules about indicator selection more so in the inclusion or exclusion of the indicators into the analysis. As a consequence, selecting indicators from this framework may still entail some levels of *methodological uncertainties*, especially when the inventory data about some indicators are non-existent.

4.4.3 Data treatment and uncertainties

The next stage of MA that requires methodological selection is related to the data used to measure indicators, especially the issue of their availability (Rajaonson and Tanguay, 2017). Data collection and treatment is performed after indicator selection; however, these two stages are also intrinsically linked (Burgass et al., 2017), as there are occasional disputes over the value of the collected data in regard to their appropriateness for the type of decisions (Martin, 2015). Data transform sustainability so that scientific inquiry can be performed, and different considerations are involved in their selection, including their relevance, accuracy, timeliness, accessibility, interpretability, and coherence (OECD, 2008). However, data are also subject to varying levels of uncertainty depending on the credibility of the source, collection methods, timing of sampling, measurement error, natural variation, and interpretation (Burgass et al., 2017). There are three areas in which uncertainties are introduced concomitant to indicator data: data quality, data structure, and missing data.

(1) Data Quality

Data quality is affected by both the uncertainty in knowledge and the intended functions of the information (Funtowicz and Ravetz, 1993). Uncertainty in knowledge is related to the inherent inadequacy of scientific models and instruments to capture complex phenomena. Measured inputs, for example, may vary compared to the real-world performance (Miller et al., 2017), which are practically irreducible forms of uncertainty. As a consequence, an indicator may be discarded in favor of another that is supported with better quality data, introducing severe model error. Different data types and scales are also used simultaneously to represent the various facets of sustainability – typical to a multicriteria analysis. Uncertainty in data type exist as some quantitative forms may take multiple or probabilistic values (e.g., ridership data in transportation measurement (Miller et al., 2017)). Qualitative data, similarly, are difficult to replicate, and thus may assume variable values, such as those collected from expert surveys. Both qualitative (soft) and quantitative (hard) data types – with qualitative *usually* reduced to point scales (Cinelli et al., 2014; Saisana and Saltelli, 2011) – are often combined in a multicriteria analysis despite their natural incongruencies.

Data are also measured on different categorical (nominal) or numerical (e.g., ordinal, interval, and ratio) scales. The scale at which the data are measured infuses *methodological uncertainty*, as this choice is also subjective. A case in point can be seen when measuring temperature, which could be expressed in various scales and units (i.e., Kelvin (ratio scale) or Celsius (interval scale)). Since these choices are arbitrarily made, there entails a requirement that the effect on data transformation (e.g., normalization) should be invariant from the choice of unit (Ebert and Welsch, 2004). Nevertheless, the *methodological uncertainties* associated with data type and scales can be resolved by setting up rigorous evaluation standards to homogenize the representation of various indicators when performing different sustainability evaluation operations.

(2) Data Structure

In a multicriteria analysis it is also important to perform statistical characterization of the data, which reveal the appropriateness of the included information. Statistical characterization describes the coherence of the data to the sustainability framework and indicates the sufficiency of information to describe the phenomenon (Saisanan and Saltelli, 2011). Multivariate analyses are helpful in disclosing the nested structure of the data set, and, when used in conjunction with the theoretical framework, can provide support for making sound inferences (Dobbie and Dail, 2013). There is a rich collection of statistical methods available to perform multivariate analysis depending on the evaluation objective. Principal component analysis (PCA), factor analysis (FA), and item analysis are just a few of these methods. The result of the multivariate statistic provides additional guidance for methodological choices in other stages of the sustainability evaluation (e.g., in weighting and aggregation of indicators) (Dobbie and Dail, 2013; Nardo et al., 2005), and may as well support the indicator selection process, such as when discarding indicators with less variability across different alternatives (see e.g., Opon and Henry, 2018a).

The assignment of weights, as an example, may depend on the correlation between different indicators. Depending on the perspective chosen, one may view high correlation among indicators as something to correct (i.e., by assigning lower weights to highly correlated indicators), or one may take it as a feature only of the problem and not to be corrected for, as correlated indicators may indeed reflect non-compensable different aspects of the problem (OECD, 2008; Nardo et al., 2005). The treatment of the interrelationship between indicators may constitute *methodological uncertainty* due to the lack of statistical resolution, which could ultimately lead to the modification of the original indicator set. The interrelationships between selected indicators, however, is an important element to be considered, as it can mislead both decision-makers and the general public (Saisana and Saltelli, 2011).

(3) Missing Data

The data that underpin the different dimensions of sustainability inevitably may contain gaps, requiring decisions about the methods to address these gaps (Burgass et al., 2017). Sustainability evaluation becomes problematic if some data are unavailable, which is a common weakness of all sustainability efforts regardless of scale or publicity (OECD, 2003; Mayer, 2008). Three generic approaches can be distinguished in dealing with missing data: case deletion, single imputation, and multiple imputation (Nardo et al., 2005). Case deletion simply ignores either the indicator or the alternative with missing indicator values. This method, however, can reduce the representativeness of the sample, and may lead to misleading inferences (Dobbie and Dail, 2013). Additionally, standard errors will be generally larger in a reduced sample, given that less information is used (OECD, 2008). Alternatively, to fill in the gaps in the set, imputing missing data – the art of filling empty spaces in a data matrix (Dempster and Rubin, 1983; Saisana and Saltelli, 2011) – is sometimes performed.

Data imputation could lead to the minimization of bias and the use of expensive-to-collect data that would otherwise be discarded by case deletion (Saisana and Saltelli, 2011). However, the use of such techniques may be constrained by time, budget, or expertise of the team (Burgass et al., 2017), and require an understanding of how the missing data arise in order to select the appropriate imputation approach (Dobbie and Dail, 2013). The two approaches see the missing data as part of the analysis, and, therefore, try to impute values through either single imputation (e.g., mean/median/mode substitution, regression imputation, etc.) or multiple imputation (e.g., Monte Carlo algorithm) (Saisana and Saltelli, 2011). The choice of imputation approach to deal with missing data constitute *methodological uncertainty* as these methods are clearly non-equivalent. Additionally, imputation can lull the user into the state of believing that the data are complete after all (Dempster and Rubin, 1983). Uncertainty in the imputed data should be reflected in variance estimates, as no imputation model is free of assumptions (OECD, 2008).

4.4.4 Normalization method and uncertainties

Since sustainability evaluation requires the management of a wide variety of information types (Cinelli et al., 2014), normalization – the next stage of MA – is performed so that different indicators can be compared within a single multicriteria framework (Burgass et al., 2017; Saisana and Saltelli, 2011; Opon and Henry, 2018b). Normalization aims to marry disparate sustainability indicators that differ in their range of values and measurement units (Mayer, 2008). Additionally, normalization considers the directionality of each indicator (Opon and Henry, 2019), as some indicators improve while others deteriorate – the classical conflictual situation dealt within the multicriteria architecture (Munda, 2005). In Chapter 3, for example, the bidirectionality of the SCMIs has been demonstrated. Through normalization, the natural dichotomy of the data set is eliminated, thus homogenizing the set.

The measurability property of indicators assumes that transformation (normalization) may be applied without altering the information context (Ebert and Welsch, 2004); however, by normalizing, there is a compromise between information loss and robustness against data particularities (Dobbie and Dail, 2013). Additionally, while the premise of normalization is to make the variability constant (i.e., standardization) and the result invariant to different techniques (Munda, 2005), this is seldom achieved because different normalization methods (e.g., ranking, standardization, min-max, and distance to as reference, among others) have varying sensitivity to extreme values (or the presence of outliers) and the skewness of the data set (OECD, 2008; Saisana and Saltelli, 2011). For example, the measurement scale used to express the indicators may have a considerable effect, particularly when combining indicators into a composite value (see e.g., Ebert and Welsch, 2004). The choice of the transformation could thus cause problems in terms of loss of the interval level of the information, sensitivity to outliers, arbitrary choice of categorical scores, and sensitivity to weighting (OECD, 2008).

Methodological uncertainty, therefore, exists in data normalization, as different normalization methods will produce different results (OECD, 2008; Bluszcz, 2016) due to their non-equivalent underlying theoretical assumptions. For instance, ranking simply ranks the alternatives in order based on indicator values and therefore does not preserve specific information (Nardo et al., 2005), while statistical standardization may still preserve some statistical characteristics of the data (e.g., variability) but assumes normal distribution. Using other, more arbitrary, methods without testing different techniques could lead to subjective judgment error, and the outcome is affected by an unknown amount due to the choice of normalization (Burgass et al., 2017).

4.4.5 Indicator weighting and uncertainties

The usual argument in a multicriteria analysis is that indicators do not necessarily have equal contribution in explaining the underlying sustainability phenomenon (Mikulic et al., 2015; Cinelli et al., 2014). This is why indicator weighting is a necessary step in the analytical framework (see Figure 4.1). Weights essentially are value judgements (OECD, 2008), in that they, ideally, reflect the relative importance of different dimensions (in this case, the indicators) in their contribution to the sustainability of a system (Gan et al., 2017). Weights are routinely used to indirectly integrate stakeholder views (see e.g., Henry and Kato, 2012) or expert opinion to the analysis, to better reflect policy priorities or theoretical factors (OECD, 2008). Weights can sometimes be exploited to elicit trade-offs among the different dimensions (Gan et al., 2017; De Keyser and Peeters, 1996; Cinelli et al., 2014), which could magnify the effect of good performing indicators or boost the effect of the underperforming ones. There are cases in literature, however, reporting that the declared importance of single indicator and the actual impacts of the indicator weights are very different, and that the data correlation structure often prevents the assigned weights from actually reaching the stated importance (Paruolo et al., 2013). Nevertheless, irrespective of the purpose of using weights, the bigger challenge in this stage of the framework is in the extraction of the individual weights.

The literature offers a menu of strategies to extract weights, which can be categorized as either subjective or mathematical (Jiang and Shen, 2013). Subjective methods rely on stakeholder inputs. Some well-known strategies include Delphi method or expert panel survey (Mikulic et al., 2015), Budget-allocation (Nardo et al., 2005 ; Gan et al., 2017), Public Opinion, and Analytic Hierarchy Process. Mathematical methods, on the other hand, involve mathematical manipulations (Jiang and Shen, 2013), which principally elucidate the statistical quality of the data (OECD, 2008). Popular methods include Factor Analysis (FA), Principal Component Analysis (PCA), and Regression Analysis.

The various strategies available, however, have been the focus of contemporary debates on weighting, since the choice of method is viewed as 'subjective' due to the lack of scientific basis for the attribution of weights (Van de Kerk and Manuel, 2008; Burgass et al., 2017). These choices may undermine the sensitivity of a complex, interrelated, and multidimensional phenomena (Saisana and Saltelli, 2011) – such as sustainability. The number of legitimate analytical and pragmatic bearings prevent stakeholders from arriving at a conceded single weighting technique, particularly if the framework is not explicit about it. Additionally, using different methods may produce weights that vary significantly and thus create variability in the result (see e.g., Jiang and Shen, 2013). The plurality of available indicator weighting strategies confuses stakeholders as to which method is appropriate. The literature, however, suggests that reaching consensus on indicator weighting may seem unlikely (Saisana and Saltelli, 2011), making it one of the main causes of *methodological uncertainties* (Saisana and Saltelli, 2011; Jiang and Shen, 2013).

4.4.6 Aggregating indicators and uncertainties

As the issues of sustainability transcends boundaries to include a wider group of stakeholders with varying interest, different coarseness of the relevant data is generated. Researchers and specialists, for instance, require the highest resolution of the data, whereas policy makers may delve only to the level of the indicators' behavior, while the general public is interested only in the integrated characteristic of the system (Wu and Wu 2012; Braat, 1991; Wu, 2013). Aggregating indicators, therefore, is an essential step to engage all groups of stakeholders – the public in particular – in conversations about key sustainability issues. The use of aggregate measures (also known as composites or indices) has become a common benchmark for sustainability science and policy-making because of their ability to track and communicate complex systems (Burgass et al., 2017). Governments, agencies, and institutions use indices to gauge the impact of incorporating sustainability actions into their decision-making process (Martin, 2015; Diaz-Balteiro et al., 2017). Examples of these indices includes Wellbeing Index, Environmental Sustainability Index, and Human Development Index, among others. A review of commonly used international benchmarking indices can be found in the works of Mayer (2008), Wu and Wu (2012), and Gan et al. (2017), among others.

The controversy in aggregating indicators can be unfolded along its analytic versus pragmatic axis (Saisana and Saltelli, 2011), which can be differentiated into three major debates: loss of information, the differences in sustainability perspective (weak versus strong) – the degree of compensability, and the meaningfulness of the aggregated data. Official statisticians may tend to resent aggregation of indicators, as a lot of work in data collection and editing is wasted or hidden behind a single number of dubious significance (Saisana et al., 2005; OECD, 2008). Aggregators, on the other hand, argue that there is value in combining indicators to produce a bottom line, which is extremely useful in garnering media interest and the attention of policy makers (Sharpe, 2004; OECD, 2008). The debate on weak versus strong sustainability is grounded in the theoretical construct of some aggregation methods, whereby compensability is a core issue. Some methods are analogous to the weak sustainability perspective, which permits substitutability between capitals (e.g., by offsetting low environmental rating with high economic gain) as long as the total capital increases or remains the same (Wu, 2013); whereas other methods correspond to the concept of strong sustainability, which assumes some ecological functions and resources cannot be substituted with technological or other man-made replacements (Mayer, 2008). There is also a legitimate argument regarding the meaningfulness of the aggregated indicators, which presuppose that the underlying preference ordering of aggregates is independent of the admissible transformations of the variables (Ebert and Welsch, 2004). This is strongly related to the scale and the method used to normalize the raw data (OECD, 2008), in which scientific rules (mathematical conditions) are often systematically neglected due to the natural inconsistencies in the data set.

The basic problem of aggregating indicators is in itself a multicriteria problem (Diaz-Balteiro et al., 2017). Several aggregation methods exist in literature with varying assumption dynamics and specific consequences (Nardo et al., 2005), which can be categorized as additive, geometric, and non-compensatory (Gan et al., 2017). Additive rules (or linear aggregation) are useful when the underlying indicators are correlated and full compensability between indicators is allowed (Saisana and Saltelli, 2011). Moreover, linear aggregation can be applied when all indicators have the same measurement unit and further ambiguities to the scale effects have been neutralized (Nardo, et al., 2005). Geometric aggregation (or multiplicative) is less compensatory (Dobbie and Dail, 2013), and is appropriate when indicators are expressed in different ratio scales (Nardo et al., 2005). On the other hand, non-compensatory methods seek to find compromise between two or more legitimate goals (Dobbie and Dail, 2013; Saisana and Saltelli; Munda, 2008), and are usually more suitable in dealing with issues related to weak versus strong sustainability perspectives (Diaz-Balteiro, 2017).

The choice of aggregation method can also be a source of model error and subjective judgment uncertainty, as it can fundamentally alter the result of sustainability evaluation (Burgass et al., 2017). The degree to which these aggregates differ in their results using the same data is due to their assumptions, biases, and methodological disparities, creating confusion for sustainability efforts (Mayer, 2008). The inadvertent selection of aggregation method thus introduces *methodological uncertainty*, as it remains unclear which aggregation method is appropriate. Despite this ambiguity, additive rules are still the most preferred method in literature (see e.g., Gan et al., 2017). Therefore, aggregating indicators is viewed as an important source of uncertainty that needs to be accounted for on the grounds that the one-size-fits-all context is unsuitable when dealing with divergent sustainability point of views.

4.4.7 Ranking and the sustainability scores

When making comparison of the sustainability performance of a set of alternatives $x = \{x_a\}$, two methods can be used. The most common way is to assign a rank R to each alternative based on the magnitude of the aggregated values of the indicators. The alternative ranked the highest is supposed to be the "more sustainable" option. This type of comparing the sustainability performance of the alternatives, however, may neglect the relative distance between the individual performance due to the rescaling effect. For example, if two or more alternatives that do not differ greatly in terms of their aggregated score could be regarded as equally sustainable. These small differences, however, would not be reflected by ranking as the ordering of the alternatives are based only on the magnitude of the aggregated scores and not the distance between them.

On the other hand, the alternatives could also be compared using sustainability scores, I, which is a standardized equivalent of the aggregated scores. This type of comparison is based on the distances of the scores from the average of the set's aggregated score, thus more reflective and sensitive of the small differences between the alternatives. A statistically standardized value using t-scores could be used because the aggregated scores would naturally have different scales as a result of the *methodological uncertainties* inherent to each step of the multicriteria analysis. By standardization, the scale effect is reduced while still preserving the relative distances between the scores of the alternatives, unlike ranking which do not preserve such information.

Ranking (R_a) and using the sustainability scores (I), however, is still not immune to *methodological uncertainties*. Because of the incongruency of the applicable methods to perform the steps of the multicriteria analysis. It is highly likely that the rank and sustainability scores of the alternatives would behave stochastically. This is further explored and demonstrated in the next section, where different methods are used for the analysis and comparison of the sustainability performances of different alternatives. The uncertainties in R and I is important to address as they will ultimately affect the selection of the "most sustainable" options amongst different choices.

4.5 Demonstration of the effects of methodological uncertainties

This section helps visualize the effect of *methodological uncertainties* of the multicriteria analysis. Four concrete mixes are compared, which were prepared by manipulating the constituent materials to make them "more" sustainable. These mixes were selected on the basis of their similar compressive strength values (from 30MPa to 40MPa). The goal is to determine the "best" sustainable option among the group by ranking the alternatives from top to bottom. The concrete mix that is ranked as number 1 is ideally the "best" option. Ranking is used here to simplify the demonstration.

In the following analysis, the uncertainty from each step of multicriteria analysis is represented methodological variability. The analysis proceeds by allowing the approaches of the step of MA of interest to vary, while fixing the others steps to a particular approach. This would allow the uncertainty to be localized to a particular step of MA, thus making it easier to examine the effect on the ranking (R_a) by changing from one method to another.

4.5.1 Settings for the demonstration

(1) Data

The data used in the analysis were sourced from Yokota el al. (2016). Two experimental variables were considered to increase the sustainability of the concrete in the set. First, the 4 mixes were prepared using different cement types: ordinary Portland cement (OPC) and fly as cement type A (FA). Using blended cements is seen to increase the sustainability of the material because part of the original cement volume (or mass) is replaced by a by-product from another industry as the case of fly ash blended cement (as in Chapter 2). Second, the mixes were prepared using 2 water-to-cement ratios of approximately 0.40 and 0.50. Using higher water-to-cement (W/C) ratio would result in the reduction of cement used, which could reduce the environmental impact of the concrete mix; however, it may also affect the mechanical performance. The mix proportions are shown in Table 4.1 for a 1 m^3

concrete. Mixes designated with OPC means ordinary Portland cement was used, otherwise, mixes with FA means a fly ash blended cement was used. Additionally, mix names with number 50 means they are prepared with approximately 0.50 water-to-cement ratio, otherwise, the mixes with number 40 are prepared using 0.40 water-to-cement ratio. The W/C of mixes also corresponds to the compressive of the mix; for instance, mixes with W/C = 0.40 and W/C = 0.50 have an equivalent compressive strength of 40 MPa and 30 MPa, respectively. The sustainability performance of these mixes is examined in the following computational analysis.

Table 4.1 Mix proportions of the concrete mix alternatives

Mix	fc' (MPa)	Unit quantity (kg/m^3)				
		W	C	S	G	Ad
OPC50	30	157	328	783	1071	0.82
FA50	30	149	290	840	1065	2.90
OPC40	40	162	411	688	1081	1.03
FA40	40	155	379	735	1081	3.79

(3) Multicriteria analytical flow, the methods, and scenarios.

The analysis followed a straightforward flow from indicator selection to aggregation as reflected in Figure. 4.2. Then the aggregated scores were used to rank the different mixes from top to bottom. In this analysis, several approaches were utilized to perform each step of MA. The brief description of these methods is contained in Table 4.2. These methods were selected as they are commonly used in multicriteria evaluation including their appropriateness to the sustainability problem at hand. The sustainability performance of each mixes was then calculated repeatedly using different combinations of these approaches.

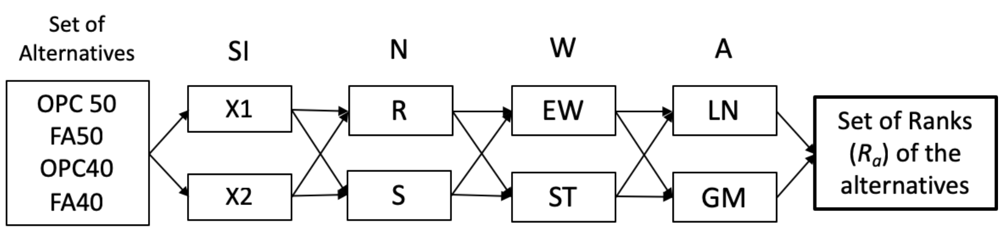


Figure 4.2 Methodological combinations of multicriteria analysis

To isolate the effect of the uncertainty of a particular step of MA, the other steps were held fixed to a particular approach while allowing the step of interest to vary. For example, to determine the effect on the ranking of the mixes using different aggregation approaches, both linear sum and geometric aggregation (see Table 4.2) are used while all other steps are fixed to a single approach. However, in the following analysis, two indicator sets were constantly used representing two different scenarios: X1 – a condition where a relatively comprehensive indicator set is use – and X2 – representing a scenario where reduced indicators set is used due to data unavailability. These scenarios were considered because as discussed in Chapter 3 and in Section 4.4.3, indicators may be arbitrarily excluded from the analysis because of the unavailability of the data. This is particularly true to some countries where inventory data is not available, or the data is so expensive to collect, diluting the benefit of including them in the analysis.

Table 4.2 Methodological approaches used

MA Step	Methods Considered	Description
SI	Creating sets X1 and X2 based on data	Indicator sets are created based on data availability.
N	Distance to a reference (R)	For a set of alternatives $x = \{x_a\}$ (where a = 1, 2, 3, …, n), the normalized value of an indicator for an alternative x_a, $N_{xa(i)}$, is the ratio of the individual indicator, $I_{xa(i)}$, with respect to the value of a reference indicator, I_r, (OECD, 2008). For i = 1, 2, …, e; $N_{xa(i)}$ is calculated as: $N_{x_a(i)} = \begin{cases} 1 + abs\left[\frac{I_{x_a(i)} - I_r}{I_r}\right], & I_{x_a(i)}\ has\ possitive\ behavior \\ 1 + abs\left[\frac{I_{x_a(i)} - I_r}{I_r}\right], & I_{x_a(i)}\ has\ negative\ behavior \end{cases}$
	Statistical Standardization use of z or t-scores (S)	The average, $I_{i(ave)}$, and the standard deviation, SD_i, for indicator i is computed across all alternatives in set $x = \{x_a\}$. The normalized value, $N_{xa(i)}$, is computed by the following expression (OECD, 2008): $N_{x_a(i)} = \frac{I_{x_a(i)} - I_{i(ave)}}{SD_i}$
W	Equal Weighting (EW)	The weight of an indicator $I_i = I_{xa(i)}$, w_i, are equal for all i = 1, 2, …, e. Equal weighting is used when all the indicators are considered equally important (Nardo et al., 2005; Gan et al., 2017).
	Stakeholder Weighting (ST) or Budget Allocation	Experts representing extensive knowledge and experience distribute points over a number of indicators (Gan et al., 2017, Nardo et al., 2005; OECD, 2008).
A	Linear Sum (LN)	Summation of the weighted and individual indicators (OECD, 2008). The aggregated value of indicators for alternative x_a is obtained by the following expression: $A_{x_a(LN)} = \sum_i^e w_{x_a(i)} N_{x_a(i)}$
	Geometric aggregation (GM)	Weighted geometric mean if Ii (Gan et al., 2017). The aggregated score is obtained by the following expression: $A_{x_a(GM)} = \prod_i^e {N_{x_a(i)}}^{w_{x_a(i)}}$

(2) The selected SCMIs and values

The indicators used to create the different sets X1 and X2 were pre-selected from the causal network introduced in Chapter 3. A total of 16 indicators (see Table 4.3) were chosen based on the completeness and availability of their data, and their appropriateness for the current concrete sustainability evaluation problem. The pre-selected indicators, however, do not necessarily represent a comprehensive set for concrete and are only used here for demonstration purposes only.

The 16 SCMIs in Table 4.3 comprised the full set that was used for X1 scenario. The indicators utilized for X2 are marked with “ * ” in Table 4.3. X2 indicator set contains indicators that require no inventory data for the derivation of their values. Since the mixes used here are locally produced in Japan, the inventory data from the Recommendation of Environmental Performance Verification for Concrete Structures (Draft) (2006) published by the Japan Society of Civil Engineers (JSCE) was used. Other inventory data – particularly the environmental impact characterization factors – were sourced from the Assessment Operational Guide by the Center for Environmental Science of Leiden University (2001) or the CML as these are internationally standardized values. The calculation of the SMCI values was based on the mix proportions in Table 4.1.

Table 4.3 Sustainable concrete materials indicators (SCMI) selected

SCMI No.	Name	Unit	Description
1	Primary energy consumption	MJ/m^3	Amount of energy consumed for raw material extraction and manufacturing.
2*	Raw material consumption	kg/m^3	Amount of raw constituent materials in concrete matrix (excluding water).
3*	Water consumption	kg/m^3	Amount of water used for concrete production.
4*	Recovered, recycled or waste material content	kg/m^3	Quantity of recovered, recycled, or waste material in the concrete matrix.
5	CO_2 emissions	kg CO_2 eq.	Mass of CO_2 associated with production.
6	SOX emissions	kg SOX/ functional unit	Amount of sulfur oxides emitted for activities associated with manufacturing and concrete production.
7	NOX emissions	kg NOX/ functional unit	Amount of nitrogen oxides emitted for activities associated with manufacturing and concrete production.
8	Particulate Matter (PM) emissions	kg PM/ functional unit	Quantifies the PM_{10} and $PM_{2.5}$ emissions due to concrete production.
9	Other Greenhouse gas (GHG) emissions	kg GHG/ functional unit	Quantifies other GHG emitted.
20*	Durability	Unitless	Note: The durability performance is determined as described in this section.
28	Global warming potential (GWP)	tons CO_2 eq.	Integrated impact of different GHG emissions to global warming.
29	Photochemical ozone creation potential (POCP)	kg C_2H_4 eq.	Estimated quantity of photo-oxidant formation.
30.02	Acidification potential (Aquatic)	kg SO_2 eq.	Reflect the maximum acidification potential of concrete.
31.01	Eutrophication potential (Terrestrial)	kg PO_4 eq./m_3	Potential impacts of macronutrients such as Nitrogen and Phosphorous.
34	Human toxicity potential	kg 1.4-Dichlorobenzene	Covers the impacts on human heath of toxic substances.
40*	Production cost	Monetary	Cost of producing a functional unit of concrete.

The derivation of the values of the SCMIs in Table 4.3 except for SCMI 20 are already discussed in Chapter 3. Generally, the indicator's value can be derived by using the appropriate inventory data from either JSCE (2009) or CML (2001). For SCMI 20, the durability performance is obtained after calculating the square root of time it takes for the initiation of steel corrosion from Fick's 2nd law of diffusion expressed in Eq. 4.1 (Erdogdu et al., 2004). Manipulating Eq. 4.1 gives the expression for the square root of time as in Eq. 4.2 (Ma et al., 2018). In Eq. 4.2, t is the time in years, x is the cover depth equal to 60 mm, C_o is the initial chloride concentration of concrete assumed as 0 in this analysis, C_s is the surface chloride concentration equal to 4.5 kg/m^3, C_{lim} is the chloride concentration threshold for the initiation of steel corrosion, and D_k is the chloride diffusion coefficient. The values of C_{lim} and D_k were calculated following the JSCE (2017) specification for different cement type with $0.30 \leq$ W/C ≤ 0.55.

$$\frac{\partial C}{\partial t} = D_k \frac{\partial^2 C}{\partial x^2} \qquad \text{Eq. 4.1}$$

$$\sqrt{t} = \frac{x}{2\sqrt{D_k} \cdot erfc^{-1}\left(\frac{C_{lim}-C_0}{C_s-C_0}\right)} \qquad \text{Eq. 4.2}$$

Eq. 4.2 was then normalized by the square root of the designed service life (t = 50 years). The normalized values, $N_{\sqrt{t}}$, were then converted to a durability performance using a membership function as in Eq. 4.3. The use of membership function is similar to desirability analysis so as to restrain the benefits of having a large resistance to chloride penetration, which will naturally result to a very long service life before the initiation of corrosion (see e.g., Ma et al, 2018; King Hing Phoa, et al., 2013). In this analysis, the benefit was restrained to twice the service life (t = 100 years). Many other membership functions (e.g., linear, s-curve, erf circular, among others) could be applied to the same concept; however, the logistics curve was systematically chosen on the basis that the durability performance obtained using the logistics curve is highly correlated with the values obtained using other membership functions of the same concavity.

$$I_{SCMI\ 20} = \begin{cases} 0, & N_{\sqrt{t}} < 1 \\ \frac{2}{1+401.37e^{-6N_{\sqrt{t}}}}, & 1 \leq N_{\sqrt{t}} \leq 2 \\ 2, & N_{\sqrt{t}} > 2 \end{cases} \qquad \text{Eq. 4.3}$$

Table 4.4 summarizes the raw indicators values and the normalized scores are shown in Table 4.5 using distance-to-a-reference and statistical standardization contained in parentheses. The raw indicator values in Table 4.4 is bidirectional in the sense that it is ideal for some indicators to have a larger value, while for others a small value is desirable as previously discussed in Chapter 3. For example, mixes with higher durability performance (SCMI 20) is more desirable in contrast to mixes with high associated CO_2 emissions (SCMI 5). By normalizing, this bidirectionality is avoided. Therefore, the values in Table 4.5 is already unidirectional, where higher values mean more desirable. For this demonstration, OPC50 was taken as the reference mix for normalization by distance to reference. As previously pointed out, in concrete there is no standard reference mix that any sustainability evaluation can refer to because of the concrete material's wide array of application. Nevertheless, OPC50, in this case, could represent a normal mix concrete for fc' = 30MPa.

Table 4.4 The raw SCMI values

Mix	SCMI raw values															
	1	2*	3*	4*	5	6	7	8	9	20*	28	29	30.02	31.01	34	40*
OPC50	1.22	2237	157	125	258	0.053	0.517	0.015	0.022	0.46	261	0.017	0.415	0.067	0.626	13300
FA50	1.04	2217	149	124	209	0.046	0.415	0.013	0.018	0.05	212	0.014	0.336	0.054	0.503	13300
OPC40	1.50	2249	162	157	321	0.063	0.646	0.018	0.028	0.99	325	0.021	0.515	0.084	0.781	14750
FA40	1.32	2223	155	162	271	0.055	0.539	0.015	0.023	0.97	274	0.018	0.432	0.070	0.653	14750

Table 4.5 Normalized values of the SCMIs

Mix	SCMI normalized scores using R and S (in parenthesis)															
	1	2*	3*	4*	5	6	7	8	9	20*	28	29	30.02	31.01	34	40*
OPC50	1.00 (0.53)	1.00 (0.46)	1.00 (0.47)	1.00 (0.40)	1.00 (0.52)	1.00 (0.51)	1.00 (0.51)	1.00 (0.51)	1.00 (0.52)	1.46 (0.46)	1.00 (0.52)	1.00 (0.51)	1.00 (0.51)	1.00 (0.51)	1.00 (0.51)	1.00 (0.60)
FA50	1.15 (0.64)	1.01 (0.62)	1.05 (0.64)	0.99 (0.49)	1.19 (0.64)	1.14 (0.64)	1.20 (0.64)	1.15 (0.64)	1.20 (0.64)	1.05 (0.35)	1.19 (0.64)	1.19 (0.64)	1.19 (0.64)	1.20 (0.64)	1.20 (0.64)	1.00 (0.60)
OPC40	0.77 (0.36)	0.99 (0.36)	0.97 (0.37)	1.25 (0.58)	0.75 (0.36)	0.82 (0.36)	0.75 (0.36)	0.81 (0.36)	0.75 (0.36)	1.99 (0.60)	0.75 (0.36)	0.76 (0.36)	0.76 (0.36)	0.75 (0.36)	0.75 (0.36)	0.89 (0.40)
FA40	0.92 (0.47)	1.01 (0.57)	1.01 (0.52)	1.30 (0.62)	0.95 (0.48)	0.97 (0.49)	0.96 (0.49)	0.97 (0.49)	0.96 (0.49)	1.97 (0.59)	0.95 (0.48)	0.96 (0.49)	0.96 (0.49)	0.96 (0.49)	0.96 (0.49)	0.89 (0.40)

(4) The weights assigned

Figure 4.3 summarizes the weight assigned to the indicators of the X1 scenario for EW and ST methods. The ST weights were adapted from the result of the survey conducted by Henry and Kato (2011). In Figure 4.3, the weights from ST vary widely across indicators; notably, SCMI 40 received the highest weight equal to 0.209. SCMI 4 and SCMI 20 are also assigned with high weights by ST. The weights for X2, on the other hand, are shown in Figure 4.4. For ST in scenario X2, SCMI 40 is still rated as the most important with average weight equal to 0.510 – almost half of the desired importance. The individual weight, however, of the indicators in X2 for EW approach is much higher than in X1 due to the reduction in the number of indicators.

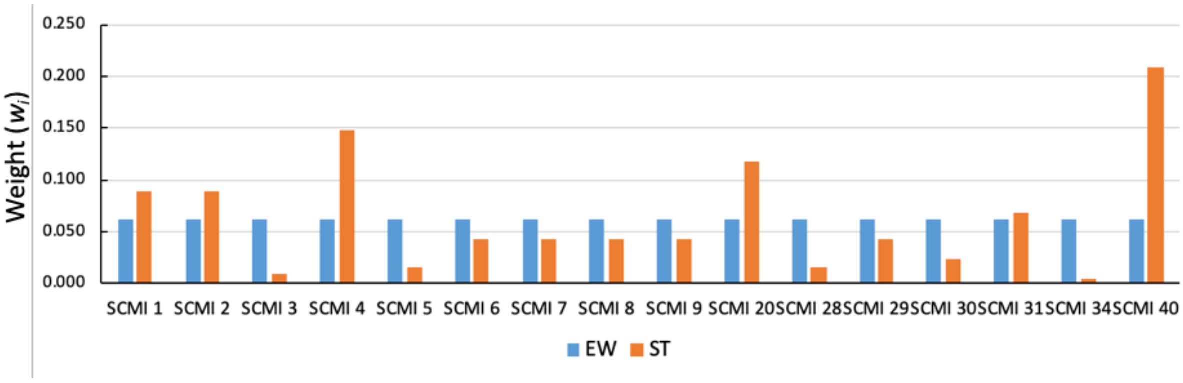


Figure 4.3 Weights assigned to the indicators by EW and ST for X1 scenario

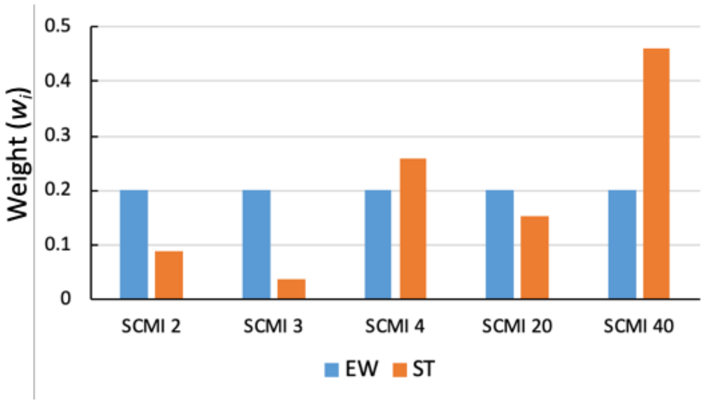


Figure 4.4 Weights assigned to each indicator by EW and ST for X2 scenario

4.5.2 Effect of uncertainties in the selection of indicator and data treatment

The effect of indicator selection and data treatment is combined in this section. For the indicator selection, the uncertainty is represented by creating different indicator sets X1 and X2. Set X2 is an example of case deletion condition in data treatment stage of MA, which assumes that the data for some indicators needing inventory data are not available, hence they are excluded in the set of indicators. To isolate the effects of indicator selection, normalization was fixed to distance-to-a-reference approach, indicator weighting used equal weighting method, and aggregation utilized linear sum approach. The mixes in Table 4.1 were evaluated using both X1 and X2 and the aggregated scores of the mixes and their corresponding rank are summarized in Table 4.6, and Figure 4.5 graphically illustrates the result. In Table 4.6, it is observable that the aggregated scores between X1 and X2 differ in terms of magnitude with Pearson's correlation equal to -0.723. The ANOVA of the aggregated scores between X1 and X2, however, produced a p-value of 0.15 greater than a significant level of 0.05, which means that there is no significant difference between the means of the aggregated scores of the mixes for the two indicator sets. This could be a misleading result as ANOVA could only test the differences in the means of the two scenarios and not the individual differences between the scores of each mix. Nevertheless, the change is still evident with regard to the values of the aggregated scores.

In Table 4.6, the aggregated score of FA50 deteriorate substantially, while others gained significant increases, most notably FA40. The variation in the aggregated scores of X1 and X2 is most likely due to structural changes of reducing the number of indicators used in the analysis as this could magnify the contribution of the indicators in X2 to the final aggregated scores. A reduced indicator set also affects the weights of the individual indicators as described in Section 4.5.1. For example, for EW approach, in X1 all indicators are given with 0.063 weights each, while for X2 each indicator receives higher weight equal to 0.200. This further magnifies the contribution of one indicator to the aggregated scores.

Table 4.6 Aggregated scores for X1 and X2 scenarios

Mixes	X1		X2	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.03	3	1.09	3
FA50	1.13	1	1.02	4
OPC40	0.91	4	1.22	2
FA40	1.04	2	1.24	1

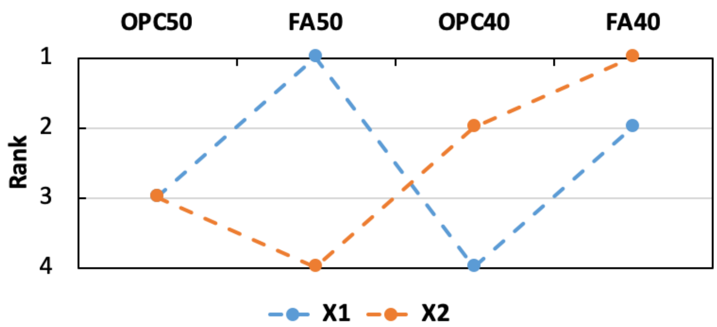


Figure 4.5 Ranking of the mixes for X1 and X2 scenarios

Figure 4.5, on the other hand, shows the effect on the ranking when changing indicator sets from X1 to X2. It is clear from this figure that the ranking is affected significantly by indicator selection. Using X1, the "most" sustainable option is FA50; however, X2 points the opposite – FA50 became the "least" sustainable option – a clear rank reversal. The correlation between the ranks of the mixes for X1 and X2 is relatively poor, equal to -0.400, implying that X2 could not be used as an alternative to X1 and vice versa. For X2, the "most" sustainable option is FA40, while it is ranked the 2nd "most" sustainable option using X1.

The clear variation of the result of the aggregated scores and the ranking between X1 and X2 suggests that the *methodological uncertainty* due to indicator set could affect the resulting conclusions significantly. This also illustrates how the uncertainty propagate to the ranking (or sustainability score) due to the uncertainty in the indicator selection process.

4.5.3 Effect of uncertainties in the normalization process

The effect of *methodological uncertainties* due to the multiplicities of applicable normalization method is examined through both X1 and X2 scenarios. Both indicator sets were retained to represent conditions where the analysis would have to start by either using a relatively comprehensive set or a small set of indicators; however, the results are presented separately so that the effect of the varying normalization methods can be isolated. The analysis proceeds by fixing the indicator sets to either X1 or X2, the normalization method is allowed to vary between distance-to-a-reference or standardization approach, the indicator weighting utilized equal weights, and the aggregation is fixed to linear sum.

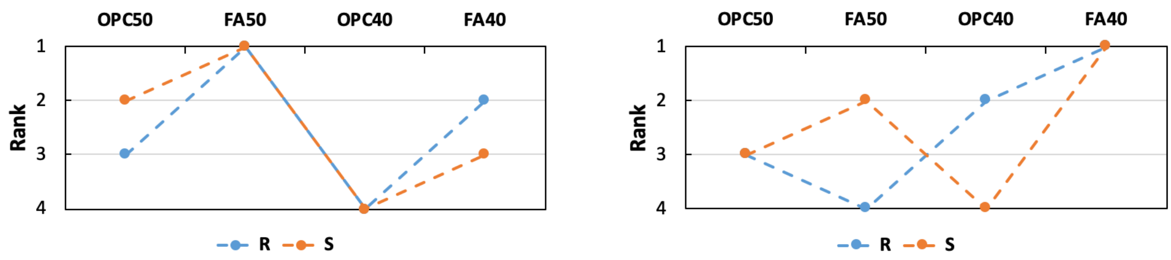
Table 4.7 and Table 4.8 show the results of the sustainability evaluation by varying the normalization method for X1 and X2, respectively. This is also supplemented by Figure 4.6. The aggregated scores of the alternative in both scenarios shows clear distinct differences. The aggregated scores using distance-to-a-reference method shows significantly higher values compared to normalization by statistical standardization. This is a clear evidence of the disparity in scale of the resulting aggregated score because of the natural incongruency of the mathematical assumptions of the two normalization approaches. This scale difference is also prevalent in Table 4.5, which hints about the scale difference of the resulting normalized indicator values. The aggregated score, therefore, just mirrors this scale difference.

Table 4.7 Result for X1 after varying the normalization method

Mixes	R		S	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.03	3	0.50	2
FA50	1.13	1	0.60	1
OPC40	0.91	4	0.39	4
FA40	1.04	2	0.50	3

Table 4.8 Result for X2 after varying the normalization method

Mixes	R		S	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.09	3	0.48	3
FA50	1.02	4	0.52	2
OPC40	1.22	2	0.46	4
FA40	1.24	1	0.54	1



(a) X1 scenario (b) X2 scenario

Figure 4.6 Effect on the ranking by varying the normalization method

Because of the scale difference, it is difficult to make direct statistical comparisons between R and S based on the aggregated scores in both X1 and X2. The effect of the *methodological uncertainty*, however, can still be examined through the ranking (*R*) of the mixes which neutralizes the scale difference of the two methods (see Section 4.4.7). For X1, Table 4.7 and Figure 4.6a reflect the effect on the ranking of the mixes by varying the normalization method. It is clear that the rank of some mixes changed between the two normalization methods. For X1, the correlation of the rank of the mixes for R and S is relatively high, equal to 0.80. Some mixes' rank did not change such as for FA50 and OPC40, while for OPC50 and FA40 the change is only a single rank order. In this scenario the "best" option remained to be FA50 using both normalization methods.

For X2 scenario, the effect of *methodological uncertainties* is still prevalent as shown by the rank differences between R and S as reflected in Table 4.8 and Figure 4.6b. In X2, however, the rank correlation between R and S is smaller, equal to 0.20, compared to X1. This is because the rank of some mixes shifted by an order of 2; however, other mixes such as OPC50 and FA40 retained their ranking. Nevertheless, the rank change is still a clear indication that varying normalization method, even using a reduced indicator set will still have an effect on the resulting sustainability analysis. For X2, FA40 is the "best" sustainable option for both normalization methods.

While in both X1 and X2 scenarios the "best" sustainable options remained unchanged for R and S normalization approaches, an evidence of rank reversal could still be observed in other mixes. This suggests the incongruency of the normalization methods, which must be addressed in sustainability evaluation as it could significantly alter the result of the analysis. Rank reversal must be avoided when substituting one method over another as this could be used to bias the analysis.

4.5.4 Effect of uncertainties in indicator weighting

The effect of *methodological uncertainties* due to the multiplicity of the weighting method is also viewed through X1 and X2 for the same reason mentioned in the previous sub-section. To isolate the effect of the uncertainty from indicator weighting the analysis proceeds by fixing the indicator set to either X1 or X2, the normalization used is distance-to-a-reference, the weighting method is allowed to vary between EW and ST approaches, and the aggregation method is fixed to linear sum. Finally, both aggregated score and the ranking is used to contrast the sustainability performances of the mixes.

The result of the analysis is summarized in Table 4.9 and Table 4.10 for scenarios X1 and X2, respectively. These tables are also supplemented by Figure 4.7, which graphically illustrates the resulting rank of the mixes. The aggregated scores for EW and ST in both scenarios are different, which indicates that the two weighting approaches may have significant effect. For X1, the correlation between the aggregated scores using EW and ST, equal to 0.640, is relatively lower compared to the result of X2, which is equal to 0.999. The result of the ANOVA is also counterproductive in this analysis for the same reason stated in Section 4.5.2. The ANOVA suggests no significant difference between the means of the aggregated scores for both scenarios for EW and ST approaches.

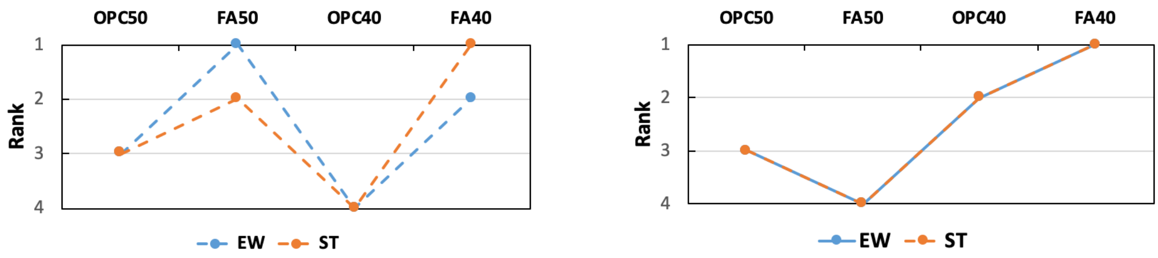
Table 4.9 Result for X1 after varying the weighting method

Mixes	EW		ST	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.03	3	1.05	3
FA50	1.13	1	1.08	2
OPC40	0.91	4	1.03	4
FA40	1.04	2	1.12	1

Table 4.10 Result for X2 after varying the weighting method

Mixes	EW		ST	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.09	3	1.07	3
FA50	1.02	4	1.01	4
OPC40	1.22	2	1.17	2
FA40	1.24	1	1.18	1

Focusing on the result of X1, Table 4.9 and Figure 4.7a show that the aggregated scores of the mixes changed, affecting the ranking. This is an indication of the effect of the uncertainty due to the multiplicity of the weighting approaches. For EW, the “most” sustainable alternative is FA50, while in the case of ST it is FA40. Both approaches produced different conclusions for the same sustainability evaluation problem, suggesting that the ranking of the mixes is also made uncertain because of the uncertainty of the weighting approach. This further implies that one approach could not readily substitute for another.



(a) X1 scenario (b) X2 scenario

Figure 4.7 Effect on the ranking by varying the weighting approaches

For X2, on the other hand, Table 4.10 shows that the aggregated scores changed only very minimally. OPC40 and FA40 have shown substantial reduction in their aggregated scores, in contrast to OPC50 and FA50. This could be attributed to the variance of the normalized indicator values (see Table 4.5), which shows that OPC50 and FA50 have little variability in their normalized values. Nevertheless, the changes in the aggregated score is a proof of the inequivalence of the two weighting approaches. In terms of the ranking of the mixes, however, as illustrated by Figure 4.7b, both EW and ST produced the same ordering. While this would imply that uncertainty from weighting has no effect on the ranking, this notion could be misleading because of the neutralizing effect on the scale when transforming the aggregated scores to ranking. In both EW and ST – based on ranking – the "most" sustainable option is FA40.

Both X1 and X2 produced similar as well as contrasting results. The changes in the aggregated scores for both scenarios for EW and ST suggest that these weighting approaches are not exchangeable. In other words, one weighting approach cannot be used to replace another. On the other hand, X1 and X2 produced contrary conclusions in terms of the ranking. In X1 the effect of uncertainty on the ranking is prevalent, while in X2 the effect is invisible. These contrasting results, however, could be explained by the scale effect due to transformation using ranking. Therefore, extracting sustainability decisions over an analysis under *methodological uncertainties* should be made judiciously.

4.5.5 Effect of uncertainties in aggregation process

The effect of *methodological uncertainties* due to the multiplicity of the aggregation method is also viewed through X1 and X2 for the same reason stated previously. To isolate the effect of the uncertainties from aggregation, the analytical flow for multicriteria analysis proceeds as follows: the indicator set is fixed to either X1 or X2, the normalization method used is distance-to-a-reference, the weights utilized are the ST weights, and the aggregation method is allowed to vary between linear sum and geometric approach. Both the aggregated scores and ranking is again used to determine the effect of the uncertainty from aggregation method.

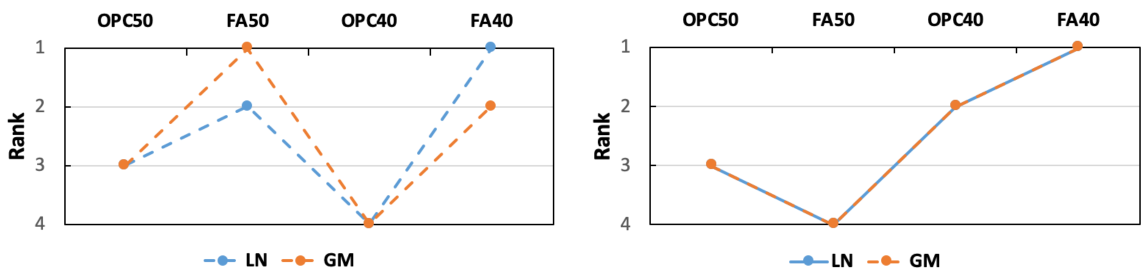
The results of the sustainability evaluation for scenarios X1 and X2 are summarized in Table 4.11 and Table 4.12, respectively. This is graphically supplemented by Figure 4.8, which reflects the ranking of the mixes for both scenarios. The aggregated scores in Table 4.11 and Table 4.12 for LN and GM shows some changes but overall the values are relatively similar. For X1 and X2, the Pearson's correlation between the aggregated scores of LN and GM is significantly high with values equal to 0.856 and 0.997, respectively. ANOVA is again not beneficial in this case as explained previously. Nevertheless, these small changes could translate to a significant effect when viewed in different perspective. The result is still suggestive about the incongruency of LN and GM, hence they contribute to the uncertainty of the output.

Table 4.11 Result for X1 after varying the aggregation method

Mixes	LN		GM	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.05	3	1.05	3
FA50	1.08	2	1.08	1
OPC40	1.03	4	0.98	4
FA40	1.12	1	1.08	2

Table 4.12 Result for X2 after varying the aggregation method

Mixes	LN		GM	
	Aggregated Score	Rank	Aggregated Score	Rank
OPC50	1.07	3	1.06	3
FA50	1.01	4	1.01	4
OPC40	1.17	2	1.12	2
FA40	1.18	1	1.13	1



(a) X1 scenario (b) X2 scenario

Figure 4.8 Effect on the ranking by varying the aggregation approaches

Focusing on the result of X1 in Table 4.11 shows that the aggregated score for OPC 50 and FA50 almost never changed, while for OPC40 and FA40 significant change in the aggregated scores occurred. This difference on the effect of the aggregated score could also be attributed to the variance of the normalized scores (see Section 4.4.7). The effect of *methodological uncertainty* on the ranking is illustrated in Figure 4.8. For X1, the effect is more prevalent using the aggregated scores.

Significant changes in the ordering of the mix, based on the aggregated scores occurred. For LN, as an example, the "most" sustainable option is FA50, while for GM it is FA40. This reversal is due to the incongruency of the two methods, which suggests that they are not exchangeable.

The analysis using X2, on the other hand, shows similar result as X1. Changes in the aggregated scores, though small, is still suggestive of the nonequivalence of LN and GM. The ranking of the mixes, however, is not affected by the uncertainty from aggregation. This is again attributable to the scale effect in transforming the aggregated scores to discrete ranks. It could be said, therefore, that the effect of uncertainty could be diluted or magnified by neutralizing the aggregated score.

4.5.6 Combined effect of the different sources of uncertainties

The previous sub-sections have shown the isolated effect of *methodological uncertainties* from each step of MA. In this section, these effects are summarized and combined to illustrate how it would affect the conclusion – the determination of the "best" sustainable option – to be drawn from the analysis. Table 4.13 summarizes the rank of the mixes resulting from varying each step of MA. The table only shows the result of X1 when varying the normalization, weighting and aggregation approaches. It is directly evident from this table how the rank of the mix deteriorates or improves with the variation of approaches.

Because of the variability of the ranking it is difficult to make distinct pronouncements as to which mix is the "most" sustainable. This is the effect of the presence of *methodological uncertainty*, which makes the extraction of the conclusions complicated and equally uncertain. Changing the indicator set alone could have a significant effect on the rank, which could be exploited to bias the decision. Because of the subjectively over methodological choices with respect to the steps of multicriteria analysis, one could select a particular methodological combination in Figure 4.2 that would yield an outcome fit to the desired outcome of a particular party doing the evaluation or being evaluated.

One way to overcome the variability of the rank is to take the average of the rank and reorder the alternatives based on this value. For example, in Table 4.13, based on average value, FA50 could be taken as the "best" option. However, this might not be the appropriate resolution as average values may not truly reflect the uncertainties in the ranking. For instance, the average value does not inform about the variability of the rank of FA50. Based on the rank variance in Table 4.13, the rank of FA50 shows high volatility to *methodological uncertainty* because it has the highest rank variance amongst the mixes, equal to 0.984. This suggests that the rank of FA50 is highly unstable when viewed across all sources of uncertainties in the stages of MA. Therefore, having FA50 as the "best" sustainable option is a questionable conclusion.

Table 4.13 Combined result by varying the steps of MA

Mixes	SI/DT		N		W		A		Average Rank	Rank Variance
	X1	X2	R	S	EW	ST	LN	GM		
OPC50	3	3	3	2	3	3	3	3	2.875	0.109
FA50	1	4	1	1	1	2	2	1	1.625	0.984
OPC40	4	2	4	4	4	4	4	4	3.750	0.438
FA40	2	1	2	3	2	1	1	2	1.750	0.438

The *methodological uncertainty* is clearly a significant issue to sustainability evaluations by multicriteria analysis. It could infuse confusion to the analyst and decision-makers about the sustainability of the alternatives being compared. It could also prevent the extraction of a good solution to a sustainability problem, which might delay policy-making activities. Therefore, the results shown in this section demonstrated that using multicriteria analysis alone is not robust enough to make sustainability evaluations, requiring a new framework for the management and resolution of the *methodological uncertainties*.

4.6 Summary

The beginning of the Chapter argued that performing sustainability evaluation is one way to demonstrate that the concept of sustainable development is operationalized. Sustainability evaluations will allow decision makers to make quantitative assessments whether their actions and proposed solutions would lead to the overall sustainability of the system (whatever that system might be, e.g., concrete materials). However, because of the complex nature of sustainability itself along with its several dimensions, there is no unique mathematical solution that could capture it holistically to make quantitative sustainability evaluations.

The most effective way of performing sustainability evaluations is through the use of multicriteria analysis, where the multidimensional character of sustainability could be underpinned in mathematical way. Multicriteria analysis takes the various criteria (or indicators) and aggregates them to a total score, which would indicate about the overall sustainability performance of a system. The elaborate process of the multicriteria analysis comprised of: indicator selection, data treatment, normalization, weighting and aggregation. Each of the step perform vital functions representing the various concerns about sustainability evaluation.

Indicator selection identifies the elementary components of the system relevant to sustainability. This is similar to the output of Chapter 3, where the indicators of sustainable concrete are identified. Data treatment is performed to provide resolution to indicators with missing or unreliable information. Since the indicators are expressed in various scales and unit, they need to be normalized so that they can be compared in a single multicriteria framework. The indicators also are viewed by various stakeholders to have unequal importance on the basis of their efficiency at representing of the sustainability of the system. As such, weighting process became an essential step in a multicriteria analysis so that the importance of indicators is properly reflected in the analysis. The last step is aggregating the normalized values and the weights of the indicators into a total score.

While the sustainability evaluation using multicriteria analysis seems to be a straightforward process, it is still susceptible to various subjectivities. Each step of the MA can be performed in a number of ways; therefore, depending on the method chosen by the analyst, different conclusion about the sustainability of the system could result. This is termed as *methodological uncertainty* in this Chapter, accounting the methodological multiplicity of the steps of MA. This Chapter provided as great deal of discussion about how uncertainty arise from each step of MA.

In indicator selection, for example, uncertainty exists by simple inclusion or exclusion of indicators on the basis of data unavailability or due to an inadvertent decision. For data treatment, the incongruency of various applicable methods cause output uncertainty. The same is true for normalization, indicator weighting and aggregation. The inequivalence of the methods undermines the validity of the sustainability evaluation process, which could be exploited to infuse bias in the analysis.

The effect of these *methodological uncertainties* is also demonstrated by comparing the sustainability performance of various concrete mixes. By isolating the effect of the uncertainty from each stage of MA, significant effects on the resulting conclusions were observed. In most cases, there was a reversal in the ranking of the mixes, which clearly indicates and validates the incongruency of the different methods applicable to perform multicriteria analysis. This means that one method is not exchangeable for another. Towards the end of the Chapter, by viewing the combined effect of the uncertainties from various sources in MA, it was clear that multicriteria analysis alone is not sufficient for sustainability evaluation, therefore a new framework is needed for the management and resolution of these *methodological uncertainties*.

Chapter 5
Treatment of methodological uncertainties in multicriteria analysis

5.1 Introduction

The common underlying architecture used in most sustainability evaluation methods is the Multicriteria Analysis. The steps of MA as described in the previous Chapter is comprised primarily of the selection of indicators, data treatment, data normalization, indicator weighting and aggregation (OECD, 2008). In MA, the indicators representing the aspects of sustainability are aggregated to a composite value to compare, i.e., a set x of sustainable options or decisions. However, one of the major challenges of sustainability evaluation by MA is *methodological uncertainties* because of the multiplicity of approaches. This could lead to output uncertainty (Saltelli et al., 2008), undermining the scientific validity of the sustainability evaluation process. Therefore, means at treating uncertainties objectively to draw robust and defensible conclusions and decisions are of paramount importance to policy makers to eradicate confusion (Ciuffo et al., 2012), bias and misinterpretation of the result.

The modified MA framework presented in this Chapter is able to systematically treat the methodological uncertainties in sustainability evaluation by integrating both uncertainty analysis (UA) and sensitivity analysis (SA). The primary aim of UA is to propagate the uncertainties from the inputs of MA to the output (Saltelli et al., 2008). The inputs in this case are the steps of MA, while the output is the rank (R_a) or sustainability scores (I) (Wei et al., 2015) of the options in set x. SA, on the other hand, is the study of how uncertainties in the input can be apportioned to different sources of uncertainty in the output (Saltelli et al., 2004). UA and SA support decision processes by disclosing what aspects of the analysis are most uncertain, and which uncertainties are most apt to affect the decision (Reckhow, 1994).

In light of the above discussions, the primary objective of this Chapter is to introduce the multicriteria analytical sustainability evaluation framework under methodological uncertainties. The uncertainties are managed in this type of framework by performing iterative sustainability evaluation of the alternatives in set x using different methodological combinations of the steps of MA per iteration. This process makes the R_a or I stochastic and volatile (Ben-Haim and Demertzis, 2015) around the choice of methods, allowing for the probabilistic comparison of the sustainability performance of the alternatives.

5.2 The multicriteria analytical framework under methodological uncertainties

The analytical framework for sustainability evaluation under methodological uncertainties is illustrated in Figure 5.1. It is designed to compare the sustainability performances a set of alternatives *x* as input. The sustainability performance of these alternatives is then measured by MA. In Figure 5.1, MA is conducted in tandem with uncertainty analysis (UA) to account for the uncertainties associated with MA, which outputs a set of sustainability scores, *SS*. Sensitivity analysis (SA) is conducted thereafter to determine which sources of uncertainties are influential and which ones are not by factor prioritization. From the result of factor prioritization, an optional step in Figure 5.1 called factor fixing can be performed to systematically eliminate one or more sources of uncertainty. If a source of uncertainty is eliminated, the MA step and UA in Figure 1 has to be performed again. The alternatives are then hierarchically ordered using probabilistic measurements. The details of the framework are discussed in the following subsections.

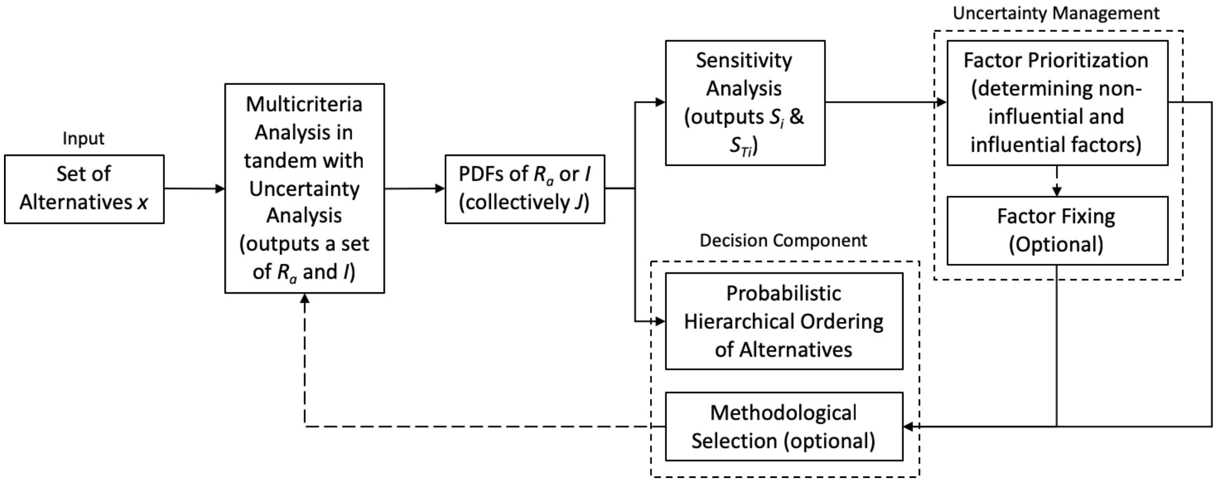


Figure 5.1 Evaluation analytical framework of the sustainability evaluation

5.2.1 Notations and common expressions

Table 5.1 below summarizes the notations used in the following discussion on the treatment of methodological uncertainty. Some are introduced along with the text.

Table 5.1 Notations and expressions

Notations and Expressions	Descriptions
$x = \{x_a\};\ a = 1, 2, 3, \ldots, n$	Set of alternatives or decisions to be compared; *n* is the total number of alternatives.
$SI = \{SI_1, SI_2, SI_3, \ldots, SI_s\}$	Set of *s* number of indicators sets.
$D = \{ D_1, D_2, D_3, \ldots, D_d\}$	Set of *d* number of data treatment methods (i.e., imputation method)
$N = \{ N_1, N_2, N_3, \ldots, N_f\}$	Set of *f* number of data normalization methods.
$W = \{ W_1, W_2, W_3, \ldots, W_w\}$	Set of *w* number of indicator weighting techniques.
$A = \{ A_1, A_2, A_3, \ldots, A_c\}$	Set of *c* number of indicator aggregation methods.

Table 5.1 (continued)

Notations and Expressions	Descriptions
$U = \{SI, D, N, W, A\}$; or generally $U = \{U_i\}$; $i = 1, 2, 3, \ldots, j$	Set of j number of uncertain input factors.
$M = \{M_m\}$; $m = 1, 2, 3, \ldots, H$	Full set of methodological combinations; H is the total number of possible methodological combinations.
$M' = \{M_b\}$; $b = 1, 2, 3, \ldots, k$; generally $k \leq H$	Subset of M with k number of randomly sampled methodological combinations.
$Y_{a/m}$ (or $Y_{a/b}$)	The aggregate indicator value of alternative x_a for method M_m (or the aggregate indicator value of alternative x_a for method M_b)
$Y = \{Y_{(1,2,3,\ldots,n)/m}\} = \{Y_{(a)/m}\}$	Set of all raw aggregated indicator values calculated using methods in set M; $_{(a)/m}$ means a certain methodological combination m is applied to all alternatives in set x.
$Y' = \{A_{(1,2,3,\ldots,n)/b}\} = \{Y_{(a)/b}\}$	Set of all raw aggregated indicator values calculated using methods in set M'; $_{(a)/b}$ means all alternatives for method b.
$R_a = \{R_{(1,2,3,\ldots,n)/m \text{ or } b}\} = \{A_{(a)/m \text{ or } b}\}$ or $I = \{I_{(1,2,3,\ldots,n)/m \text{ or } b}\} = \{I_{(a)/m \text{ or } b}\}$	The sets formed after neutralizing set Y or Y' either by ranking (R_a) or statistical standardization (I).
J	A dummy variable signifying either R_a or I.
V_{Ra} (or V_I)	Total variance of R_a (or I).
V or $V(J)$	A simpler notation (free of subscript) used to signify the total variance of either R_a or I.
$V_{J\|Ui}$ (or V_i)	Conditional variance of J over all possible U_i.

5.2.2 Formalizing the neutralization of the aggregated scores

The methodological plurality of the evaluation stages will generate a set $M = \{M_m\}$, the total number of applicable methodological combinations. Each element M_m assigns an alternative x_a with a raw aggregate indicator value $Y_{a/m}$. Since each M_m will inevitably produce non-equivalent aggregate values, the set of raw aggregate indicator values, $\boldsymbol{Y} = \{Y_{(a)/m}\}$ (or later $\boldsymbol{Y'} = \{Y_{(a)/b}\}$), therefore, needs to be neutralized to make it internally compatible. Neutralization is often achieved by either ranking the alternatives in order based on the aggregate values, $Y_{a/m}$ (or later $Y_{a/b}$), (i.e., rank (R_a) from 1 to n) or by statistically standardizing the aggregated indicators (i.e., sustainability score (I) from 0 to 100 range) for method M_m (or later M_b) to obtain the sets $\boldsymbol{R_a} = \{R_{(a)/m \text{ or } b}\}$ or $\boldsymbol{I} = \{I_{(a)/m \text{ or } b}\}$. By formally neutralizing the aggregated scores as described in Chapter 4, the total variance, V_R or V_I, can then be calculated. Generally, V_{Ra} and V_I are also not equivalent due to the disparity in the scale of transformation. In the following discussions, it is assumed that only one of the two neutralizations is used, and thus only the notation V (free of subscript), representing the total variance, is retained, unless otherwise stated. In actual evaluation, however, both neutralizations can be performed, and the results compared.

5.2.3 Uncertainty analysis

To perform MA in tandem with UA in Figure 5.1 the sources of uncertainties are identified first, delimiting the extent of the analysis. The first phase to deal with methodological uncertainties is to identify the uncertain input factors that would cause variability on the output (i.e., V_{Ra} or V_I). This phase is extensively discussed in Chapter 4, where methodological uncertainties are said to arise at every stage of the analytical framework, as summarized in Table 5.2. The main purpose of UA is to propagate the uncertainties from the inputs (i.e., the methodological uncertainty from the stages of the analytical framework) to the model output (Wei et al., 2015). Propagating uncertainty is important to elucidate the end-to-end nature of uncertainty quantification. UA gives more weight to the relationship of both the inputs and outputs, and not just the clarification of their certainty, bearing in mind that they are subject to different forms of uncertainty (Sullivan, 2015). Output uncertainty is often characterized by the estimated probability distribution functions (PDF) of R_a or I based on simulations carried out for each M_m (or later M_b) (see e.g., Saisana et al., 2005).

Set M needs to be generated first to perform an uncertainty analysis. This is analogous to a Monte Carlo experiment (see e.g., Saltelli et al., 2004), wherein all sources of uncertainty are explored simultaneously to capture all possible synergy effects among uncertain input factors (OECD, 2008). This is achieved by first assigning each source of methodological uncertainty with their corresponding PDF, then generating the set M (or later M') by exhaustively (or randomly) combining different methodological approaches. Table 5.2 reflects the recommended PDF for each methodological source of uncertainty to aid in sample generation. A uniform distribution, for example, means that each methodological approach has an equal probability of being included in a particular methodological combination.

Figure 5.2 illustrates the process of generating the set M, by mapping how each M_m is created through exhaustive combination of different applicable methodological approaches. The figure also shows that the total number of methodological combinations possible is equal to $(s)(d)(f)(w)(c) = H$. The number of elements in M needed to estimate the PDF of R_a and I, however, may sometimes be less than H. Following this, a reduced sample, M', is sometimes more preferable to not overwhelm the analytical process and to substantially reduce the computational effort and time. Several random sampling techniques can be used to generate M', which must be decided when crafting the experimental design or model framework (Ciuffo et al., 2012). Example of these techniques include one-at-a-time (OAT) sampling, fractional factorial sampling, Latin hypercube sampling, stratified sampling, and quasi-random sampling (Saisana et al., 2005; OECD, 2008; Saltelli et al., 2008).

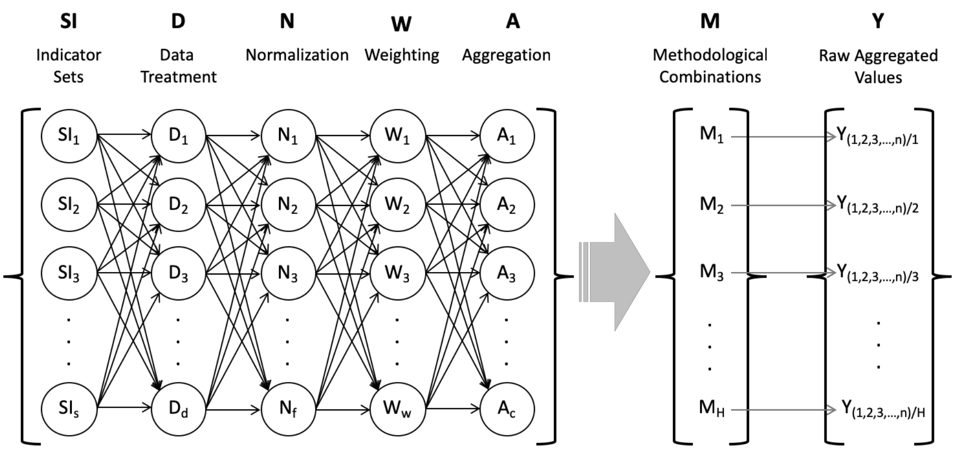


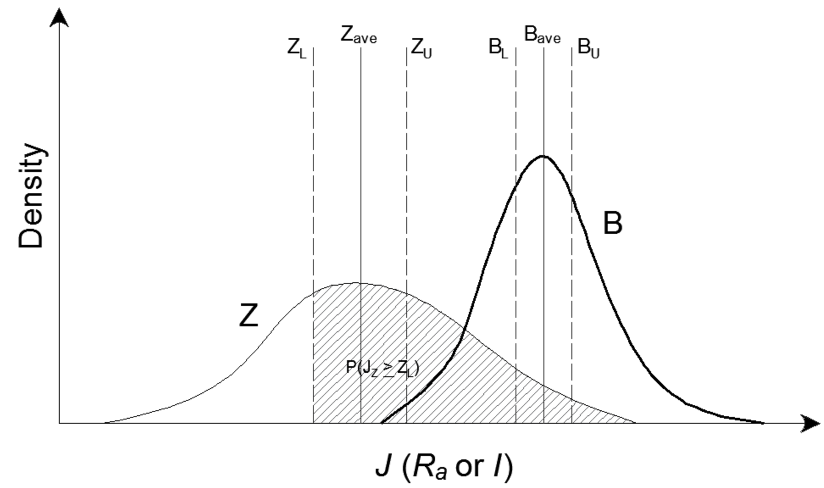
Figure 5.2 Map of exhaustive methodological combinations applicable to each individual alternative

The resulting elements in *M'* are highly dependent on the PDF assigned to each uncertain input factor. Sustainability evaluation simulations can then proceed after generating *M* or *M'* by performing calculations for each alternative in *x* utilizing each element of *M* or *M'* successively and neutralizing the results thereafter. This part is when methodological uncertainties are propagated towards the output. The result of UA is a PDF generated for each alternative in *x* by utilizing all neutralized values from *H* or *k* number of sustainability evaluation simulations. Generally, each alternative in *x* will have a different PDF. The characteristics of the PDF of R_a or *I*, such as the variance, average output, standard deviation, quantiles, confidence intervals (Saltelli et al., 2008), and higher order moments can be estimated with an arbitrary level of precision that is related to the size of the set *M*' (Saisana et al., 2005). In most cases, the variability exhibited by each alternative is summarized as the total variance, *V*, or the expected variance across all alternatives, which is used as a single measure of output uncertainty and is utilized in sensitivity analysis. The statistics generated from the PDF, including the total variance *V,* explain the extent of uncertainty of the result of the sustainability evaluation, which provide insight on how to systematically manage and reduce these uncertainties.

Table 5.2 Summary of methodological sources of uncertainty and their PDF

Source	Issue	Recommended PDF
Indicator Selection (SI)	Multiple sets	Discrete and uniform (OECD, 2008)
Data (D)	Data quality (or accuracy): probabilistic value	Continuous (uniform, normal, exponential); depending on data trend
	Data imputation: multiple methods	Discrete and uniform (OECD, 2008)
Normalization (N)	Multiple methods	Discrete and uniform (Saisana et al., 2005; OECD, 2008)
Indicator Weighting (W)	Multiple methods and arbitrary assignment by experts	Discrete and uniform (Saisana et al., 2005; OECD, 2008)
Aggregation (A)	Multiple methods (weak versus strong sustainability perspective)	Discrete and uniform (Saisana et al., 2005; OECD, 2008)

From the set J an empirical probability distribution function (PDF) can be created as in Figure 5.3, which graphically represents the output of UA. PDFs illustrate the volatility of J to methodological uncertainties. Figure 5.3 shows hypothetical examples of the PDFs of two alternatives Z and B after performing MA and UA. The uncertainty present is said to be higher for wider and shorter distributions (Hodgett and Siraj, 2019) as in the case of alternative Z in Figure 5.3, which can be measured quantitatively by variance estimates. Generally, alternatives would have different distributions.



Note: Z_L and Z_U, and B_L and B_U are the lower and upper bound of the confidence interval of the mean of the PDF of alternatives Z and B.

Figure 5.3 Hypothetical results of UA for two alternatives Z and B

Characterizing the output uncertainty may lead to a more informed decision (Dorini et al., 2011), increasing the robustness of the multicriteria decision-making process. For instance, without discounting output uncertainty the PDFs can be used to compare the relative performance of the alternatives to support the selection of the "best" sustainable option. The relative performance of the alternatives, for example, can be contrasted based on the placement of their PDFs when plotted together as in Figure 5.3. In this hypothetical example, the alternative to the right – option B – is regarded as more sustainable than Z. For highly overlapping distribution, however, the visual confirmation of the relative performance of alternatives may prove challenging. The mean of the sustainability score PDF can also be used to compare the alternatives. The use of a mean value, however, is a deterministic approach and may under-represent the output uncertainty. Since the sustainability score is not a single value but a random variable with a known probability distribution (Zhu et al., 2018), therefore, the output uncertainty must be central when comparing alternatives.

5.2.4 Variance-based sensitivity analysis

Sensitivity analysis is performed after the uncertainty analysis to determine the relative contribution of the uncertain input factors (i.e., in the set $U = \{SI, D, N, W, and\ A\}$) to the total variance, V, of the sustainability evaluation result or model output (Saltelli et al; 2008). This approach defines variables or processes which are most important to a system's dynamics, and their interactions, thereby mapping the system and the linkages within it (Niemeijer and de Groot, 2008; Burgass et al., 2017). An uncertain input factor, U_i, can be assigned with an importance measure via the so-called sensitivity index S_i (also known as the importance measure, correlation ratio, or *first order effect* in other literature (Saltelli et al., 2004)). S_i is defined as the fractional contribution to the model total output variance, V, due to the uncertainty in U_i (Saisana et al., 2005). In literature, there exist several methods to measure the importance of factors (or variable importance analysis (VIA), see e.g., Wei et al., 2015), depending on the characteristics of the model to be considered, which can be categorized into: difference-based, parametric regression techniques, nonparametric regressions techniques, random forest, and variance-based, among others (see e.g., Wei et al., 2015; Saltelli et al., 2008).

In the analytical framework, the method adopted is variance-based due to the unique character of the sustainability evaluation problem. In sustainability evaluation, several layers of uncertainty are present simultaneously, making the analytical process non-linear and, possibly, non-additive (OECD, 2008). For such cases, model-free methods are appropriate (Chan et al., 2000; OECD, 2008). Sensitivity analysis using variance-based techniques is model free (OECD, 2008). Model free methods do not rely on special assumptions about the behavior of the model, such as linearity, monotonicity, and additivity of the relationship between input factors and model output (Saltellli et al., 2004).

The goal of variance-based sensitivity analysis is to decompose the total variance of J (or $V(J)$) into its elementary components, comprised of the isolated effect of the uncertain input factors U_is – expressed as variances (i.e., $V_{J|Ui}$ or V_i) – and their interactions, as in Eq. 5.1 (Saltelli et al., 2008). In this way, the contribution of U_i to the total output variance V can be defined precisely. The model is said to be additive if the second-order, and all other higher order terms of Eq. 5.1, are zero – meaning no interactions occur among the input factors (OECD, 2008).

$$V(J) = \sum_i V_i + \sum_i \sum_{l>i} V_{il} + \ldots + V_{il\ldots k} \qquad \text{Eq. 5.1}$$

(1) First-order sensitivity index

The sensitivity analysis proceeds by computing the conditional variance $V_{J|Ui}$ *or* V_i (see Eq. 5.2) (Saltelli et al., 2008) – conditional in the sense that the variance of J is conditioned over an input factor U_i. Eq. 5.2 is actually part of the two complement operations of the total unconditional variance, V, defined in textbook algebra as Eq. 5.3 (Saltelli et al., 2004). However, between the complementary terms of Eq. 5.3, Eq. 5.2 is the norm used to define the sensitivity index in literature. The importance of an input factor (i.e., *SI*) is often investigated by fixing it temporarily to a particular value to obtain a new total variance, and then comparing it to the original total variance. This is the kind of operation performed using Eq. 5.2.

The $E_{U\text{-}i}(J|U_i)$ part of Eq. 5.2 is an operation that takes the average values of J after choosing an input factor U_i to investigate (i.e. *SI*) and fixing it to a particular value (i.e., if $SI = SI_1$), while allowing all other values of U to vary (hence the subscript $_{U\text{-}1}$). In other words, the calculation is only performed on the subset of M containing the fixed factor U_i (e.g., SI_1). Additionally, since U_i is by itself a set (meaning it could have multiple values, i.e, if $U_i = SI = \{SI_1, SI_2, SI_3, \ldots, SI_s\}$), the value of $E_{U\text{-}i}(J|U_i)$ will eventually have a dependency on the chosen U_i value (e.g., SI_1). To remove this dependency, $E_{U\text{-}i}(J|U_i)$ must be evaluated over all possible values of the chosen U_i (i.e., all values of *SI*) (see e.g., Saltelli et al., 2004). The V_{Ui} part of Eq. 5.2, on the other hand, is an operation to calculate the variance (V_i) of $E_{U\text{-}i}(J|U_i)$. If V_i is large, this would imply that the investigated factor is important; however, in any case, $V_i \leq V$.

$$V_i = V_{Ui}\{E_{U\text{-}i}(J|U_i)\} \qquad \text{Eq. 5.2}$$

$$V = E_{Ui}\{V_{U\text{-}i}(J|U_i)\} + V_{Ui}\{E_{U\text{-}i}(J|U_i)\} \qquad \text{Eq. 5.3}$$

V_i is called the first order effect of U_i on J, and the sensitivity measure S_i, given in Eq. 5.4, is known as the first-order sensitivity index of U_i on J (Saltelli et al., 2008). S_i is a model-free sensitivity measure, and always gives the expected reduction in the variance of the output that one would obtain if one could fix an individual factor (Saltelli et al., 2004). In other words, the larger S_i is, the more reduction of output variance can be obtained by removing the uncertainty in U_i (Wei et al., 2015). If the model is additive – a model without interactions – the $\sum_1^j S_i = 1$; but generally, $\sum_1^j S_i \leq 1$.

$$S_i = [V_{Ui}\{E_{U\text{-}i}(J|U_i)\}]/V = V_i/V \qquad \text{Eq. 5.4}$$

(2) Total-effect sensitivity index

If the higher order terms of Eq. 5.1 are non-zero, interactions are present, requiring each of the terms be calculated to properly decompose the total variance. In most cases, however, higher order sensitivity indices are usually not estimated, as, in a model with j number of input factors, the total number of sensitivity indices (including S_is) that should be estimated is as high as $2^j - 1$ (Saisana et al., 2005), making the calculation of indices too cumbersome for practical use unless the computation quickly converges to 1, as in Eq. 5.1 (Saltelli et al., 2004). For this reason, a more compact sensitivity measure, called the total effect sensitivity index (S_{Ti}) is used (OECD, 2008). S_{Ti} denotes the total effect – the isolated and interactions with other factors – of a factor U_i (Saltelli et al., 2008).

The total effect is obtained by solving Eq. 5.5, which can be derived by algebraically manipulating Eq. 5.3. The idea of the second term of Eq. 5.5 is analogous to Eq. 5.2 above; however, in this case, instead of conditioning the variance to the factor of interest, the second term is conditioned on all other factors except the factor of interest (hence the subscript $_{\sim i}$). The expectation and variance operations present of the second term of Eq. 5.5 has the same operation as described in the previous section. If one is interested in determining the total effect of *SI*, as an example, the other uncertain input factors must be fixed temporarily (i.e., the combination $\{D_1, N_1, W_1, A_1\}$ and others), then the computation proceeds by successive evaluation over all possible values of *SI*. With the presence of interactions, the sum of the first-order terms of Eq. 5.1 is less than one, while the sum of the total order effects is greater than 1 (generally, $\sum_1^j S_{Ti} \geq 1$) (Saisana et al., 2005).

$$S_{Ti} = 1 - [\{V(E(J|U_{\sim i})\}/V] \qquad \text{Eq. 5.5}$$

The result of sensitivity analysis is the determination of S_i and S_{Ti} values for each U_i. Both the first-order effects and the total effects explain, quantitatively, the relationship between the input factors and the output. S_{Ti} highlights the presence of interactions between input factors and the strength of these interactions, which help improve the understanding of the structure of the problem or a model (Saisana and Saltelli, 2004). Both indices clarify the credibility of an uncertain input factor as a source of methodological uncertainty by measuring its contribution to the total output variance.

The variance-based sensitivity analysis is invasive, in that it demands all sources of uncertainties to be modelled explicitly (Paruolo et al., 2013), which allows the evaluators to evaluate, in quantitative terms, the importance of each uncertain input factor, as well as predict the presence of interactions. The target of SA is to explain how the uncertain input factors contribute to the total output variance V to identify the factor, or factors, with negligible contribution to the variability, so that the focus of the analysis emphasizes only the key factors (Saltelli et al., 2008). SA complements UA by providing measures of importance for the sources of uncertainty and the operational means, whenever allowable, to reduce the total output variance, V. The result of SA can be pictured, hypothetically, as shown in Figure 5.4, for a 4-uncertain input factor analysis, e.g., U_1, U_2, U_3, and U_4, with equivalent first order effects S_1, S_2, S_3, and S_4, respectively. The $\sum_1^j S_i$ in Figure 5.4 represents the part of the output variance that can be explained by the combined isolated effect of the uncertain input factors. The remaining part of the pie in Figure 5.4 explains the extent of the interactions of the factors – part of which is explained by S_{Ti}. The difference between S_{Ti} and S_i flags the important role of interactions for a particular uncertain input factor U_i. The importance of a factor can thus be easily evaluated by how much it explains the variance of the output (or, equivalently, the area of the pie it occupies in Figure 5.4). In this example, the input factor U_3, with equivalent first-order effect S_3, can be regarded as the most influential uncertain input factor. Similarly, U_1, with equivalent S_1, can thus be discriminated as the least influential uncertain input factor.

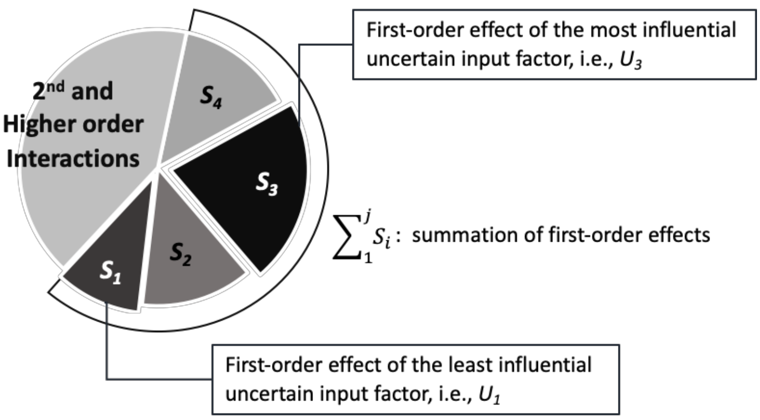


Figure 5.4 Sample representation of importance of the uncertain input factors as part of the total output variance.

The sensitivity indices (S_i and S_{Ti}) of the uncertain input factors can be decomposed to the level of the individual alternatives (see Figure 5.5 for a sample S_i decomposition) to further explain what causes the variability of R_a and I. Doing so allows the result of SA to be scrutinized at the level of the alternative. Reviewed literature (see e.g., Opon and Henry, 2018b; OECD, 2008, Saisana et al., 2005; Saltelli et al., 2004, Saltelli et al., 2008) has pointed out that uncertainties in the input factors affect the alternatives unevenly, which may be due to disparity in the data structure (e.g., skewness and distribution) of the indicators between alternatives. The decomposition of sensitivity indices can corroborate this observation and helps verify which methodological uncertainties are influencing the behavior (i.e., rank or sustainability score) of a particular alternative the most or the least. Correspondingly, the relative importance of the uncertain input factors may also vary per alternative, as can be deduced from Figure 5.5 (similar behaviors are also reported in OECD, 2008; Opon and Henry 2018b). Decomposition also facilitates the identification of alternative, or alternatives, that are highly susceptible (and those that are invariant) to methodological changes. Decomposition reveals, therefore, that the sensitivity of an alternative to methodological choices correlates with the variability of R_a or I.

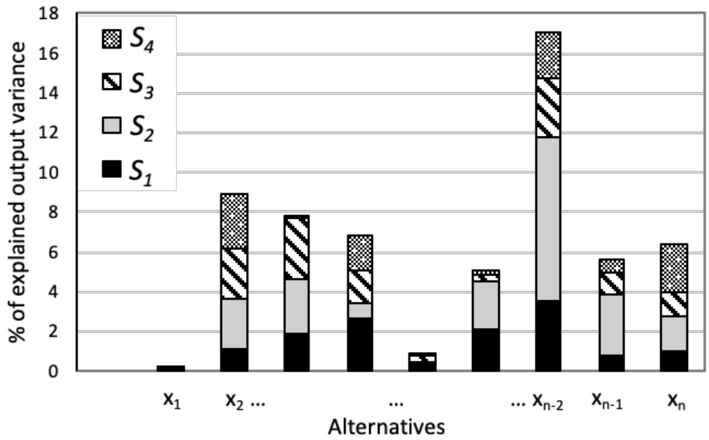


Figure 5.5 Sample decomposition of S_i to each alternative

The ranking of factors' importance using sensitivity measures (S_i and S_{Ti}), however, is best viewed in terms of their effect on the total output variance as shown in Figure 5.4, rather than at the level of the alternatives (i.e., the decomposed values shown in Figure 5.5). This is to remove bias to any particular alternative, since any manipulation involving uncertain input factors should be applied across all alternatives.

5.2.5 Factor prioritization and fixing

The importance of uncertain input factors has a substantial impact on the sustainability evaluation, as it identifies the factor, or factors, to be prioritized or fixed to a certain value whenever possible. The goal of factor prioritization is to sort out both the non-influential and the influential factors, and, especially, to identify the most influential factor. This can be done by creating a setting that would discriminate each factor based on either S_i or S_{Ti} values. From the perspective of S_i, for example, one can discriminate a factor as non-influential if it explains less than 10% of the output variance (or, alternatively, a setting when an input factor explains less than *1/n* of the output variance (see e.g., Saisana et al., 2005)). The most influential factor, on the other hand, would be that factor which, on average, once fixed, would cause the greatest reduction in variance (Saltelli et al., 2008), which can also be identified graphically in Figure 5.4 – the factor occupying the largest area.

From the perspective of the S_{Ti}, on the other hand, customarily, factors with very small S_{Ti} can confidently be declared as non-influential (Saltelli et al., 2008). It is important to note, however, that importance in SA is a relative notion as there is no established threshold (Saisana et al., 2005) to ascertain whether a factor or group of factors is important or not. Indiscriminate use of the result of SA may lead to three types of errors: assessing as important a non-important factor (type 1 error); assessing as non-important an important factor (type 2 error); or analyzing the wrong problem (type 3 error) (Ciuffo et al., 2012).

The identification of non-influential factors is particularly important to reduce the methodological uncertainties of the sustainability evaluation, as it can lead to factor fixing. Factor fixing simplifies the sustainability evaluation by operationally discounting the quantified minor sources of uncertainty, and the result of SA is instrumental to achieve this goal (Saltelli et al., 2008). For instance, if the choice of aggregation is found to be non-influential under a particular setting, then this can be interpreted as meaning that an arbitrary aggregation method can be used without significantly affecting the output variance – a form of factor fixing. Since the aggregation method is fixed in this way, any issues regarding weak versus strong sustainability are also eliminated operationally. This removes the uncertainty conditionally and redirects the focus of the analysis to the influential factors which may require more prioritized deliberation regarding methodological choices.

However, identifying factors as non-influential, by either S_i or S_{Ti} perspective alone, is insufficient for fixing a factor (see e.g., Saltelli et al., 2004). Only in ideal cases when $S_i = 0$ and $S_{Ti} = 0$ (Saisana et al., 2005; Saltelli et al., 2008) can a factor truly be fixed to a certain value. In other words, a factor can be fixed mathematically if its first order effect is zero and it does not interact with any other factors (Saltelli et al., 2008). Factor fixing is also intrinsically related to probabilistic ranking, as the PDF changes when the uncertainty from an input factor is removed. Nevertheless, factor fixing is only an optional step in the analytical framework because its conditions are difficult to achieve, and there is, currently, a serious lack of rationally, pre-established thresholds upon which to make the decision that a non-influential factor can, indeed, be fixed.

The reduction of uncertainty is essential to improve decision-making (Raskob et al., 2018). Fixing a factor to a particular value may lead to either reduction or increase in the total output variance; however, the change in V will be very small for non-influential factors. Figure 5.6 shows a hypothetical example factor fixing. In this figure, the original and the modified PDFs after fixing U_i to either Method 1 or Method 2 are similar since S_i of this U_i is very small. Fixing U_i to Method 1 may reduce the variance G%, while fixing it to Method 2 may increase the V_{TSS} by B%. On average the reduction of variance is (G% + B%)/2, which is equivalent to the factor's S_i. The effect can also be visualized by the empirical cumulative distribution function (ECDF) as shown in Figure 5.6, highlighting the small effect of fixing as illustrated by the similarity of original and modified PDFs.

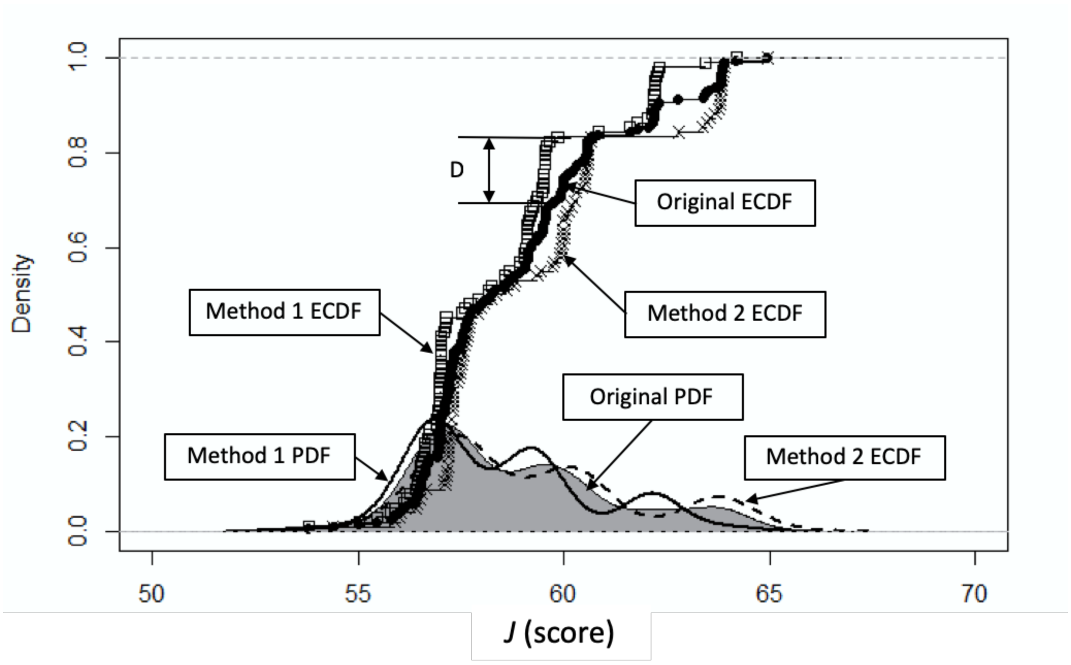


Figure 5.6 Hypothetical output of fixing a factor in MA

To support the validity of factor fixing, a statistic called Kolmogorov-Smirnov (KS) test is used to measure the similarity of the original and the modified PDFs by using the ECDFs. KS test calculates the maximum absolute distance, D, as shown in Figure 5.6 between two ECDFs $F_g(J)$ and $F_h(J)$ (subscripts $_g$ and $_h$ are the sample sizes) as an indicator of similarity by Eq. 5.6 (Stephens, 2012). The null hypothesis of the KS test – two samples are drawn from the same distribution – is accepted if D_{crit} is greater than the computed D as in Eq. 5.7 (Stephens, 2012) for a significance level α. Additionally, a Dvoretzky-Kiefer-Wolfowitz (DKW) inequality bounds for a confidence level 1 - α can also be used to determine how close the modified ECDFs to the original after factor fixing. The DKW confidence interval for the original ECDF $F(J)$ for given natural number k is defined by Eq. 5.8, where Ɛ (Eq. 5.9) is a non-parametric value based on the level of confidence α (Dvoretzky et al., 1956). KS test and DKW inequality bound help avoid committing both type 1 and type 2 errors.

$$D = sup_J |F_g(J) - F_h(J)| \qquad \text{Eq. 5.6}$$

$$D_{crit} = \sqrt{-\frac{1}{2}\ln(\alpha)}\sqrt{\frac{g+h}{gh}} \qquad \text{Eq. 5.7}$$

$$F_k(J) - \varepsilon \le F(J) \le F_k(J) + \varepsilon \qquad \text{Eq. 5.8}$$

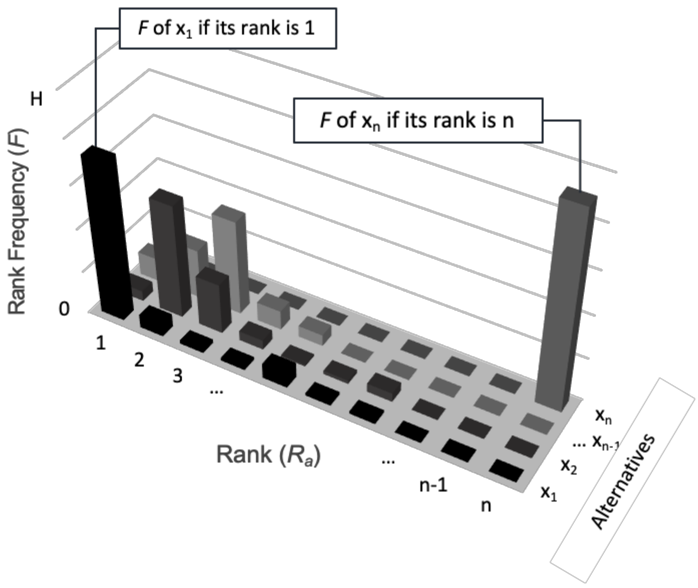
$$\varepsilon = \sqrt{\frac{ln\frac{2}{\alpha}}{2k}} \qquad \text{Eq. 5.9}$$

5.3 Interpreting the results of the multicriteria analysis under methodological uncertainties

5.3.1 Probabilistic interpretation

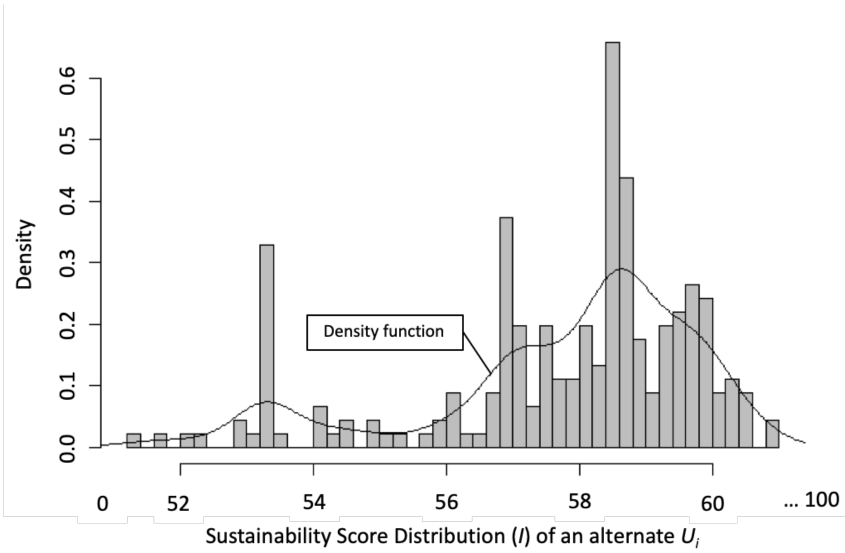
The propagation of uncertainty by UA produces an output distribution in the form of a histogram, whereby the PDF of R_a (discrete) and I (continuous) for each alternative, and their corresponding statistics. Figure 5.7 shows a hypothetical sample result of UA when either ranking (Figure 5.7a) or sustainability score (Figure 5.7b) is used. The generation of these PDFs confirm that the value of R_a and I is never distinct for a given alternative x_a. There is an appreciable range of variability, which is an important feature of the sustainability evaluation problem, and not to be interpreted as an error in the analysis, as this variability simply reflects input uncertainties (similar behaviors are reported in Saltelli et al., 2004 and OECD, 2008).

The output uncertainty, characterized as the total variance, V, should be scrutinized carefully if the range of R_a and I it represents is narrow enough to be useful (Saltelli et al, 2008). A high total variance means that the resulting R_a or I are more spread out, producing low probability values, and affecting the credibility of the decision selection. Situations may arise in which, after incorporating all uncertainties into the evaluation, the output varies so wildly as to be of no practical use (Saltelli et al., 2008). Current literature, however, offers no guidance regarding the acceptable limit of the output variance, which may depend on the problem being analyzed. The result of SA contributes to an in-depth understanding of what influence the behavior of total output variance, and how, if possible, it can be reduced.



(a) Hypothetical sample result for ranking (R_a).

Figure 5.7 Hypothetical sample results of UA using (a) ranking and (b) sustainability score



(b) Hypothetical sample result for Sustainability Score (I).

Figure 5.7 (continued)

Regardless of the magnitude of V, for both R_a and I distributions, statistics such as the measures of central tendencies (mean, median, mode), measures of variabilities (range of values, variance, standard deviation, etc.), and probabilities (occurrence, confidence intervals, etc.) can be computed, which can then be used to compare the alternatives. Using the rank, as an example, an ordering (e.g., 1 to n) of alternatives can be created based on the average rank computed from the PDF. The order (or rank) assigned to an alternative, however, is not distinct (deterministic) in this case due to methodological uncertainties, in that ranks are no longer constant, but random variables with certain probability distributions (Zhu et al., 2018). The effect of methodological uncertainties, as an example, could be reflected by associating the assigned rank with an equivalent probability of occurrence. This type of ordering is *probabilistic ranking*, with the probability of occurrence determined by frequentist computations using the PDF of the distribution, i.e., R_a (or, similarly, using the continuous distribution of sustainability score I). In Figure 5.7a, for example, the probability that an alternative x_1 is rank 1 can be computed by dividing the frequency (F) of occurrence with the total number of simulations H or k. Similar probabilistic approaches have been used in other fields (e.g., weather forecasting (Mylne, 2002) and flood control operations (Zhu et al., 2018)), to take account of uncertainty and aid the decision-maker who understands the impact of a wrong decision (Mylne, 2002).

In complex systems involving uncertainties, the probabilistic approach has been proven to have greater value for decision- and policy-makers than deterministic forecasts (see e.g., Mylne, 2002; Ahmadisharaf et al., 2016; Zhu et al., 2018). A probabilistic approach, such as probabilistic ranking, is favorable for sustainability-related problems, because it facilitates the selection (or prioritization) of the best (or optimum) alternative. A probabilistic approach can help guide sustainability decisions, as it provides additional insights on whether the variability of the output is of practical value for decision-making purposes, and it helps for the quantitative assessment of risk associated with sustainability decisions. The best alternative or decision is oftentimes selected straightforwardly if it is both ranked as the top alternative and its associated probability of occurrence is relatively high. This type of selection is similar to deterministic approaches, wherein top-ranking alternatives are marketed as the best solutions. However, deterministic selection can be very misleading without considering the level of uncertainty associated with every decision (Ahmadisharaf et al., 2016). In contrast to the deterministic approach, the uncertainty level associated with selecting a given alternative is provided by probabilistic approach (Ahmadisharaf et al., 2016); however, decision-makers should be cautious about the selection of alternatives in this way, as the uncertainty may be too high (or, equivalently, the probability of occurrence too low).

There are situations, for example, that the associated rank probability may not be practical for decision-making purposes as a result of high total output variance. For the purpose of discussion, for instance, decision-makers may find it inconvenient to select an alternative ranked number one if its probability of occurrence is below their expected value (e.g., 80% or higher). In another, similar, situation, decision-makers may be torn between the first-ranked alternative and a second-ranked alternative with significantly higher probability value compared to the first-ranked alternative. In both situations, selection of the “best” alternative is not straightforward, as decision- and policy-makers may require a high level of confidence to decide, and they may establish the values of some decision variables (e.g. probability of occurrence) independent of the analysis (Yoe, 2012). Low probability scores are merely a consequence of having high total output variance; however, there are few courses of action available to the analyst to further examine if this kind of result can be reinterpreted in a manner that could support decisions, unless the variance is reduced by operationally discounting the uncertainties from the input factor, i.e., by factor fixing. In such situations, instead of using a specific rank for an alternative, a rank range (e.g., within rank 1 to 3) may be more desirable. A probabilistic approach delineates a performance range of the alternatives (Ahmadisharaf et al., 2016). The cumulative probability of an alternative, ordered in a particular rank range, is substantially higher than using only a specific rank, which may further provide decision- and policy-makers additional confidence and persuasive direction (Martin, 2015) on which to base their decisions. Provided that the probabilities resulting from the use of range ranking are within the acceptable limit set by decision-makers, range ranking may add more insight regarding the practical value of the total output variance.

Probabilistic ranking can also be utilized to characterize the risk of a particular decision as it directly links the uncertainties from the input to decision choices in the form of probabilities. Uncertainty is the reason for risk evaluation; if there was no uncertainty, there would be no question about whether, or when, a loss would occur, or how large it would be (Yoe, 2012) if a particular decision is taken.

The most common way to measure risk is to multiply the measure of probability of the risk with the measure of the impact of the risk (Fenton and Neil, 2013). The probability measure in this case can be computed from the PDFs of the R_a or I; for example, the likelihood of an alternative not being the top alternative – the opposite of the probability of occurrence. Coupled with the assessment of impact, the risk associated with the decision can then be fully characterized (impact assessment, however, is beyond the scope of this manuscript. The issue of risk in the context of decision making helps move the concept of uncertainty analysis and quality of decisions from the periphery of scientific methodology to become a central concept for solving sustainability policy-related problems (Funtowicz and Ravetz, 1993).

5.3.2 The hierarchical exceedance probability matrix.

Determining the "best" option amongst the alternatives in x under uncertainty is generally problematic, as the rank of alternatives due to the randomness of the sustainability score could just easily deteriorate from best to worst (Dorini et al., 2011; Xiong and Qi, 2010; Zhu et al., 2018). For J presented as PDFs, using probability expressions to compare different alternatives is only appropriate. By using a confidence level, as an example, one may assign an alternative "B" in Figure 5.3 with a probability "P" as being the best alternative. In contrast, $1 - P$ is the probability that alternative "B" may not be the best option – a simple illustration of the risk.

There are several ways with which to extract the value of P. For example, by frequentist operation of how many times an alternative is ranked better than others (or the probability of occurrence) after performing MA. Another is through threshold setting (probability of exceedance), which defines the probability of J of an alternative exceeding a particular value. These methods are simplistically described in the previous sub-section. In any case, an alternative with the higher P can be regarded as the "probabilistically" the better option. There are, however, issues with this kind of probability assignment. For the probability of occurrence, as an example, one may encounter a situation where none of the alternatives shows particularly large value of P or for some alternatives, the probability may have very similar value (see, e.g., Zhu et al., 2018). On the other hand, using exceedance probability may also be limiting because of the difficulty of setting the threshold value. Additionally, some alternatives may have equivalent probabilities with respect to the threshold, rendering comparison counterproductive. Nevertheless, probabilistic comparison is still the suitable approach to compare alternatives when uncertainty is involved (see, e.g., Ciuffo et al., 2012).

To respond the above-mentioned issues on probability assignment in order to compare the alternatives efficiently, another method of probability extraction is developed in this work. The idea of the exceedance probability is exploited in the assignment of P; however, the threshold is not set to a single value, rather, it takes up multiple values that are linked to the mean of the PDFs. This systematically removes the arbitrariness in threshold assignment and the dependency of the alternatives to a single threshold value. In this method, each alternative in x is used as a reference alternately similar to the process of pairwise comparison. This process provides more chance to hierarchically organize the alternatives from the "best" to the "least" sustainable.

The threshold per alternative is determined using the confidence interval of the mean of the PDF. The use of a confidence interval is due to the fact that there might be other unaccounted sources of uncertainty, which might affect the location of the mean of the distribution. This confidence interval can be obtained by bootstrapping with replacement for Q desired number of iterations. In Figure 5.3, for instance, the 95% confidence interval of the mean is shown for both alternatives Z and B (the subscripts $_L$ and $_U$ mean the lower (2.5%) and upper (97.5%) bound of the confidence interval, respectively). Once this confidence interval is obtained the threshold value for an alternative is set to the lower bound (e.g., Z_L) of the interval to be more conservative.

In Figure 5.3, as an example, the probability of exceedance of alternative B is calculated by how much of the area of its PDF is located above the threshold Z_L, when using Z as the reference. This probability is conditional on Z_L, therefore, it can be expressed as P ($J_B \geq Z_L$), or the probability that the sustainability score of B, J_B, is higher than or equal to Z_L. In Figure 5.3, P ($J_B \geq Z_L$) is equal to 1.00, as the entire area of the PDF of B is above Z_L. For alternative Z, the P ($J_Z \geq Z_L$) can also be computed in a similar manner to examine how alternatives Z and B compare with respect to Z_L. P ($J_Z \geq Z_L$) is the hatched area of PDF of Z in Figure 5.3.

In this hypothetical example P ($J_B \geq Z_L$) > P ($J_Z \geq Z_L$), which means the sustainability score of B is more likely to exceed Z_L than the sustainability score of Z, placing B higher in the hierarchy than Z. The same analysis can also be done when the threshold is moved to B_L; however, the interpretation of the magnitude of P remains the same. When comparing several alternatives, a matrix of P is created – termed as the hierarchical exceedance probability matrix (HEPM) in this work – showing how the exceedance probability of alternatives change as the threshold is moved to the lower bound of the confidence interval of the mean of each succeeding alternative as in Figure 5.8, for n number of alternatives.

$$
\begin{Bmatrix} x_1 \\ x_2 \\ x_3 \\ \dots \\ x_n \end{Bmatrix} = \begin{Bmatrix} P(J_{x1} \geq x_{1L}) & P(J_{x1} \geq x_{2L}) & P(J_{x1} \geq x_{3L}) & \dots & P(J_{x1} \geq x_{nL}) \\ P(J_{n2} \geq x_{1L}) & P(J_{x2} \geq x_{2L}) & P(J_{x2} \geq x_{3L}) & \dots & P(J_{x2} \geq x_{nL}) \\ P(J_{n3} \geq x_{1L}) & P(J_{x3} \geq x_{2L}) & P(J_{x3} \geq x_{3L}) & \dots & P(J_{x3} \geq x_{nL}) \\ \dots & \dots & \dots & \dots & \dots \\ P(J_{xn} \geq x_{1L}) & P(J_{xn} \geq x_{2L}) & P(J_{xn} \geq x_{3L}) & \dots & P(J_{xn} \geq x_{nL}) \end{Bmatrix}
$$

Figure 5.8 Sample hierarchical exceedance probability matrix (HEPM) for *j* number of alternatives

5.4 Implications to decision-making process

Multiple stakeholders may bring different perspectives on the nature of sustainability problems informed by different values (Martin, 2015). As such the assumptions of unpredictability, incomplete control, and the plurality of legitimate perspectives cannot be simply ignored (see e.g., Funtowicz and Ravetz, 1993) as these may lead to decision-making uncertainties. In the presence of uncertainties, ineffective decisions are often taken, which may result in more overall harm than good (Raskob et al., 2018).

The framework demonstrated herein could be a great tool for decision-making under uncertainties. Given the right framing, the sustainability evaluation framework could integrate the different values expressed by stakeholders. These values are often represented by the selection of utility models (or methods) by decision-makers for each criterion in a decision problem (Hodgett and Siraj, 2019). This situation is taken as input uncertainty in the framework, outputting probabilistic measurements that help guide and select the optimum sustainability decision amongst different options, reducing substantially the disagreements between decision-makers. The use of HEPM, for example, permits a quick comparison of alternatives without discounting uncertainties, facilitating a straightforward decision-making process. In a complex system involving uncertainties, a probabilistic approach has been proven to have a greater value for decision- and policy- makers. Therefore, the rigorous structure of the analytical framework with its many attributes working together to handle the uncertainties in MA supports in reaching robust and defensible sustainability decisions.

5.5 Summary

Sustainability is a heavily contested topic because it has no precise definition, eliciting critical debates on various fronts that could undermine its importance in present and future generations. These debates, however, remain a challenge to be resolved due to the vagueness of the sustainability concept, which inspires innumerable framings. The contrasting and, oftentimes, irreconcilable perspectives on what constitute sustainable development have been the catalyst of the existence of multiple evaluation methodologies, which aim to operationalize the conceptual nature of sustainability in a mathematical and scientific manner. The plurality of evaluation methodologies, however, motivates legitimate controversies, as the methods are clearly non-equivalent due to their incongruent structural assumptions. This, in turn, introduces methodological forms of uncertainty to the entire sustainability evaluation process, producing variable and, sometimes, conflicting results. The current Chapter addressed the issue of methodological uncertainties in sustainability evaluation by rigorously identifying the main sources of uncertainty and their causes, and proposed an uncertainty- and sensitivity-based sustainability evaluation framework to manage these uncertainties to produce homogenized results under the heterogenous sustainability environment.

Analysis of the sources of uncertainty in sustainability evaluation is realized through the architecture of multicriteria analysis – considered as the appropriate tool to quantitatively capture the multifaceted nature of the sustainability concept. Multicriteria analyses are especially applied to compare different alternatives or sustainability decision scenarios, as these involve multiple scales and various mathematical manipulations. The current Chapter pointed out that the main sources of uncertainty in sustainability evaluation occur at the stages of the multicriteria analysis, which includes the selection of sustainability indicators, the statistical treatment of the data, data normalization, indicator weighting, and the data aggregation process. Uncertainties from these stages arise due to the multiplicity of methodologies with differing consequences, as well as the subjective judgments committed by the sustainability evaluator in methodological selection due to the lack of standards to guide the selection process. These uncertainties, if not objectively managed, can confuse stakeholders about the sustainability performance of the alternatives (or the system), preventing stakeholders from selecting the "best" alternative for a particular sustainability problem. This necessitated the use of unique analytical tools to scrutinize the methodological uncertainties objectively to raise the scientific rigor of the evaluation process.

The scientific tools uniquely applicable for uncertainty management are the variance-based uncertainty- and sensitivity analyses, which are the primary analytics of the proposed multicriteria framework for sustainability evaluation. The framework subjects all stages of the multicriteria analysis to uncertainty- and sensitivity analysis. Uncertainty analysis draws a picture of how uncertainties propagate from the methodological stages towards the output (i.e., ranking or sustainability score), providing stakeholders with a quantitative basis, in probabilistic form, to evaluate the volatility of their decisions. Uncertainty propagation transforms the result to probabilistic, which proves to be valuable in facilitating the selection of the "best" alternatives or in guiding sustainability decisions. For example, the use of probabilistic ranking or the hierarchical exceedance probability matrix (HEPM). A probabilistic approach provides additional insights about the practical value of the output total variance to support sustainability decision-making process, as well as helps characterize the risk involved with every sustainability decisions. With *probabilistic ranking* (or, alternatively, the sustainability score), the alternatives can be ordered in terms of the average values of the probability density function. This ordering could be associated with the probability of occurrence, representing input uncertainty. In some cases, using range ranking is also suitable than assigning a single rank to increase the stakeholder confidence over a particular alternative or decision, as range ranking utilizes cumulative probability, which might be substantially higher in magnitude than the probability of occurrence of a single rank. Using HEPM, on the other hand, the alternatives can be ordered in terms of the exceedance probability of a distribution of the sustainability scores (or ranking) from a threshold value. HEPM associates the order/rank of the alternatives with the probabilistic measure that is more illustrative of the of uncertainty of the output due to the methodological uncertainty of the approach of MA.

Sensitivity analysis, on the other hand, affords the stakeholders quantitative measures (sensitivity indices) about the effects – both the isolated effect of an uncertain input factor, and its interactions with other factors – of each methodological sources of uncertainties to the total output variance. The calculation of the sensitivity indices is useful to determine the relative importance of each uncertain input factor, which may enable factor prioritization and fixing. Prioritization discriminates the uncertain input factors as non-influential – the precondition of factor fixing – or as influential. Influential factors guide the focus of the sustainability evaluation and support future deliberations on methodological choices. Factor fixing, on the other hand, simplifies the sustainability evaluation through the elimination of the uncertainty from the source; however, its mathematical condition is too rigid, as it requires that the factor's isolated effect to the total output variance is zero, and the factor should have no interaction with any other factors. Both factor prioritization and fixing, whenever mathematically allowable, aim to reduce the output variance so that the probabilities associated to each alternative will increase to an acceptable level pre-set by stakeholders in order to accept or choose the most credible sustainability decision. Tools such as uncertainty analysis and sensitivity analysis allow to decision- and policy-makers to select decisions that are substantiated scientifically and corroborated extensively by various legitimate perspectives.

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Chapter 6
Demonstration studies

6.1 Introduction

The multicriteria analytical framework introduced for sustainability evaluation in Chapter 5 could be applied to decision problems of analogous structure. The applicability of the analytical framework is demonstrated in this Chapter through a sustainability decision problem involving various concrete materials. One of the strategies to tackle sustainability challenges in concrete is to use blended cements using supplementary cementing materials (SCMs) (e.g., fly ash and blast furnace slag). As the availability of these blended cements become widespread, decision problems may emerge the selection of the "most" sustainable option between concrete of similar performance produced using different blended cements. Therefore, the case studies presented in this Chapter is quintessential to this concrete sustainability decision problem.

In addition, to be sensitive to some of the generic issues surrounding the sustainability concrete materials in the demonstration, two issues were considered: the durability performance of the material and missing data. Making durable concrete structures has a larger impact on improving sustainability since times to rehabilitation and replacement can be extended (Hooton and Bickley; Hooton et al., in Hooton). There are still trade-offs, however, between that of durability and the other criteria for sustainability that remained to be resolved. For example, contractors may resent the use of blended cements for specific construction application because of their limited experience and the availability of these cements, affecting considerably the construction cost. Another debate points to the stochastic nature of durability performance itself (see e.g., Akiyama et al., 2012), which is affected by many randomly behaving variables, i.e., environmental conditions. Despite the uncertainty on the estimation of the durability performance, it remains a recurring theme when it comes to the topic of concrete sustainability.

Missing data, on the other hand, is an inherent phenomenon to most concrete sustainability evaluation work as some indicator data may differ temporally and spatially (Opon and Henry, 2019a) or even nonexistent. As a consequence, some indicators could be excluded in the analysis on the basis of missing data. This is particularly an important issue to examine as inventory data is not readily available for most countries or too expensive to collect, hence the exclusion of indicators. Therefore, both the issues on durability and missing values needed to be examined in the following demonstration, aside from considering the effect of methodological uncertainties in multicriteria sustainability evaluation of the concrete material.

6.2 Settings for the demonstration

6.2.1 The data

As an illustration of the applicability of method discussed in Chapter 5 to sustainability decision problem, six ready-mix concretes locally produced in Japan were selected based on two criteria: (i) they have similar characteristic compressive strength (fc') of at least 30 MPa, and (ii) they should at least be used for a design period of 50 years in a corrosion inducing environment (i.e., high chloride concentration environment or when carbonation induced corrosion could occur). The mixes are produced using different cementing materials, such as ordinary Portland cement (OPC), blast furnace slag cement type B (BB) and fly ash type A (FA). These concrete mixes constitute the set of alternatives *x*. The data for these mixes were sourced from Yokota et al. (2016), which represents the commonly used ready-mixed concrete for the specified fc' with their proportions shown in Table 6.1.

Table 6.1 Mix proportions of concrete

Mix	Cement Type	fc' (MPa)	Unit quantity (kg/m^3)				
			W	C	S	G	Ad
OPC50	Ordinary Portland Cement	30	157	328	783	1071	0.82
BB50	Slag cement type B	30	156	332	764	1076	0.83
FA50	Fly ash cement type A	30	149	290	840	1065	2.90
OPC40	Ordinary Portland Cement	40	162	411	688	1081	1.03
BB40	Slag cement type B	40	161	419	672	1081	1.05
FA40	Fly ash cement type A	40	155	379	735	1081	3.79

In the set *x*, two groups are distinguishable: one group is comprised of mixes with water-to-cement (W/C) ratio of about 0.50 with fc' = 30 MPa, the other group is comprised of mixes with approximately W/C = 0.40 and fc' = 40 MPa. In Table 6.1, the proportions shown are for 1 cubic meter of concrete, which was also the functional unit used for the succeeding sustainability evaluation.

6.2.2 The analytical scenarios

Three analytical scenarios were considered in the sustainability evaluation of the 6 concrete materials focused on durability performance influenced by environmental conditions and the issue on missing data. Durability performance can be expressed in many measurements as presented in Chapter 3 (see e.g., Opon and Henry, 2019). In the succeeding analysis, however, the durability performance of concrete is measured by the initiation of steel reinforcement corrosion – an environment-dependent condition – for period of 50 years by assuming the surface chloride concentration, Cs = 4.5 kg/m^3 for and 60 mm concrete cover. The initiation of steel corrosion could result into cracking and spalling of a reinforced concrete element (Akiyama et al., 2012), deteriorating the serviceability of structures. Additionally, to reflect the unavailability of some inventory, which is not uncommon for sustainability evaluation works, the analysis considers the use of both full and reduced indicator sets. Based on these considerations, the following evaluation scenarios are created:

i. CL: this scenario simulates a high chloride concentration environment wherein the ingress of chloride ions into concrete is the major contributor for the initiation of steel corrosion. Also, for this scenario a full indicator set is used.

ii. CB: this scenario simulates an environmental condition where the ingress of CO_2 into concrete is the major factor of the initiation of steel corrosion. Also, for this scenario a full indicator set is used.

iii. CL*: this scenario is the same as CL except that it uses a reduced indicator set by removing those that require inventory data – simulating a condition of inventory data unavailability.

6.2.3 The analytical structure

The concrete mix alternatives in the set x are compared in terms of their sustainability performance by following the analytical structure in Figure 6.1. All mixes are analyzed through each scenario as shown in the analytical set-up part of Figure 6.1. The sustainability evaluation part of Figure 6.1, on the other hand, is where the stage of MA is operationalized. The steps of MA considered in this analysis are the SI, N, W, and A only. The step on data treatment was considered as part of the issue on missing data, which is resolved by case deletion through exclusion of indicators that do not have inventory data.

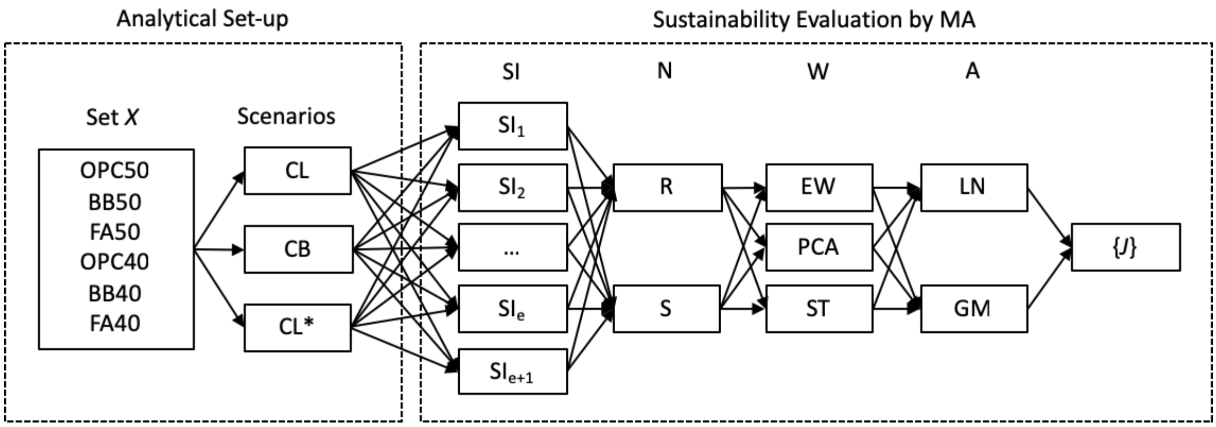


Figure 6.1 Sustainability evaluation analytical structure

In the sustainability evaluation part of Figure 6.1, the natural inconsistency of the indicator set formation is reflected by creating various indicator sets from the full set of e number of indicators by dropping alternatively one indicator at a time, creating a total of e + 1 set of indicators per scenario. Several methodological approaches applicable in each step of MA for concrete sustainability evaluation were considered in the other steps of MA, which are already describe in Chapter 4 (see Table 4.2), except for the addition of the PCA as another weighting method. PCA extracts the orthorhombic or perpendicular factors (principal components) that highly correlated indicators are likely to share (Gan el al., 2017). The weight of each indicator is then calculated from the factor loadings of each indicator to the principal components, as these factor loadings express the ratio of the overall variance of the indicator explained by the principal components (OECD, 2008; Gan et al., 2017). An example of weight extraction by PCA for a set of indicator in CL scenario is shown in Appendix B.

For the other parts of the evaluation, 2 normalization methods were used, 3 weighting scenarios were considered, and 2 aggregation steps were performed, mapped as in Figure 6.1. As a result, the total number sustainability evaluation simulations, or alternatively, the number of methodological combinations per scenario is $h = (e + 1)(2)(3)(2)$. What this means is an alternative in x_a in x could be given an h number of rank (R_a) or sustainability scores (I), which could be represented as a distribution PDF (see also Chapter 5). For this demonstration, sustainability score is used and is henceforth referred to as the variable J (see Table 5.1). Further, the sustainability score, J, is rescaled from 0% (lowest J) to 100% (highest J) after the aggregation using statistical standardization for the reason previously mentioned in Chapter 5 (see Section 5.2.3).

The choice of R and S as normalization methods is due to their applicability in concrete sustainability evaluation. R could represent a condition where a reference or standard mix is available, allowing for the calculation of the linear deviation of the performances of each mix in x from the reference value. In contrast, S could represent the unavailability of a reference mix wherein the spread of indicators' value could only be based on the internal structure of the data.

The weighting scenarios also represents different conditions. EW, for instance, could represent a situation where replicability of result is aimed or when no statistical or empirical evidence supports a different weighting scheme (Gan et al., 2017; Nardo et al., 2005; Land, 2006). PCA is used to reflect the structure of the data set as some indicators may be highly correlated. The use of PCA reduces the risk of double weighting as may be the case of EW (Gan et al., 2017; Yeheyis et al., 2013). The ST, which is a form of budget allocation method represents the viewpoints of different experts regarding the relative importance of each indicators.

For EW and PCA, the process of weight extraction is already established mathematically (for PCA, see e.g., OECD, 2008; Berlage and Terweduwe, 1998). The extraction of stakeholder weights, on the other hand, is not straightforward. In this analysis, the ST weights were assigned based on the survey conducted by Henry and Kato (2011) among stakeholders of the concrete industry in Japan regarding the relative importance of the different aspects of concrete sustainability. The scores by assigned by stakeholders to each indicator, however, were not used directly as weights, but they were utilized to rank the indicators from highly important (rank 1) to the least important (e.g., rank 16). After indicator ranking, the weights were assigned randomly by sampling from a uniform distribution such that the sum of the sampled weights is equal to 1 (see e.g., Butler et al., 1997; Hodgett and Siraj, 2019). This is to eliminate the bias in assigning a numerical value of the weight of each indicator. The indicator ranked as no. 1 is assigned with a weight correspondent to the highest value obtained from random sampling, and the other indicator's weight were assigned in the same way following the rank order. This type of weight assignment was repeated for 1000 times to remove the dependency of the weight to a single sampling set. The final indicator weight is equal to the normalized arithmetic average of the 1000 re-samplings such that the sum of all indicator weights is again equal to 1.

For the aggregation methods, LN and GM were considered because of their simplicity and applicability for the analysis; however, both methods also represent divergent situations. Between the two methods, LN is the commonly used aggregation (see e.g., Gan et al., 2017). LN could be used in situations where compensability is permitted, meaning the deficit of one indicator could be offset by the surplus in another (OECD, 2008). In contrast, GM represents a situation where reduced compensability is desired; GM, however, is not fully non-compensatory (OECD, 2008; Gan et al., 2017).

The selected analytical methods for the succeeding analysis for normalization (R and S), weighting (for EW and PCA) and aggregation (LN and GM) already have established mathematical foundations. The inconsistency of the indicator set, and the different situations considered in the choice of analytical methods lead to multiple methodological combinations as the inclusion or exclusion of one method over another infuse some subjectivity on the part of the analyst. This is the situation that the MA under methodological uncertainties is trying to replicate in this demonstration work.

6.2.4 SCMIs and their values

The SCMIs used to define the relative sustainability performance of the mixes in the set $\boldsymbol{x}$ were pre-selected from the causal network introduced in Chapter 3. A total of 16 indicators previously used in the demonstration in Chapter 4, Section 4.5.1, Table 4.3 were also used in the following analysis based on the completeness and availability of their data, and their appropriateness to comprehensively define the sustainability performance of the mixes. The 16 SCMIs in Table 4.3 comprised the full set that was used for evaluation scenarios CL and CB. The indicators utilized for CL*, on the other hand, are marked with "*" in the same table. CL* indicator set are those indicators that require no inventory data for the calculation of their values. The calculation the indicators value followed the same procedure as discussed in Chapter 3 and in Chapter 4 Section 4.5.1.

Table 6.2 summarizes the raw indicators value and Table 6.3 shows the normalized scores for distance-to-a-reference and standardization contained in parentheses. OPC50 was taken as the reference mix for normalization using R, while the designed service life remained t = 50 years. The values of SCMI 20 in Table 6.2 is for the durability performance based on chloride penetration only as initial calculation using carbonation resulted into lifetimes beyond twice the designed value for all the mixes. Therefore, for carbonation the durability performance for all mixes are equivalent. As such the durability performance (SCMI 20) of the mixes was excluded in the indicator set for CB scenario.

Table 6.2 The raw SCMI values for CL, CB and CL* scenarios

Mix	SCMI raw value															
	1	2*	3*	4*	5	6	7	8	9	20*	28	29	30.02	31.01	34	40*
OPC50	1.22	2237	157	125	258	0.053	0.517	0.015	0.022	0.46	261	0.017	0.415	0.067	0.626	13300
BB50	0.86	2057	156	216	151	0.040	0.314	0.010	0.014	1.00	153	0.011	0.260	0.041	0.381	13500
FA50	1.04	2217	149	124	209	0.046	0.415	0.013	0.018	0.05	212	0.014	0.336	0.054	0.503	13300
OPC40	1.50	2249	162	157	321	0.063	0.646	0.018	0.028	0.99	325	0.021	0.515	0.084	0.781	14750
BB40	1.06	2027	161	273	189	0.046	0.393	0.012	0.018	1.00	192	0.013	0.322	0.051	0.477	15150
FA40	1.32	2223	155	162	271	0.055	0.539	0.015	0.023	0.97	274	0.018	0.432	0.070	0.653	14750

Table 6.3 The normalized values of the SCMI using method R and S for CL, CB and CL*

Mix	Normalized SCMI value using R and S (in parenthesis)															
	1	2*	3*	4*	5	6	7	8	9	20*	28	29	30.02	31.01	34	40*
OPC50	1.00 (0.47)	1.00 (0.42)	1.00 (0.49)	1.00 (0.40)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.46 (0.42)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.00 (0.46)	1.00 (0.61)
BB50	1.29 (0.65)	1.08 (0.62)	1.01 (0.52)	1.73 (0.58)	1.41 (0.65)	1.25 (0.64)	1.39 (0.64)	1.31 (0.64)	1.36 (0.64)	2.00 (0.57)	1.41 (0.65)	1.37 (0.64)	1.37 (0.64)	1.39 (0.64)	1.39 (0.64)	0.98 (0.58)
FA50	1.15 (0.56)	1.01 (0.45)	1.05 (0.68)	0.99 (0.40)	1.19 (0.54)	1.14 (0.56)	1.20 (0.55)	1.15 (0.55)	1.20 (0.56)	1.05 (0.31)	1.19 (0.54)	1.19 (0.55)	1.19 (0.55)	1.20 (0.55)	1.20 (0.55)	1.00 (0.61)
OPC40	0.77 (0.34)	0.99 (0.41)	0.97 (0.38)	1.25 (0.46)	0.75 (0.34)	0.82 (0.33)	0.75 (0.34)	0.81 (0.34)	0.75 (0.34)	1.99 (0.57)	0.75 (0.34)	0.76 (0.34)	0.76 (0.34)	0.75 (0.34)	0.75 (0.34)	0.89 (0.42)
BB40	1.14 (0.55)	1.01 (0.66)	0.97 (0.40)	2.19 (0.68)	1.27 (0.58)	1.13 (0.56)	1.24 (0.57)	1.19 (0.57)	1.19 (0.55)	2.00 (0.57)	1.27 (0.58)	1.22 (0.57)	1.23 (0.57)	1.24 (0.57)	1.24 (0.57)	0.86 (0.37)
FA40	0.92 (0.43)	1.01 (0.44)	1.01 (0.54)	1.30 (0.47)	0.95 (0.43)	0.97 (0.44)	0.96 (0.44)	0.97 (0.44)	0.96 (0.44)	1.97 (0.56)	0.95 (0.43)	0.96 (0.44)	0.96 (0.44)	0.96 (0.44)	0.96 (0.44)	0.89 (0.42)

Figure 6.2 shows the Pearson's correlation matrix of the normalized values of the indicators for both R and S method. Interestingly, both R and S produced the same correlation matrix which is also equivalent in magnitudes when the raw indicator values are used in the computation of these correlations. It is apparent the most indicators are highly correlated with each other, particularly the environmental state and impact indicators. This would mean that there is some data overlap due to the high correlation, which is why PCA is included as part of the weighting methods.

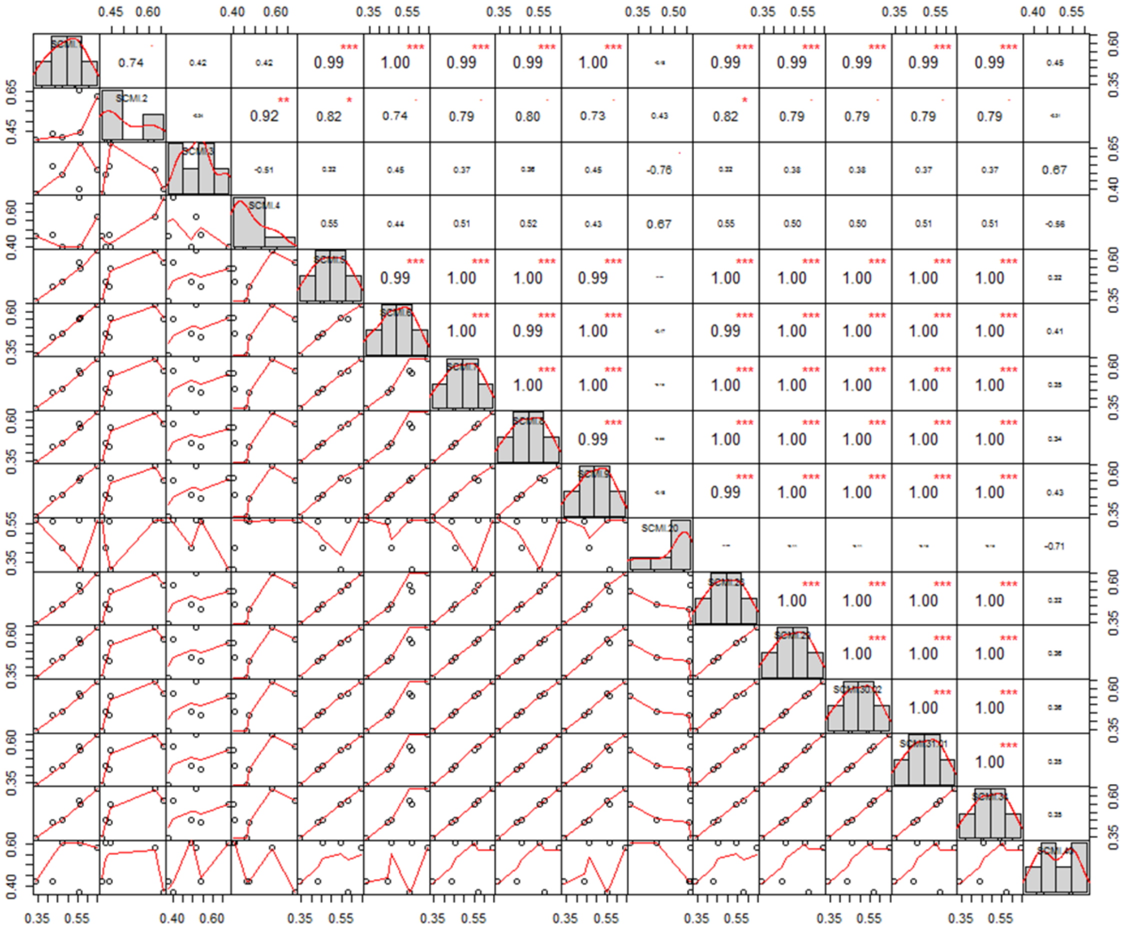


Figure 6.2 The Pearson's correlation matrix of the SCMIs used in the demonstration

6.2.5 The indicator weights

Dropping one indicator at a time also affects indicator weighting using EW, PCA and ST. As a result, an indicator can be assigned with *e* number of weights for each weighting method. Figure 6.3 summarizes the average weight assigned to the indicators for the CL scenario. The numerical values of the weights for each weighting method can be found in Appendix C. For EW and PCA methods, the weights shown in Figure 6.3 are fairly similar. Between PCA weights, the SCMIs are given relatively similar weights due to the high correlation between indicators as a natural consequence of the interrelationship that exists between them as described in Chapter 3.

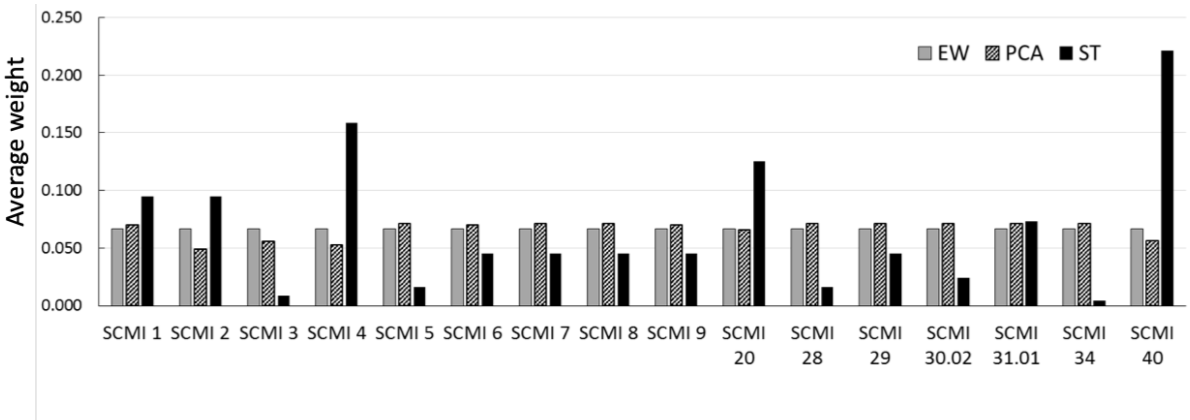


Figure 6.3 Average weight assigned to each indicator by EW, PCA and ST approach for the CL scenario

The driving force indicators SCMIs 2, 3 and 4 and the impact indicator SCMI 40 on average are awarded with lower weights by PCA. The weights from ST, on the other hand, vary across the indicators. Notably the production cost (SCMI 40) receives the highest weight. SCMI 4 and SCMI 20 are also weighted highly. The highly weighted indicators are also the ones rated by stakeholders as the most important indicators for sustainable concrete. The indicators SCMI 3, 5, 28 and 34 are on average among the least important according to stakeholder ratings.

In the case of scenario CB, the indicator weights are shown in Figure 6.4, reflecting similar behavior with the weights in Figure 6.3 as the input data are the same except for the exclusion of SCMI 20. For CL*, the weights are shown in Figure 6.5 where EW and PCA weights are also similar. PCA, however, awarded SCMI 20 with the lowest weight equal to 0.155 on average (see Figure 6.5). For ST, SCMI 40 is still rated as the most important with average weight equal to 0.510. It can be said that the weights extracted by ST are just reflective of the importance assigned by stakeholders. The numerical values of the weights for CB and CL can also be found in Appendix C.

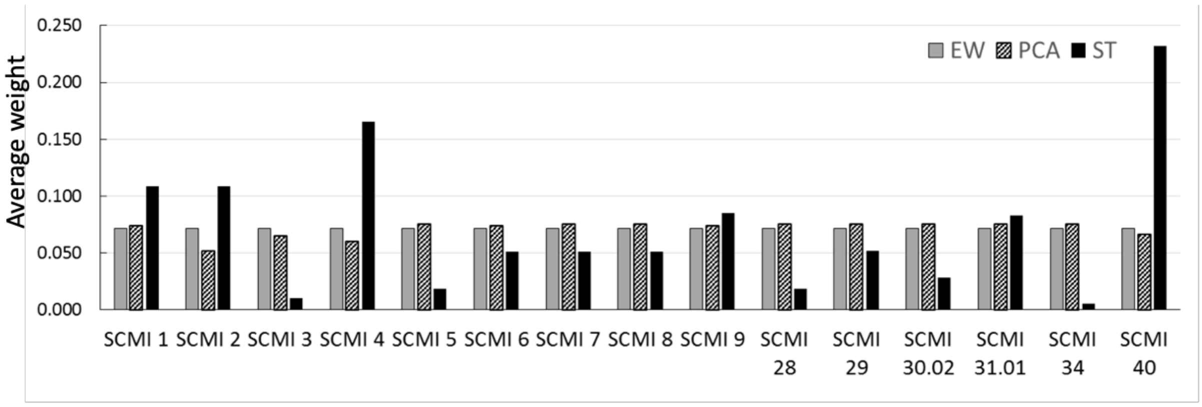


Figure 6.4 Average weight assigned to each indicator by EW, PCA and ST approach for the CB scenario

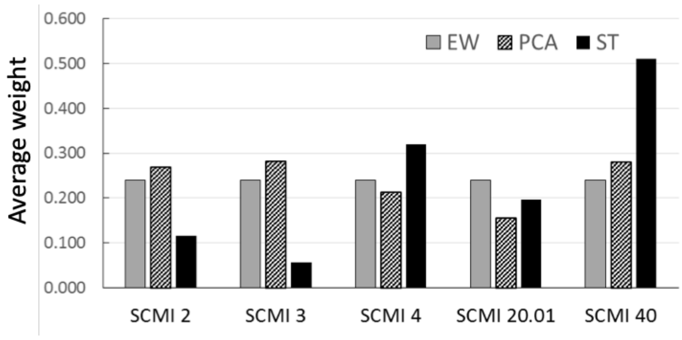


Figure 6.5 Average weight assigned to each indicator by EW, PCA and ST approach for the CL* scenario

6.3 Result of analytical scenario 1: CL

6.3.1 Multicriteria analysis and uncertainty analysis

The MA and UA result for CL is illustrated as PDFs of J in Figure 6.6 for each mix in $\boldsymbol{x}$. Table 6.4 supplements Figure 6.6 by showing the primary statistics, i.e., the minimum, mean and maximum J and the variance calculated from the PDFs. Figure 6.6 confirms that J behaves stochastically given the presence of methodological uncertainties. The J of OPC50, for example, ranges from a minimum score of 40.57 to a maximum of 47.95 (see also Table 6.4). This means that any single methodological combination in the sustainability evaluation part of Figure 6.1 would just be a single value within this range for OPC 50. The same is true for other mixes in the set.

The range of J per concrete mix vary largely from each other, which is characterized by the differences in the spread and height of the PDFs in Figure 6.6. These differences are captured quantitatively by the variance estimates in Table 6.4, measuring the spread of J from the mean of the distribution. Between the 6 mixes, FA50 has the highest variance equal to 13.27 and correspondingly has the widest PDF with J ranging from 41.08 to 55.66. In contrast, BB50 mix has the lowest variance (0.98) and with the narrowest PDF (see Figure 6.6). The differences in the spread and height of the PDFs implies that methodological uncertainties affect each mix differently, which correlates to the magnitude of the uncertainty (Davidson-Pilon, 2016; Hodgett and Siraj, 2019) expressed by the variance.

Based on variance, the mixes with relatively the lowest uncertainties in their J are BB50 and FA40 with variances equal to 0.98 and 1.09, respectively. Their relative low variance means that their J is not largely affected by the changes in methodological combinations used in the analytical structure in Figure 6.1. On the other hand, the concrete mixes with relatively higher uncertainties in their J are FA50 and BB40 with variances equal to 13.27 and 5.38 (see Table 6.4), respectively. For these mixes, any minor change in methodological combination in Figure 6.1 could just easily alter the value of their sustainability score. Therefore, the higher the variance, the more susceptible and uncertain the sustainability score becomes.

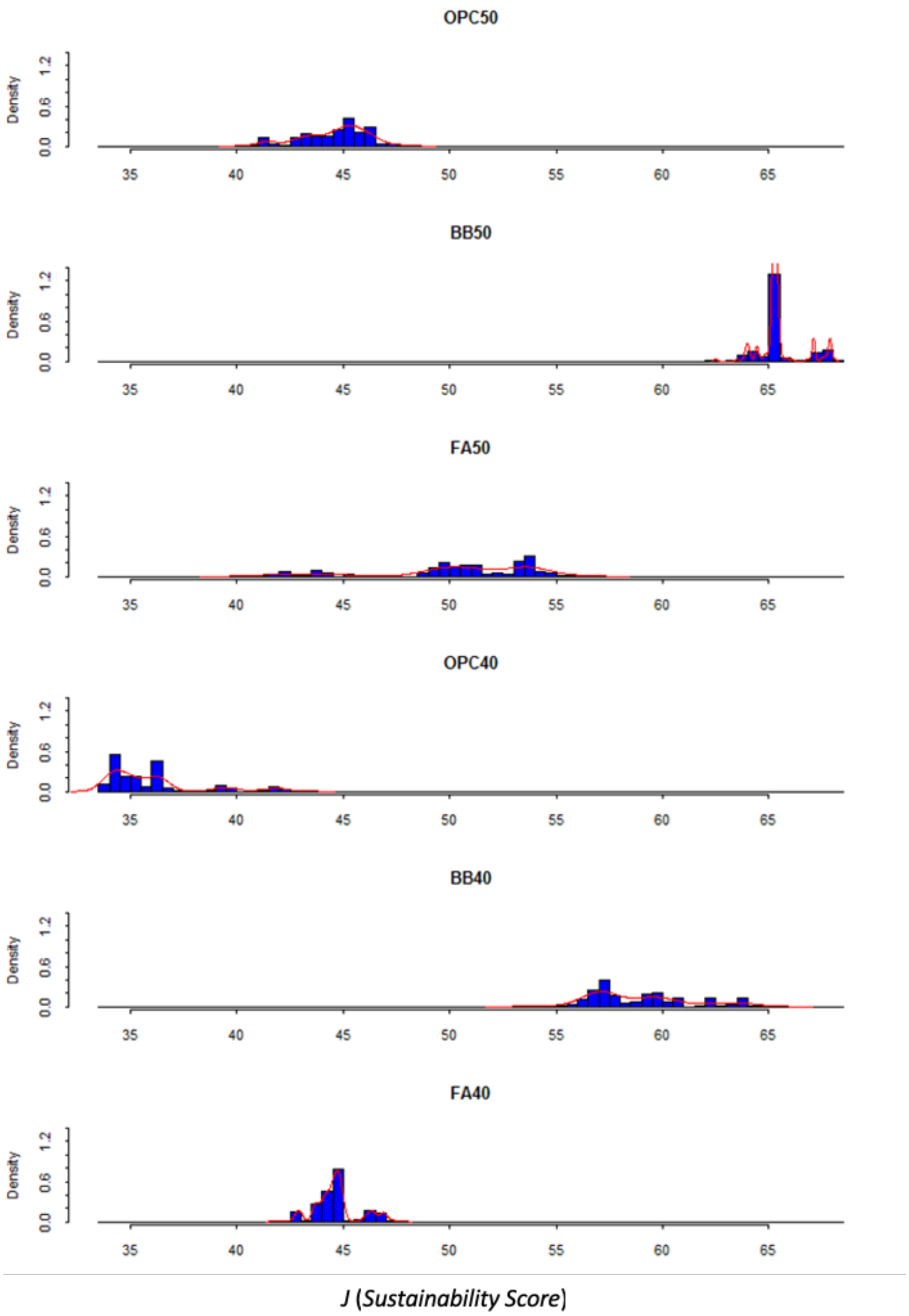


Figure 6.6 PDFs of the sustainability scores of the mixes in *x* for CL scenario

Table 6.4 Summary statistics of the PDFs for the CL scenario

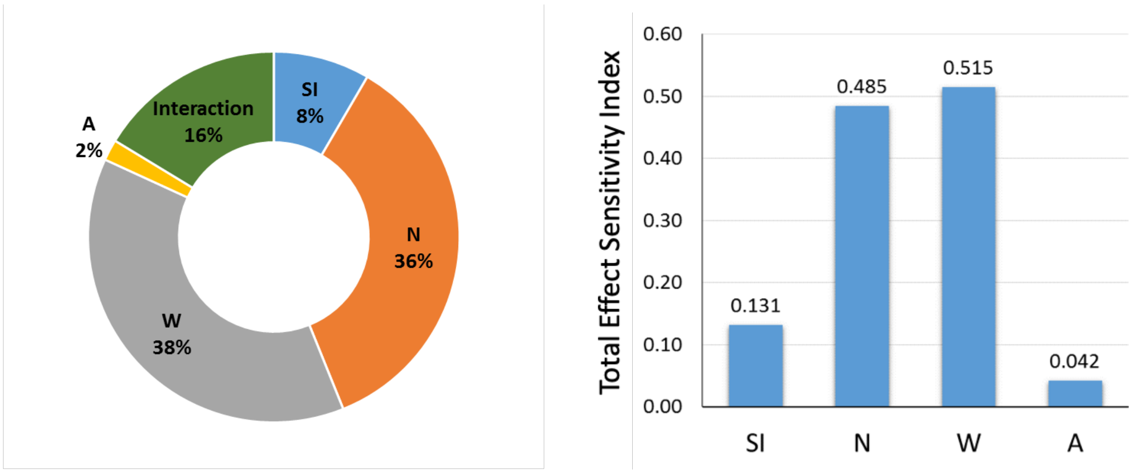
Mix	Summary statistics of the PDF of J (%)			
	Min	Mean	Max	Variance
OPC50	40.57	44.60	47.95	2.23
BB50	62.49	65.47	68.08	0.98
FA50	41.08	50.42	55.66	13.27
OPC40	33.68	35.99	43.16	4.95
BB40	53.78	58.87	64.95	5.38
FA40	41.84	44.65	47.75	1.09

Figure 6.6 and Table 6.4 also illustrate that the PDFs of some of the mixes overlap. In the case of BB50 and BB40, for example, their PDFs overlap in the range of 62.49 to 64.95. The overlapping distributions would make it difficult to make outright comparisons between the sustainability performance of the mixes. Further, using the mean of the PDFs in Table 6.4 to contrast sustainability performance of the concrete mixes may also undermine the uncertainty of the output. Another way to compare the relative sustainability performance of the alternatives from the result of UA is by graphical inspection of the PDFs. In Figure 6.6, for example, mixes with PDFs located to the right side, i.e., BB50 and BB40, can be regarded as mixes with the "best" sustainability performance. While those distributions that tend to the left side in Figure 6.6, i.e., OPC40 could be regarded as the "least" sustainable alternative. However, for completely overlapping distribution such as OPC50 and FA40, contrasting their sustainability performance based on J distribution could prove counterproductive and may promote subjective judgment on the part of the analyst.

If distinct ranking is instead assigned to the mix alternatives based on the J value, a rank reversal could occur due to the overlap of the PDFs. For example, BB50 and BB40's rank could interchange within the 62.49 to 64.95 range (see Table 6.4). It follows, therefore, that ranking is also not distinct from the point of view of methodological uncertainties. For any two distribution that does not overlap, however, as in the case of OPC50 and BB50 (see Figure 6.1), the possibility of rank interchange is zero. Rank reversal phenomenon due to methodological choices in sustainability evaluation can be exploited to bias the conclusion. UA, therefore, illuminates such vulnerabilities due to methodological uncertainties, making sustainability evaluation robust and defensible to scientific inquiry (Ciuffo, et al., 2012; Saltelli et al., 2004).

6.3.2 Sensitivity analysis and decomposition

The uncertainty of J can be examined in detail using the result of the sensitivity analysis (SA) as summarized in Figure 6.7. In Figure 6.7.a, the first-order effect, S_i, of the individual source of uncertainty is shown, while Figure 6.7.b reflects their total effect sensitivity index (S_{Ti}). Figure 6.7.a suggests that on average, 84% ($\sum S_i$) of the total variance can be explained by the first-order effects, while 16% is due to the interaction of the sources of uncertainties.



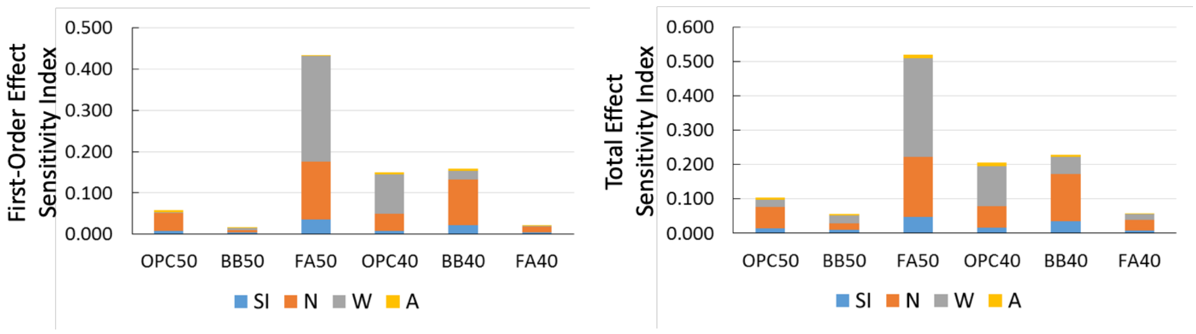
(a) S_i (b) S_{Ti}

Figure 6.7 Result of the sensitivity analysis for the CL scenario

Figure 6.7.a establishes that bulk of the variability of J, around 38% and 36 % is due to the isolated effect of the choice of weighting (W) and normalization methods (N). On the other hand, only about 2% of the variability is caused by the isolated effect of the choice of aggregation method (A). The degree of influence of the sources of uncertainty could also be interpreted as the average reduction in the variance if the source of uncertainty can be set to its true value as describe in Chapter 5. For example, setting the aggregation method to LN will increase the variance by 18% while setting it to GM will reduce the total variance by 22%. On average, the reduction in the variance of SS is 2%, which is equivalent to the S_i of A.

Figure 6.7.b, on the other hand, also reflect a similar extent of influence by each source of uncertainty to the total output variance when accounting for their interactions. The total effect still identifies, on average, W and N as the highly influential factors. Significant increases in influence due to interactions can be observed in W and N at the order of 18% and 16%, respectively. For SI and A, on the other hand, the increase in the influence is just about in the order of 5% and 2%, respectively. This implies that SI and A interact less with other sources of uncertainties.

S_i and S_{Ti} can also be decomposed to the alternative level to explain what input factors are affecting the J distribution of the alternatives in Figure 6.6 the most. Figure 6.8 shows the decomposed S_i and S_{Ti} per mix. Both figures corroborate Figure 6.6 and the computed variances in Table 6.4 regarding the extent of uncertainty of the sustainability scores of each mix. In Figure 6.8, the most affected by *methodological uncertainty* is FA50, and in contrast the least affected is BB50. In Figure 6.8, FA50 remains the most affected by *methodological uncertainties*, while BB50 and FA40 are nearly equally the least affected by the methodological uncertainties.



(a) S_i (b) S_{Ti}

Figure 6.8 Decomposed sensitivity indices for CL scenario

The decomposed sensitivity indices simply explain which source of uncertainty are causing the spread of the distribution of J for each mix in Figure 6.6. The decomposition further prove that each methodological uncertainty affects the sustainability score of each mix differently. Focusing on FA50 in Figure 6.8a, as an example, the PDF of the sustainability score (see Figure 6.6) is most influenced by the choice of weighting method, while this is not the case of BB40 in which the PDF of *SS* (see Figure 6.6) is most influenced by the choice of normalization method according to Figure 6.8a.

The total effects decomposition in Figure 6.8b, reveals similar variation in the degree of influence with the first-order effects. The decomposition of both sensitivity indices has a relative impact on factor prioritization and factor fixing as the level of influence of the sources of uncertainties to the PDFs of the mixes vary widely. However, since any changes in the analytical process based on the value of S_i and S_{Ti} – such as factor fixing – should be carried out across all mixes in the set. The values of S_i and S_{Ti} in Figure 6.7, therefore, must be used for factor prioritization and fixing.

6.3.3 Factor prioritization and fixing

By factor prioritization, the influential and non-influential sources of uncertainties can be determined. For this analysis, as a demonstration, a source of uncertainty is considered influential if on average its S_i (or S_{Ti}) is greater than or equal to 10%. Based on this setting, for the first-order effect (Figure 6.7a), the choice of weighting method (W) and normalization (N) are the influential factors affecting the randomness of *J*. This means that changing the N, for example, to either R or S (see Figure 6.1) has a big impact on the evaluation. Whereas, the selection of indicators (SI) and the aggregation (A) method are non-influential. This implies that changing A to either LN or GM may have less impact on the sustainability evaluation result.

For the total effect (Figure 6.7b) using the same setting, SI can now be considered as influential. This is an evidence that the interaction of a factor with other sources of uncertainty has significant contribution to its influence on the resulting sustainability score. The choice of aggregation method, however, is still be regarded as non-influential based on the same setting. From this classification, it is easily identifiable which source of uncertainty is ideal for factor fixing (those classified as non-influential) and which ones should be the focus of methodological deliberation (the influential sources of *methodological uncertainties*).

The values of S_i and S_{Ti} in Figure 6.7 for aggregation imply that it could be fixed to either LN or GM. As an illustration of fixing A, Figure 6.9 shows the original PDF and the modified PDFs including the ECDFs after fixing the aggregation to either LN or GM for mix BB50. In Figure 6.9, the modified PDFs are very similar to the original distribution, which supports that the choice of aggregation method is indeed not influential to the sustainability evaluation. Since the total effect, S_{Ti}, of A is just 4.23% (Figure 6.7b) of the total variance, the ECDF of J for BB50 after factor fixing also did not change substantially from the original ECDF. This is an additional evidence that the aggregation method can be fixed to either LN or GM. This is not only true for BB50, but might be true to all alternatives, as the decomposition of sustainability indices (Figure 6.8) in the previous section have shown that the effect of aggregation across all mixes is generally very small.

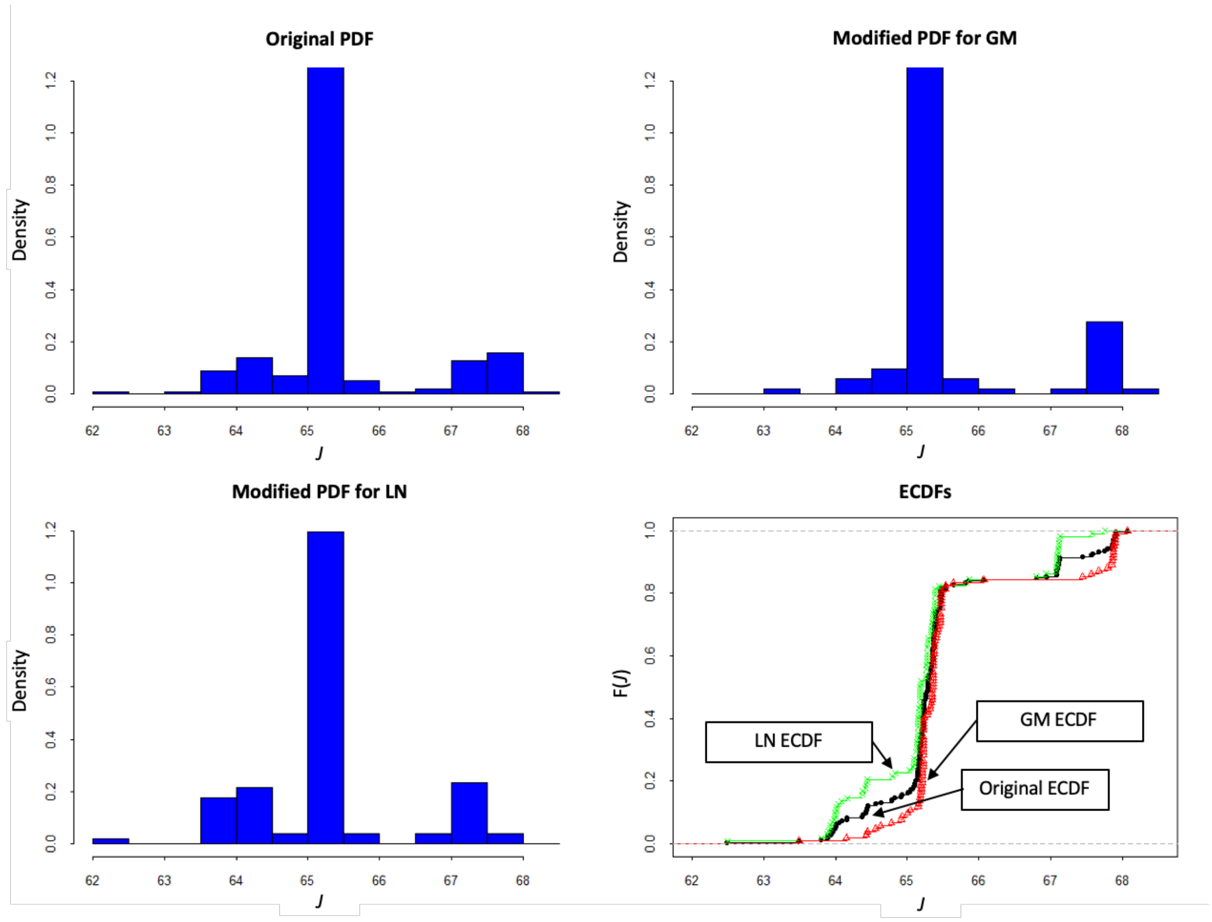


Figure 6.9 Effect of fixing aggregation method to either LN or GM for BB50 for CL scenario

To test quantitatively the effect of fixing A, the similarity between the original ECDF and the ECDF for LN and between the original ECDF and the ECDF for GM for BB50 was measured using KS D-statistic. For both LN and GM, the $D = 0.176$, which is less than the critical value, $D_{crit} = 0.184$ for the significance level of $\alpha = 0.01$. This implies that the original ECDF and the modified ECDFs by fixing A to either LN or GM are similar and could have been drawn from the same distribution (see Chapter 5, Section 5.2.5). Additionally, majority of the parts of the ECDFs of LN and GM falls within the 99% confidence interval (see Figure 6.10) of the original ECDF from DKW inequality bound (see Chapter 5, Section 5.2.5), which corroborates the finding of the KS test. This means that the modified ECDF of LN and GM – with points resampled from the original ECDF – are close to the original ECDF.

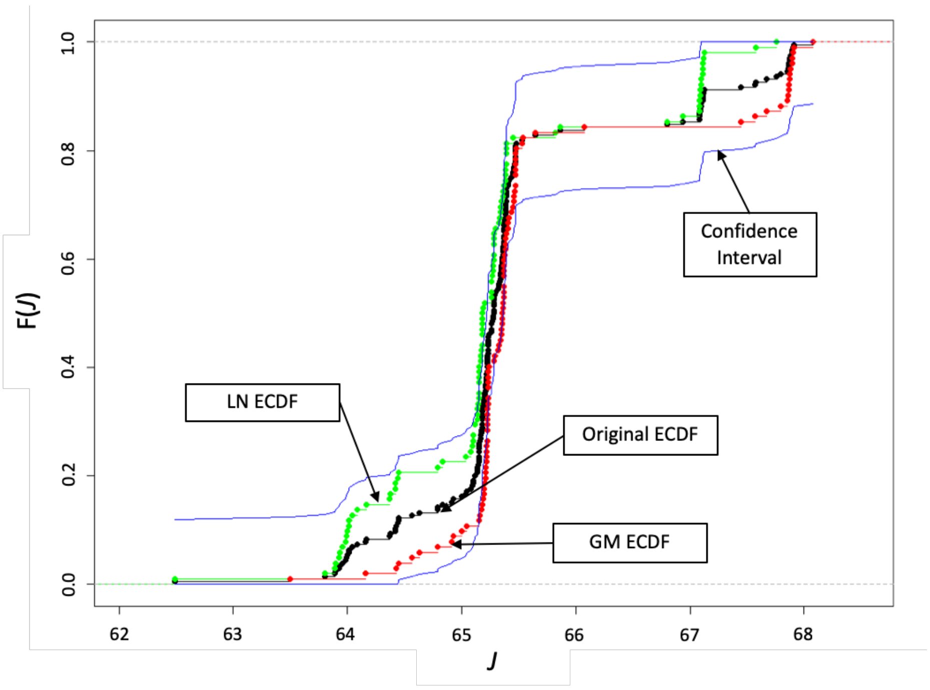


Figure 6.10 The original and the modified ECDFs of *J* for BB50 after fixing A to either LN or GM for CL scenario

The result of fixing A for BB50, however, might not be similar to other mixes in the set as the level of influence of sources of uncertainty to the PDFs vary per alternative as has been previously shown by the variance decomposition. This is one of the reasons why, fixing a factor must follow a very stringent requirement ($S_{Ti} = 0$), so that the effect on the resulting sustainability score across all mixes will be insignificant. Nevertheless, KS and DKW statistics help substantiate that for CL scenario a single aggregation method could be used in the analysis without significantly affecting the sustainability evaluation result. This result would help systematically eliminate one source of uncertainty in the sustainability evaluation, thereby increasing the robustness of the analysis. It is important to note, however, that it is still difficult to underpin using KS and DKW statistics which of the two aggregation methods is the correct methodological approach. Nevertheless, the choice between LN or GM is immaterial in this case, as the aggregation method has less influence on the result.

6.3.4 Probabilistic interpretation

HEPM was used to compare probabilistically the sustainability performance of the mixes in *x*. For the CL scenario, Table 6.5 summarizes the hierarchical exceedance probabilities of the mixes in *x* including the lower bounds of the mean of the PDFs at which these probabilities were based. Figure 6.11 shows an example of how some of the exceedance probability values of BB50 and BB40 are obtained. The mean and the 95% confidence interval of the mean of the PDF of both mixes are shown in Figure 6.11, which were used for the calculation of probability of exceedance. Taking the lower bound of the confidence interval of the mean for BB40 in Figure 6.11 (see also Table 6.5) as the threshold, it is evident that the PDF of BB50 is always above this value; therefore, the probability that the of the *J* of BB50 is above the BB40 threshold is 1.00 (see Table 6.5). For BB40, on the other hand, using the same threshold, Figure 6.11 shows that 48% of *J* of BB40 can be located above this threshold, which is equates to its probability of exceedance (see Table 6.5).

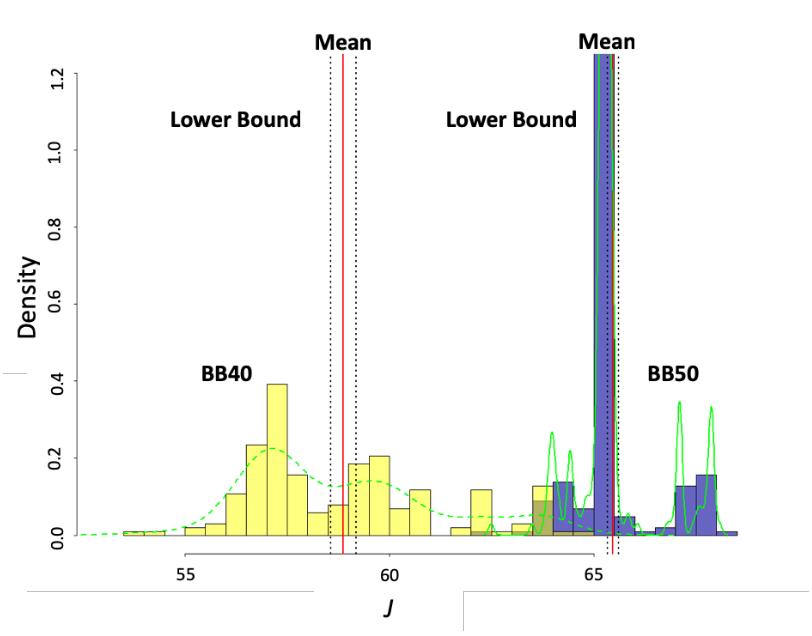


Figure 6.11 Sample set-up for probability computation for BB50 and BB40 for CL scenario

The exceedance probabilities of the other mixes are calculated similar to BB40 and BB50 example. In Table 6.5, if the lower bound of OPC40 equal to 35.68 is used as the threshold for the probability of exceedance, *P*, the probability that all the other alternatives' *J* is above this value is 1.00. This suggests that the other alternatives have superior sustainability performance than OPC40, subsequently placing OPC40 at the bottom of the hierarchy. For the CL scenario, BB50's *P* is consistently 1.00 with respect to the other alternatives (see Table 6.5). This means that the PDF of

BB50 is constantly above the lower bound of the confidence interval of the mean of *J* of the other alternatives, placing BB50 on the top of the hierarchy.

Table 6.5 Hierarchical exceedance probabilities of mixes for CL scenario

Mix	Lower Bound of the 95% confidence interval of the mean of *J*	Exceedance Probability (*P*) based on the lower bound of the mean of *J* of:					
		OPC40	FA40	OPC50	FA50	BB40	BB50
BB50	65.34	1.00	1.00	1.00	1.00	1.00	0.44
BB40	58.56	1.00	1.00	1.00	1.00	0.48	0.00
FA50	49.89	1.00	0.85	0.86	0.67	0.00	0.00
OPC50	44.40	1.00	0.60	0.65	0.00	0.00	0.00
FA40	44.52	1.00	0.55	0.62	0.00	0.00	0.00
OPC40	35.68	0.45	0.00	0.00	0.00	0.00	0.00

The other mix alternatives were ordered based on the magnitude of *P* especially those with overlapping PDFs. Taking OPC50 and FA40 as an example, due to the complete overlap of their PDFs (see Figure 6.6) the magnitude of their *P* is very close. This could mean that both mixes have equivalent sustainability performance. For both mixes, however, the *SS* of OPC50 is 5% more likely to be above the lower bound of FA40. Further, when the threshold is set at the lower bound of OPC50, the *P* of OPC50 is also slightly higher than FA40 (see Table 6.5). Based on the magnitude of *P* alone, OPC50 is placed higher in the hierarchy than FA40.

The placement of the mixes in a hierarchical order based on HEPM is beneficial for decision-makers in the selection of the "best" sustainable option. For the CL scenario, Table 6.5 points out that BB50 is the "best" sustainable alternative. However, it is still difficult to single out which indicator or group of indicators is causing this result as the uncertainties of the individual indicator's value were not part of the analysis. Much of the behavior of *J* is due to the *methodological uncertainties* in the analytical structure; nonetheless, the value of the indicators cannot be simply discounted.

A quick inspection of Table 6.3 may help illuminate why mixes using blast furnace slag cement are on the top of the hierarchy. For BB50, as an example, its normalized indicator values are consistently above the reference except for SCMI 40. BB50's score for durability is the highest among the mixes with a normalized value equal to 2.00, and it also scores highly on SCMI 4, 5 and 28. The relatively good performance of BB50's indicators can be attributed to the high cement replacement by blast furnace slag, which consequentially reduces the environmental load of the concrete mix. This high replacement translates to lower CO_2 emissions and GWP, and reduced values of SCMI 29, 30.02, 31.01 and 34, which are beneficial to sustainability (see e.g., Opon and Henry 2019a). Similar behavior could also explain why based on *P*, BB40 places second to BB50 in the hierarchy, implying that the use of blast furnace slag is beneficial for concrete material sustainability.

For concrete mixes using OPC and FA, on the other hand, the W/C seems to drive their placement in the hierarchy with mixes having W/C = 0.50 at the higher-order than those with W/C = 0.40. A concrete mix having higher W/C will naturally require a lesser amount of cement, which translates to lower environmental loading and lower unit production cost. However, having a higher W/C could also mean a reduction in durability performance; for example, OPC50 and FA50 have lower durability performance compared to OPC40 and FA40 (see Table 6.3), respectively. Nevertheless, this lower durability did not have a profound effect on the hierarchy because durability is only captured by a single indicator (SCMI 20).

6.4 Result of analytical scenario 2: CB

6.4.1 Multicriteria analysis and uncertainty analysis

The MA and UA result of scenario CB is illustrated in Figure 6.12 with the primary statistics summarized in Table 6.6. The effect of methodological uncertainty is still prevalent in all mixes, as illustrated by the spread of the distribution of *J* in Figure 6.12. The effect of the methodological uncertainties to *J*, however, is unequal per alternative, which is also captured quantitatively by the variance estimate in Table 6.6. BB40 and FA50, for example, have the most uncertain sustainability scores with values spreading over 52.47 to 64.30 and 47.48 to 57.13, respectively. On the other hand, the mix with least uncertain *J* is BB50, which varies between 62.81 to 66.21. The variance in Table 6.6 is also indicative of the spread of *J* values of each alternative; mixes with higher variance have wider spread of sustainability scores, thus have higher output uncertainty. This suggests that mixes with higher (or lower) variance is more (or less) susceptible to methodological changes.

It also evident from Figure 6.12 and Table 6.6 that the distributions of *J* overlap. For example, the distributions for BB50 and BB40 slightly overlap over the range of 62.81 to 64.30. On the other hand, distributions for OPC50 and FA40 completely overlap within the *J* range 41.65 to 45.01. For slightly overlapping *J* distributions, distinguishing which one outperforms another could be easily determined. However, those that are completely overlapping it is not easily discernable which one is better (see e.g., Dorini et al., 2011). Therefore, characterizing the relative performance of the alternatives based on the result of uncertainty analysis may not be a straightforward. However, propagating uncertainty in this way can help increase the effectiveness of the evaluation and lead to a more informed decision (Dorini et al., 2011).

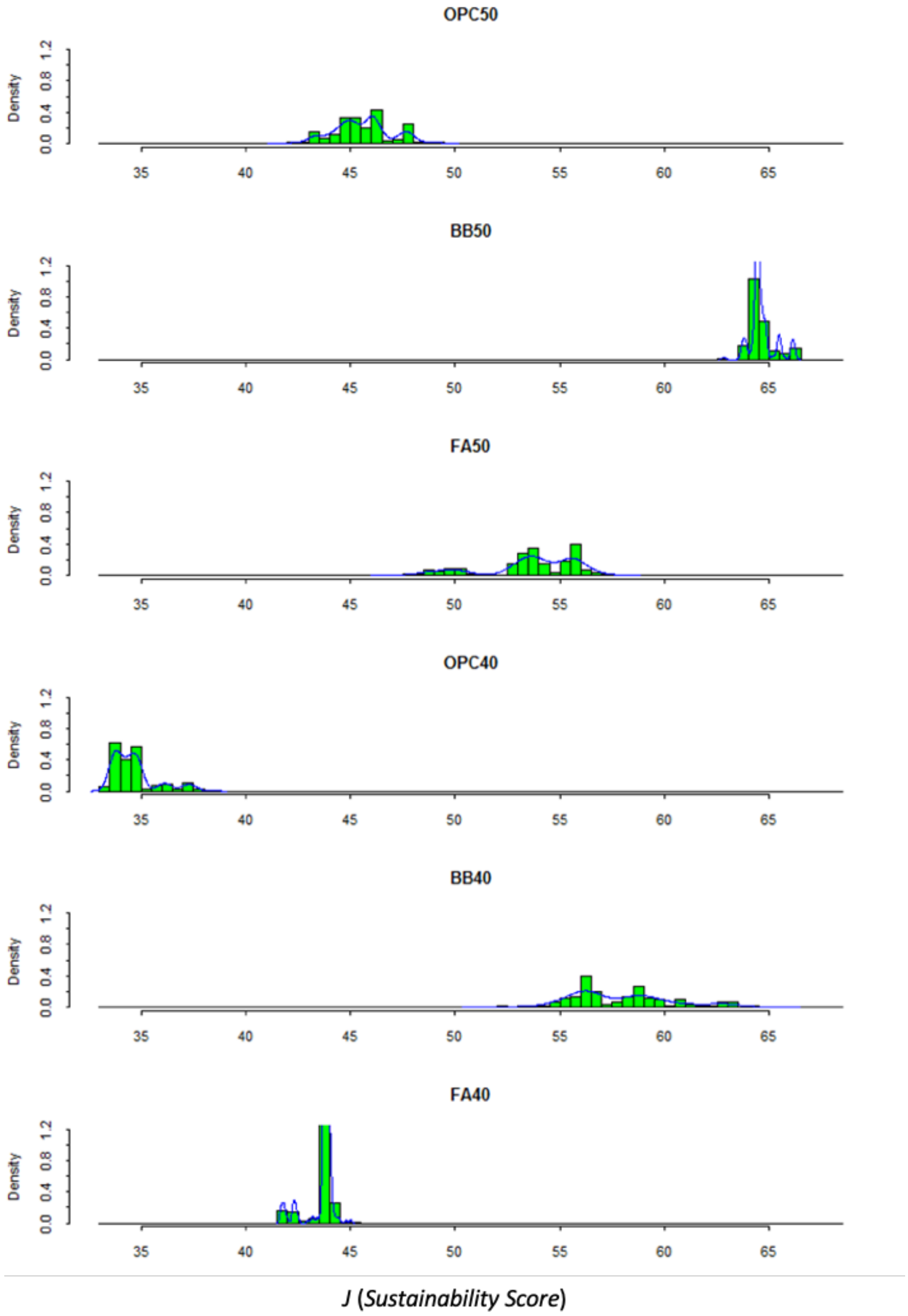


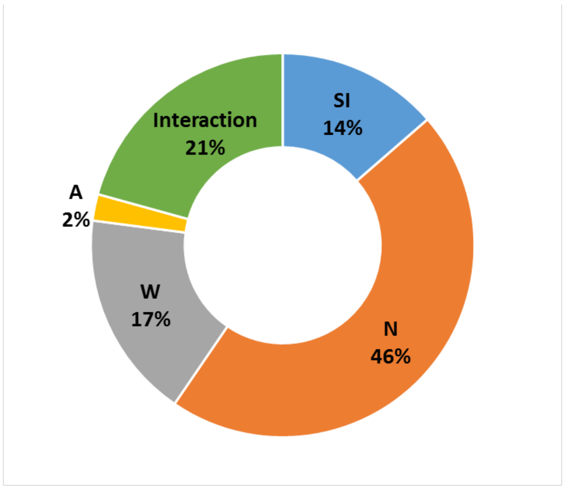
Figure 6.12 PDFs of the sustainability scores of the mixes in *x* for CB scenario

Table 6.6 Summary statistics of the PDFs of the mixes in *x* for CB scenario

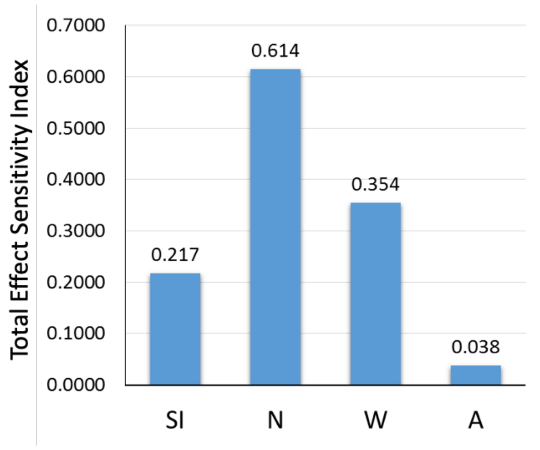
Mix	Summary statistics of the PDF of *J* (%)			
	Min	Mean	Max	Variance
OPC50	42.10	45.57	49.11	1.81
BB50	62.81	64.62	66.21	0.32
FA50	47.68	53.68	57.13	4.60
OPC40	33.35	34.65	38.31	1.12
BB40	52.47	57.91	64.30	5.45
FA40	41.65	43.58	45.01	0.48

6.4.2 Sensitivity indices and decomposition

The result of the sensitivity analysis of CB scenario is summarized in Figure 6.13. The total variance after UA is apportioned in Figure 6.13a, which shows that 79% of the total variance is due to the first-order effects of the sources of uncertainties, while 21% is due to their interactions. From Figure 6.13a, almost half (46%) of the variability of the *J* can be explained by the choice of normalization method. While only 2% can be explained by the choice of aggregation method, which would imply that aggregation might not be influential for this analysis.



(a) S_i

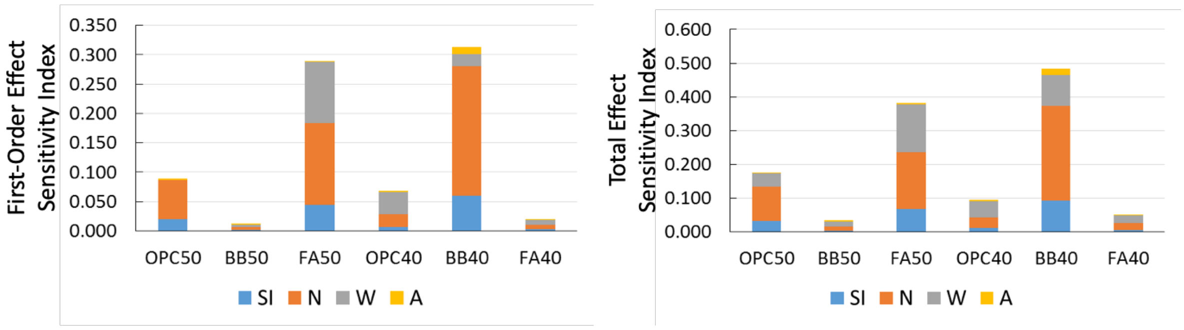


(b) S_{Ti}

Figure 6.13 Result of the sensitivity analysis for the CB scenario

The total effects show similar trend as S_i, whilst considering the interactions of a factor (or a source of *methodological uncertainty*) with others in the analysis. Based on S_{Ti}, normalization remained as the most influential source of uncertainty, explaining about 61% of the total variance as shown in Figure 6.13b – an increase of about the order of 15% from its S_i. The influence of W also increased by the order of 17%, which is almost twice its S_i value, while SI increased by an order of 8%. The aggregation method, however, seemed to have lesser interaction with other factors, with an increase only of about the order of 2%.

Decomposing the sensitivity indices as shown in Figure 6.14 to explain the individual variability of *J* of each mix reveals the same disproportionate influence of the sources of uncertainty found in the CL scenario. The influence of W (see Figure 6.14a), for example, shows has higher influence on FA50 compared to BB40. The same is true for the normalization method for both mixes. The total effects decomposition in Figure 6.14b show similar non-uniform influence of each source of uncertainty to the variability of *J* of each mix. The choice of aggregation, however, seems to have generally less impact on *J* of the mixes based on the decomposition of S_i and S_{Ti}.



(a) S_i (b) S_{Ti}

Figure 6.14 Decomposed sensitivity indices for CB scenario

6.4.3 Factor prioritization and fixing

Using the same setting in CL scenario to classify the sources of *methodological uncertainties* as influential or non-influential; based on S_i values, aggregation is the only non-influential factor. Both the SI and W are almost equally influential with S_i 14% and 17%, respectively, while the choice of normalization method is the most influential factor, explaining almost half of the total variance. The total effects, on the other hand, shows slightly similar trend to S_i with the choice of aggregation method identified as non-influential. However, between SI and W, by including the interactions, W became more influential than SI as opposed to the result of S_i.

The values of S_i and S_{Ti} imply that aggregation is a good candidate for factor fixing as its influence on the total variance is relatively small. As an example of fixing the aggregation method, Figure 6.15 shows the original and modified PDFs as well as the ECDFs of J of BB50 after fixing the aggregation method to either LN or GM. While the influence of the choice of aggregation is small, the modified PDFs, however, show little dissimilarity from the original. Most notably, the PDF of LN and GM are not quite similar in terms of the location of peaks of the distribution. This would indicate that fixing the aggregation might actually have a significant effect in this case. On the other hand, the ECDFs of the modified and original distributions seems to suggest otherwise. The ECDFs are very similar in trend and are close to each other.

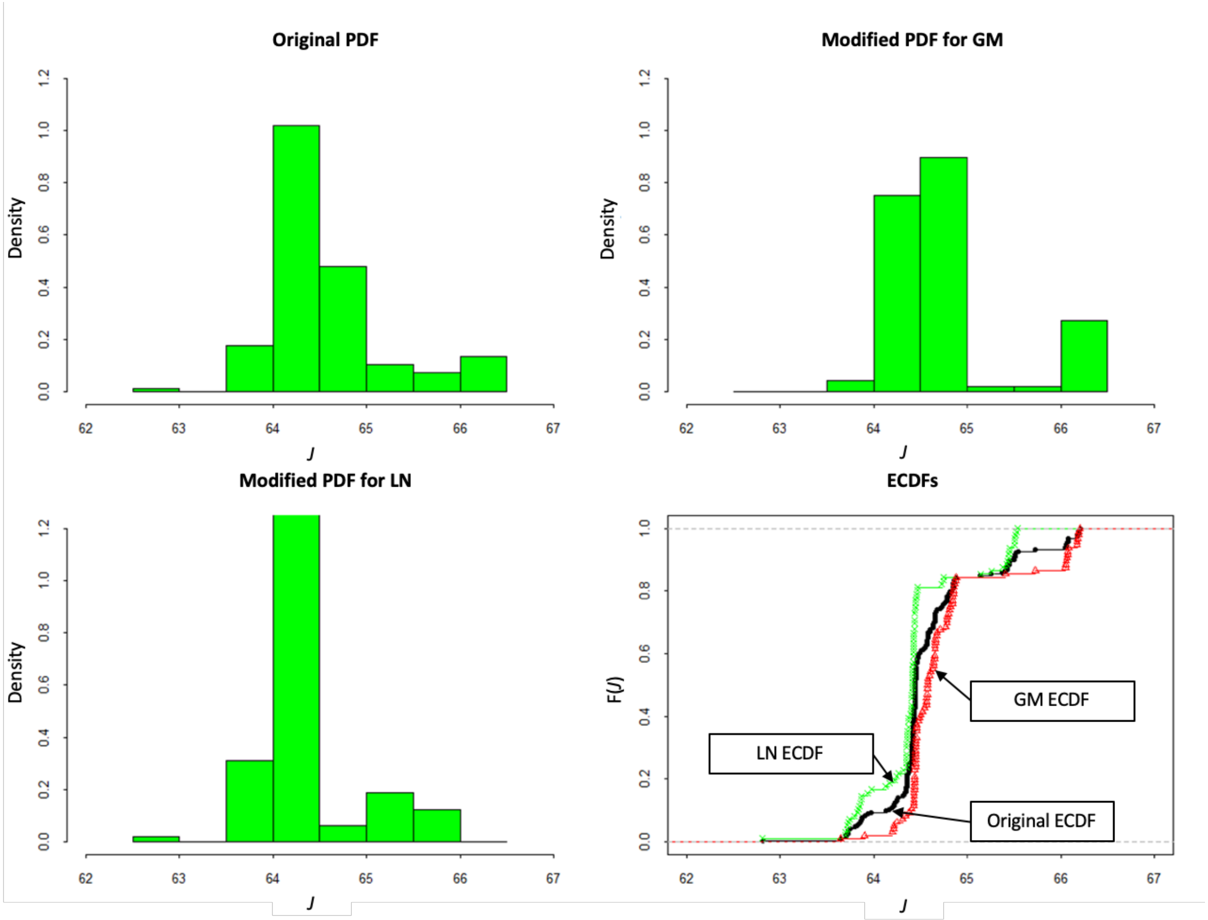


Figure 6.15 Effect of fixing aggregation method to either LN or GM for BB50 for CB scenario

To measure the similarity of the ECDFs quantitatively, a KS test was performed, which produced a D = 0.276 with p-value 0.001162 for both LN and GM. For a confidence level alpha of 0.01, this D is greater than D_{crit} = 0.1897, which means that the original and the ECDFs for LN and the original and the ECDF for GM shows statistical dissimilarity. This was previously observed by the difference in the distributions in Figure 6.15. This dissimilarity can also be graphically observed from the 99% confidence interval of the original distribution created from the DKW inequality bound as in Figure 6.16. In this figure, a good number of re-sampled points fell outside the confidence interval particularly around the steep part of the ECDF, which could be the reason for the dissimilarity between the ECDFs. The result of KS and DKW statistics, therefore, imply that eliminating the uncertainty from aggregation method by fixing it to either LN or GM could have significant effect on the conclusions that maybe drawn from the new J distributions. On the other hand, fixing the other sources of uncertainty is largely not possible for CB scenario as the effect on the total variance of SI, W and N is still substantial. Force-fixing them to eliminate the uncertainties could skew the conclusion depending on which method is chosen.

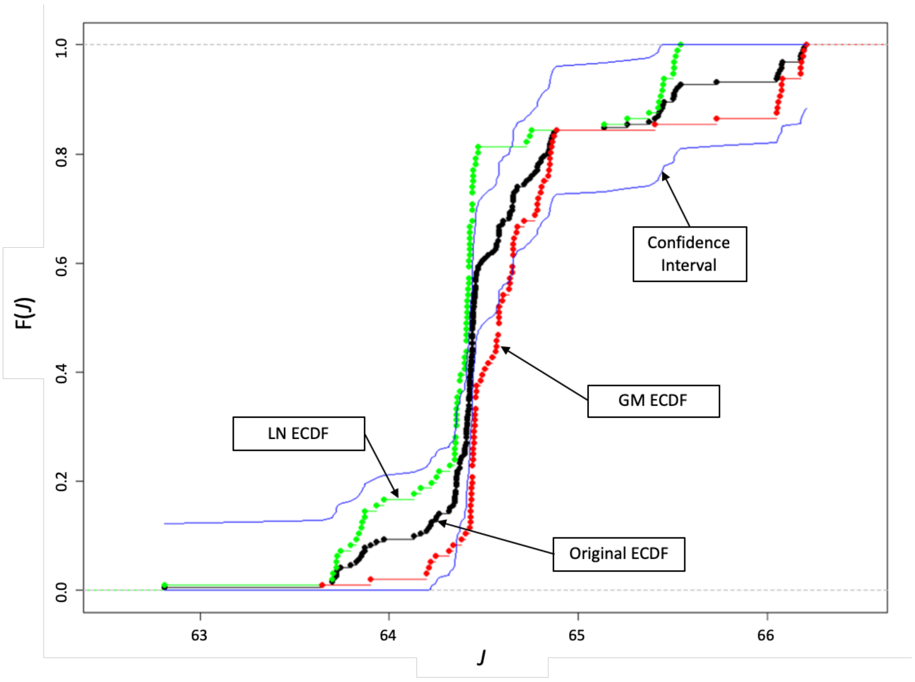


Figure 6.16 The original and the modified ECDFs of *J* for BB50 after fixing A to either LN or GM for CB scenario

6.4.4 Probabilistic interpretation

HEPM was used to compare the sustainability performance of the alternatives in *x* for CB scenario as summarized in Table 6.7. The distribution of BB50 and BB40 are again were used as examples on how some of the exceedance probability values are derived as in Figure 6.17. It is apparent from Figure 6.17 that the distribution of BB50 and BB40 highly overlap, which is challenging for graphical comparison. Using the lower bound of the mean of the PDF of BB40 as the threshold reveals that the distribution of *J* of BB50 is above this value, therefore its P = 1.00. While in the case of BB40, only 52% of its *J* are located above this threshold. Using BB40 bas the basis for comparison results to BB50 as more sustainable than BB40.

Table 6.7Hierarchical exceedance probabilities of the mixes for CB scenario

Mix	Lower Bound of the 95% confidence interval of the mean of *J*	Exceedance Probability (*P*) based on the lower bound of the mean of *J* of:					
		OPC40	FA40	OPC50	FA50	BB40	BB50
BB50	64.49	1.00	1.00	1.00	1.00	1.00	0.40
BB40	57.43	1.00	1.00	1.00	0.99	0.52	0.00
FA50	53.15	1.00	1.00	1.00	0.74	0.00	0.00
OPC50	45.26	1.00	0.92	0.52	0.00	0.00	0.00
FA40	43.41	1.00	0.82	0.00	0.00	0.00	0.00
OPC40	34.41	0.49	0.00	0.00	0.00	0.00	0.00

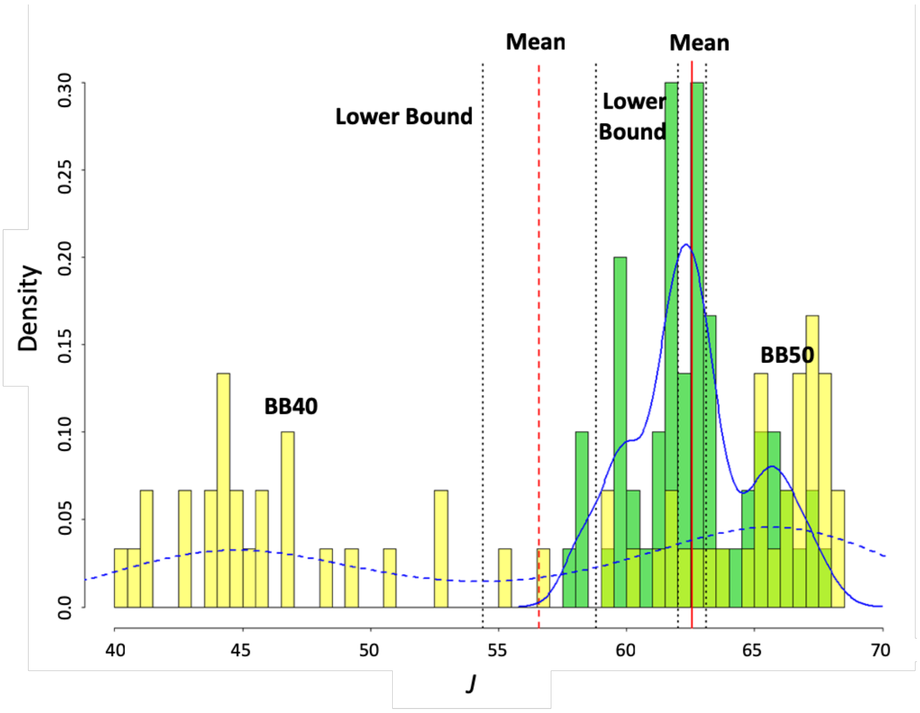


Figure 6.17 Sample set-up for probability computation for BB50 and BB40 for CB scenario

In Table 6.7, taking the lower bound of OPC40 as the threshold value, the exceedance probability of all other alternatives is 1.00. This implies that none of the *J* of the other alternatives is below this value, assigning OPC40 at the bottom of the hierarchy. On the other hand, based on *P*, BB50 is at the top of the hierarchy as its probability of exceedance values is constantly 1.00 with respect to the other mixes. It is evident from Table 6.7 that mixes using blast furnace slag cement are still the top alternatives (i.e., BB50 and BB40) for CB scenario. This result can be attributed to the high replacement of OPC by blast furnace slag, which translates to reduced environmental loadings. For the intermediate and the "least" sustainable alternatives, again W/B seems to drive their placement in the hierarchy, with mixes having W/B = 0.50 ranked higher than those with W/B = 0.40.

6.5 Result of analytical scenario 3: CL*

6.5.1 Multicriteria analysis and uncertainty analysis

The MA and UA result of CL* scenario is illustrated by the PDFs in Figure 6.18. Table 6.8 supplements this figure by showing the summary statistics of each distribution. The PDFs in Figure 6.18 in most cases spread over a wider range compared to the PDFs in CL, suggesting that using a limited number of indicators could potentially increase the uncertainty of the sustainability score. For example, the distribution for OPC50 spreads over a wider range compared to its CL counterpart. The spread of the PDF is also captured by the variance estimates in Table 6.8, showing values significantly higher than in CL scenario. Therefore, based on variance estimates alone, the *J* for the CL* scenario is more uncertain.

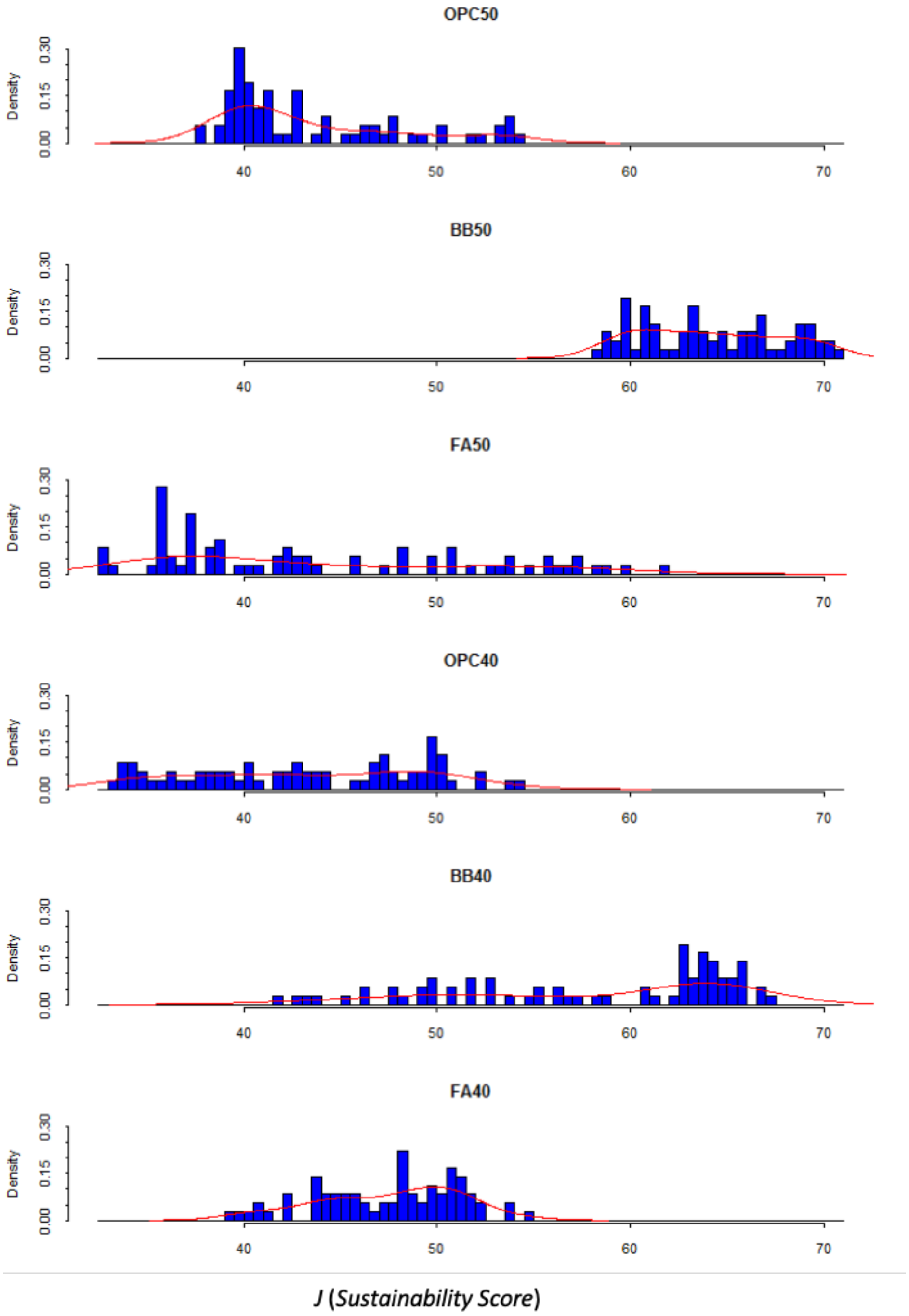


Figure 6.18 PDFs of the sustainability scores of the mixes in *x* for CL* scenario

Table 6.8 Summary statistics of the PDFs of *J* for the CL* scenario

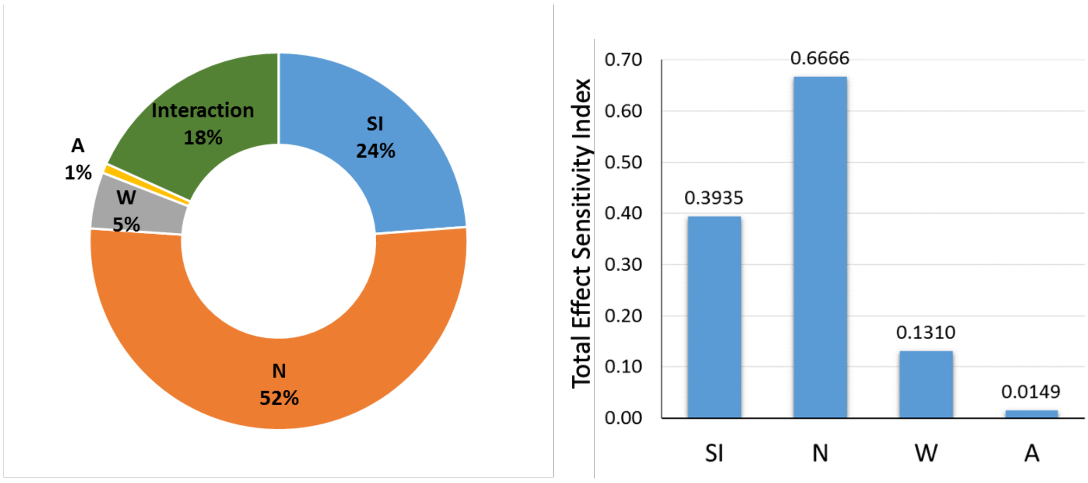
Mix	Summary statistics of the PDF of *J* (%)			
	Min	Mean	Max	Variance
OPC50	37.69	43.43	54.10	21.28
BB50	58.25	64.11	70.69	12.85
FA50	32.60	43.66	61.77	65.72
OPC40	33.43	43.29	54.21	35.00
BB40	41.56	58.00	67.34	54.22
FA40	39.36	47.51	54.61	13.41

Table 6.7 and Figure 6.18 further suggest that the *methodological uncertainties* affect each alternative differently – similar to the finding of the CL scenario. Based on variance, the most uncertain J is for FA50 (variance = 65.72, see Table 6.7) with values from 32.60 to 61.77. This range is very wide in that the distribution of FA50 completely overlaps with many other distributions including that of OPC50, OPC40 and FA40. This complete overlap makes the comparison of sustainability performance between these 4 mix alternatives on the basis of the results of UA alone counterproductive, as their ordering could just easily reverse where their PDFs overlap. On the other hand, the least affected by methodological uncertainties is BB50 with variance equal to 12.85 and with J ranging from 58.25 to 70.69. The distribution of BB50 only slightly overlaps with FA50 and BB40.

Using the result of UA directly to compare the relative sustainability performance of the alternatives is impractical for CL* due to the high degree of overlap between the PDFs of the mixes. Using the average values of J (Table 6.7) is also not favorable as it may underrepresent the output uncertainties. Graphical comparison of highly overlapping PDFs is challenging as some distributions completely overlap. In Figure 6.18, for example, BB50 and BB40 may be regarded as equivalently the "most" sustainable mixes as their PDFs both overlaps and tend to the right. However, between these two mixes, it is not directly evident which one is more sustainable than the other due to their overlapping PDFs. The same degree of overlap poses a problem when contrasting OPC50, FA40, OPC40 and FA40.

6.5.2 Sensitivity indices and decomposition

The sensitivity analysis result of CL* scenario is summarized in Figure 6.19. This figure shows that 82% of the variance can be explained by the first-order effect, while 18% is due to the interactions of the sources of *methodological uncertainties*. From Figure 6.19a, more than half (52%) of the variability of J can be attributed to the choice of normalization method. This is followed by the selection of the indicator set (SI), explaining about 24% of the variability. With the reduced set of indicators, the first-order effect of N is increased substantially, almost masking the effect of weighting and aggregation method which only accounts for 5% and 1% of the variability, respectively. This would mean that the analysis should focus on finding the appropriate normalization method for CL* scenario as this could result to a very significant reduction in the total variance, thereby increasing the certainty of the sustainability score.

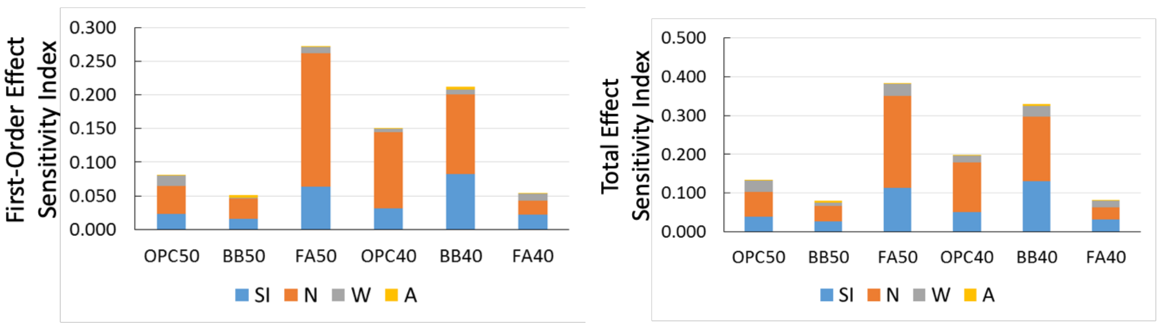


(a) S_i (b) S_{Ti}

Figure 6.19 Result of the sensitivity analysis for the CL* scenario

On the other hand, the total effect sensitivity indices shown in Figure 6.19b reveal very similar pattern of influence of the sources of *methodological uncertainties* to the total output variance. By including the interaction, the normalization method could now explain about 67% of the total variance, an increase by the order of 15%. Substantial increases in the magnitude of influence could also be noticed for SI and W by an order of 15% and 8%, respectively. This means that N, SI, and W have significant interactions with other factors, while aggregation seemed an inactive factor.

Decomposing S_i and S_{Ti} as shown in Figure 6.20 to explain the individual variability of the PDFs of J of the mixes revealed a disproportionate effect of the sources of uncertainty. In some cases, i.e., OPC40 in both S_i and S_{Ti} decomposition, bulk of the variability can be attributed to the choice of normalization method. While BB40, however, the influence of N is equivalent to SI. Notably, the choice of aggregation method seem to not contribute much to the variability of the individual J for both S_i and S_{Ti}, which corroborates the findings shown in Figure 6.19. Nevertheless, generally N and SI are the factors that influence most the variability of J of the mixes in this scenario.



(a) S_i (b) S_{Ti}

Figure 6.20 Decomposed sensitivity indices for CL* scenario

6.5.3 Factor prioritization and fixing

Applying the same setting used in CL for factor prioritization to sort the sources of *methodological uncertainties* as influential or non-influential in CL*, The values of S_i in Figure 6.19a shows that both A and W are non-influential factors. On the other hand, SI and N are influential factors. Notably, the choice of normalization is the most influential factor, while the least influential is A. On the other hand, using the total effect as a basis for factor prioritization (Figure 6.19b), W became influential based on the same setting.

Both S_i and S_{Ti} suggest that aggregation method is a good candidate for factor fixing. If, for instance, the aggregation is fixed to LN, the total output variance will increase by as much as 5%, while fixing it to GM, the variance will reduce by 7%. On average, the reduction in variance should the aggregation is set to its true methodological approach is 1% – equal to the S_i of A (see Figure 6.19a). As an example, Figure 6.21 shows the effect on the PDF and ECDF of J of BB50 by fixing aggregation method. Because the influence of the choice of aggregation is relatively small, the modified and the original PDFs are similar. This similarity is also supported by the ECDFs of the distributions, which also show similar trend and are closed to each other as reflected in Figure 6.21.

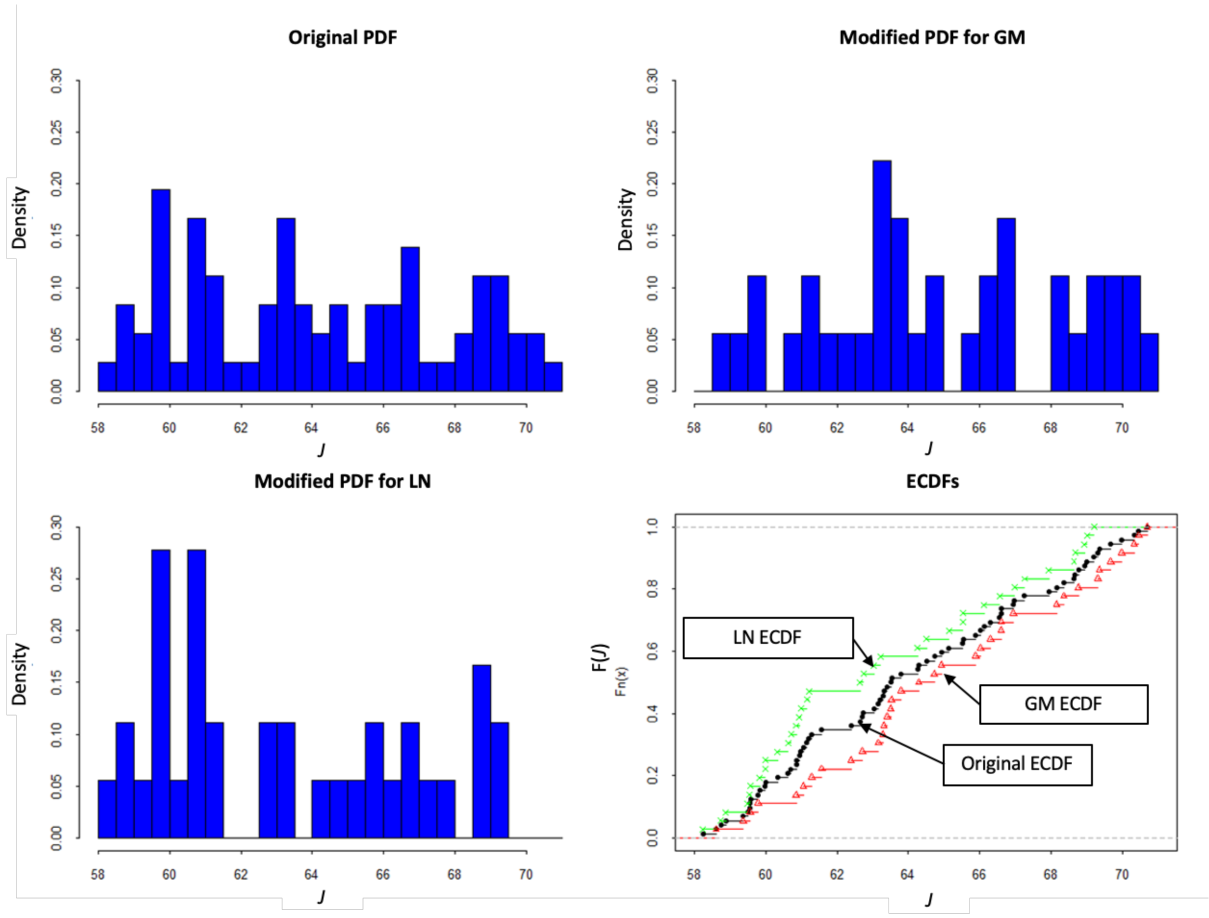


Figure 6.21 Effect of fixing aggregation method to either LN or GM for BB50 for CL scenario

The KS test performed to compare the ECDF of the original distribution and the modified ECDFs for LN and GM calculated a D = 0.153 for both aggregation methods. This D is below D_{crit} = 0.309 for this scenario at a significance level α = 0.01, implying that the original and the modified ECDFs for LN and GM are statistically similar and could have been drawn from the same distribution. The finding of the KS test is further substantiated by the DKW inequality bound, defining the 99% confidence interval of the original ECDF as shown in Figure 6.22. From this figure, all parts of the two modified ECDFs for LN and GM fall within the confidence interval of the original ECDF. Therefore, using either LN or GM as aggregation method will have no significant effect on the resulting sustainability evaluation, eliminating systematically the uncertainty from the choice of aggregation method.

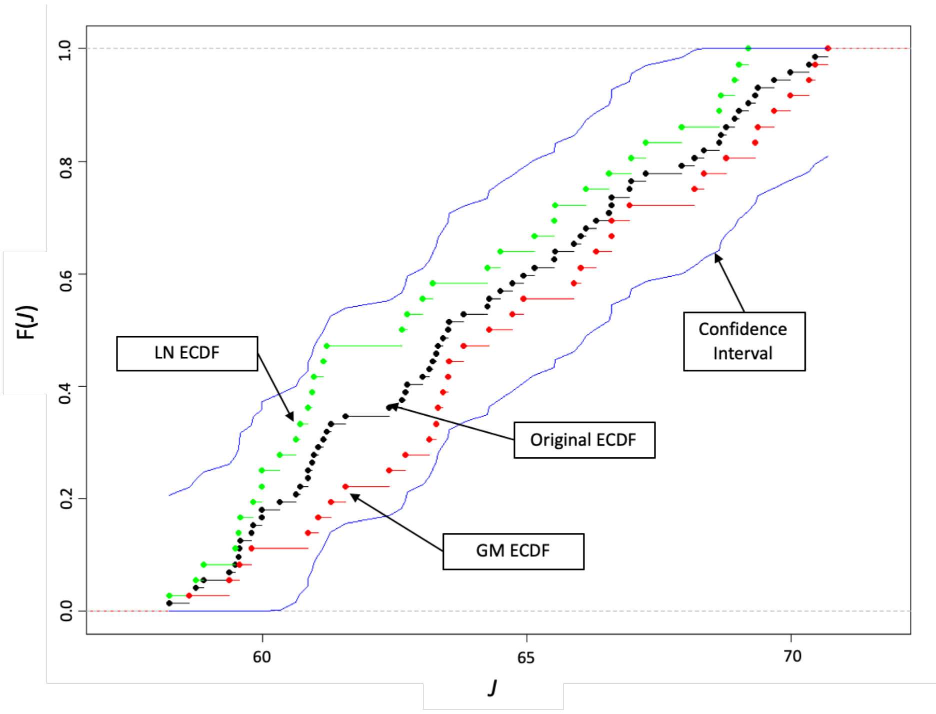


Figure 6.22 The original and the modified ECDFs of J for BB50 after fixing A to either LN or GM for CL* scenario

6.5.4 Probabilistic interpretation

Table 6.9 shows the exceedance probabilities and the lower bounds of the mean of the PDF of J from which the P were computed. Figure 6.23 shows an example of the interval of the mean for BB50 and BB40 from which some of the exceedance probabilities of both mixes are computed. It is noticeable that some parts of the distribution of BB50 exceeds the lower bound of the mean of BB50. Using the lower bound of BB50 as threshold, about 0.38 (see also Table 6.9) chance that J of BB40 will exceed this threshold value. Similar probability assignment method was done for the other mixes in the set.

From Table 6.9, based on the lower bound of OPC50, the probability that J of BB50 is above this value is 1.00, because the PDFs of J of OPC50 and BB50 do not overlap (see also Figure 6.18). Using the same threshold, the P of OPC40 is 0.56, which imply that there is an overlap between the PDFs of OPC50 and OPC40, which can be confirmed from Figure 6.18. Due to the high degree of overlap between PDFs in CL* scenario, HEPM was beneficial to hierarchically order the mixes in x.

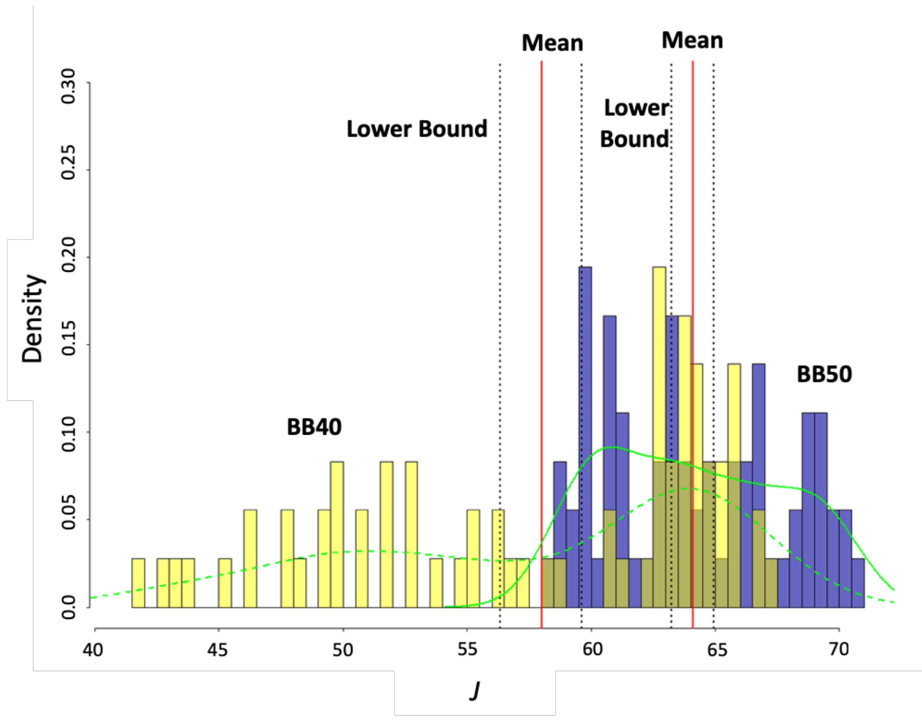


Figure 6.23 Sample set-up for probability computation for BB50 and BB40 for CL* scenario

Table 6.9 Hierarchical exceedance probabilities of mixes for CL* scenario

Mix	Lower Bound of the 95% confidence interval of the mean of J	Exceedance Probability (P) based on the lower bound of the mean of J of:					
		OPC50	OPC40	FA40	FA50	BB40	BB50
BB50	63.24	1.00	1.00	1.00	1.00	1.00	0.56
BB40	56.33	0.99	0.99	0.90	0.99	0.61	0.38
FA50	41.91	0.44	0.49	0.35	0.48	0.10	0.00
FA40	46.70	0.89	0.91	0.60	0.91	0.00	0.00
OPC40	41.98	0.56	0.60	0.39	0.61	0.00	0.00
OPC50	42.45	0.44	0.47	0.22	0.47	0.00	0.00

Based on HEPM (Table 6.9), BB50 is placed on the top of the hierarchy, while BB40 is the second. The P of BB50 and BB40, however, are very close particularly when the threshold is set at BB50. At this threshold, there is still a 0.38 chance that J of BB40 exceeds this value due to the overlap of their distributions (see Table 6.9). Nevertheless, since the P of BB50 (equal to 0.56) for the same threshold is greater than BB40, BB50 is placed on top of the hierarchy.

For this scenario both BB50 and BB40 are the top alternatives, implying that using blast slag cement improves the sustainability performance of the concrete material. For concrete mixes within the intermediate and bottom of the hierarchy, the driver of their placement seems to be the type of blended cement used in the concrete matrix – a different finding compared to CL scenario. For instance, mixes using fly ash type A blended cement are placed higher than those using OPC. Such result, however, could not be easily attributed to any notable fluctuation in an indicator value between mixes but more on the structural condition of the analysis. For example, a quick observation of the values of the indicators in CL* in Table 6.3 reveals that based on the average of the normalized score FA50 (average = 1.01), which is lower than OPC50 (average = 1.06), yet their placement in HEPM proves otherwise. Further, when comparing the average values of the indicators of FA50 and OPC50 by statistical standardization, the result seems to support the hierarchy using HEPM. This clearly suggests that their order in the hierarchy is structural in nature, which can also be attributed to the choice of normalization method – the most influential source of uncertainty for this scenario.

Interpreting the result by singling out certain indicators may bias the sustainability evaluation since much of the uncertainties are due to the analytical structure. While the values of the indicators could become the predictor of the sustainability scores of the alternatives for some methodological combinations, it is not generally the case because of the complex nature and interactions of the sources of uncertainties.

6.6 Comparison of results

Table 6.10 is used for the comparative analysis between the result of the different scenarios in the following subsections. The table also shows the result of the KS test and the D_{crit} for $\alpha = 0.01$, which were used as indicators of the similarity between scenarios. Additionally, Figure 6.24 shows the ECDFs for BB50 for each analytical scenario used as an example in the following discussions.

Table 6.10 KS statistics of corresponding mixes in CL, CB and CL* scenarios

Mix	KS test summary statistics			
	CL vs. CB		CL vs. CL*	
	D	Dcrit	D	Dcrit
OPC50	0.30	0.153	0.50	0.223
BB50	0.70		0.51	
FA50	0.48		0.54	
OPC40	0.39		0.65	
BB40	0.33		0.41	
FA40	0.72		0.58	

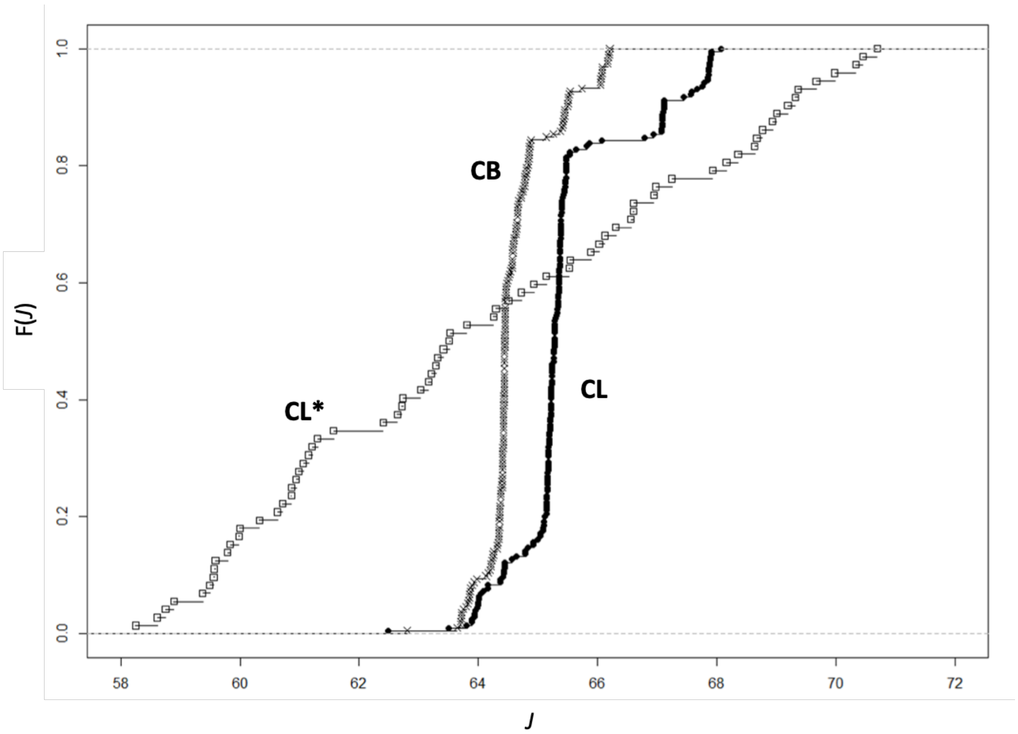


Figure 6.24 ECDFs of BB50 for scenarios CL, CB and CL*

6.6.1 CL vs CB

Table 6.10 shows that there is significant difference between the result of CL and CB scenarios based on the D-statistic. All computed D is greater than the D_{crit}, which means significant differences can be observed in the distributions of the sustainability scores of the corresponding mixes in both scenarios. As an example, Figure 6.24 illustrates the difference of CL and CB scenario for BB50. Additionally, the difference can also be seen in Figure 6.25 by comparing the distributions of J generated by CL and CB scenario for BB50. While the trend of the ECDFs seem similar in Figure 6.24 (see also Figure 6.25) for CL and CB, the variation of the ECDFs is still significant since $D = 0.70 > D_{crit} = 0.153$ (Table 6.10). Therefore, it can be said that different environmental conditions used as setting for the sustainability evaluation, which affect the value of the durability indicator may have significant effect on the resulting sustainability scores.

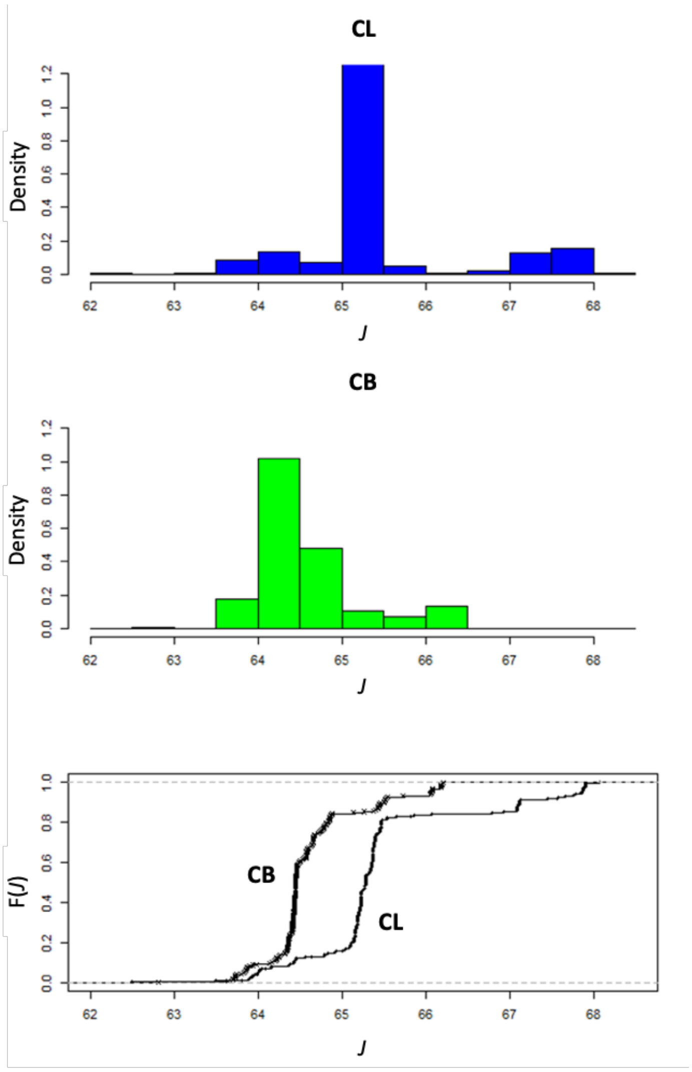


Figure 6.25 Comparison of the distribution of *J* of BB50 for CL and CB scenario

The result of SA for both scenarios, on the other hand, are similar, which identifies SI, N and W as the influential sources of uncertainty based on S_{Ti}; however, they vary in terms of their magnitude of influence to the total output variance. For the CL scenario N and W are considered as equally influential (see Figure 6.7), while for CB scenario the influence of W is just a little over half of the magnitude of influence of N (see Figure 6.13). SI in CB scenario has higher influence than in the CL scenario. The interactions of the sources of uncertainties in both cases do not vary widely.

Both CL and CB scenarios identify that the choice of aggregation method is non-influential, which suggests that it can be fixed to either LN or GM. However, the result of the KS test and DKW inequality bound validation for both scenarios is contrasting. In CL for BB50, for example, fixing A produced modified ECDFs for LN and GM that are statistically similar to the original ECDF. While in CB for BB50, the ECDFs of LN and GM is statistically different from the original ECDF despite the total effect (S_{Ti}) for CB of A is smaller (at 3.78%) compared to CL (at 4.23%). This contrasting result could be attributed to the variance of the distributions of SS, since in CB scenario the variances are generally smaller compared to that of the CL scenario (see Table 6.4 and Table 6.6), thus for any small changes in the analytical structure (i.e., fixing the aggregation) in CB will become more visible than in CL. This is further explored in Section 6.6.3.

The HEPM of CL and CB scenarios (see Table 6.5 and Table 6.7), however, produced the same ordering of the alternatives with BB50 mix on top of the hierarchy. This implies that in both scenarios the use of blast slag cement type B is beneficial for sustainability. Additionally, higher W/B also improves the sustainability of the mix based solely on the result of HEPM in both scenarios. While the environmental condition is the primary variable contrasting CL and CB trhough the value of durability indicator (SCMI 20), this did not translate to rank reversal of the mixes as the condition is only captured by a single indicator. Therefore, it can be said that despite the changes in J found by the KS test, ultimately CL and CB resulted in the same ordering of the mixes.

6.6.2 CL vs. CL*

For CL and CL*, Table 6.10 shows there is a significant difference between the result of both scenarios based on KS test as all the computed D-statistics is greater than D_{crit} for $\alpha = 0.01$. This result implies that a reduced indicator set may not be representative of the result of a sustainability evaluation using a relatively comprehensive set. One notable difference is the increase in the uncertainty of J with the distribution spreading over a wider range in CL* than in CL scenario. The ECDF of BB50 for CL* in Figure 6.24, as an example, covers a wider range of J and its slope is much gentler compared to the ECDF of BB50 for CL scenario. This is further detailed in Figure 6.26, which shows the comparison of the distribution of BB50 for both scenarios. The spread of the distributions is also captured quantitatively by the increase in variance of J in CL* scenario (see Table 6.7). Using a reduced set of indicators, therefore, could magnify the uncertainty of the sustainability evaluation result as can be found in the comparison between the CL and CL* scenarios.

The result of SA are also different for both scenarios CL and CL*. For CL the most influential source of uncertainty is W, while for CL* normalization is the most influential. Both scenarios, however, identified SI, N and W as the influential factors but with varying levels of magnitude of influence to the total output variance. Additionally, CL and CL* point that aggregation method is non-influential and could be fixed to either LN or GM. In both cases, and following the conditions of KS test, fixing A to either LN or GM has no significant effect on the J. Therefore, in both scenarios the uncertainty from the choice of aggregation method can be systematically eliminated.

In terms of the hierarchical ordering of the mixes based on HEPM, CL and CL* differ. Rank reversal happened for OPC50, OPC40 and FA40 (see Table 6.5 and Table 6.8). However, the top 3 alternatives in CL* retained their order as in CL scenario. Nevertheless, for the CL* to be representative of CL, rank reversal must be avoided in all cases. Therefore, using a reduced set of indicators may not truly represent of the extent of sustainability evaluation, and may present a different conclusion.

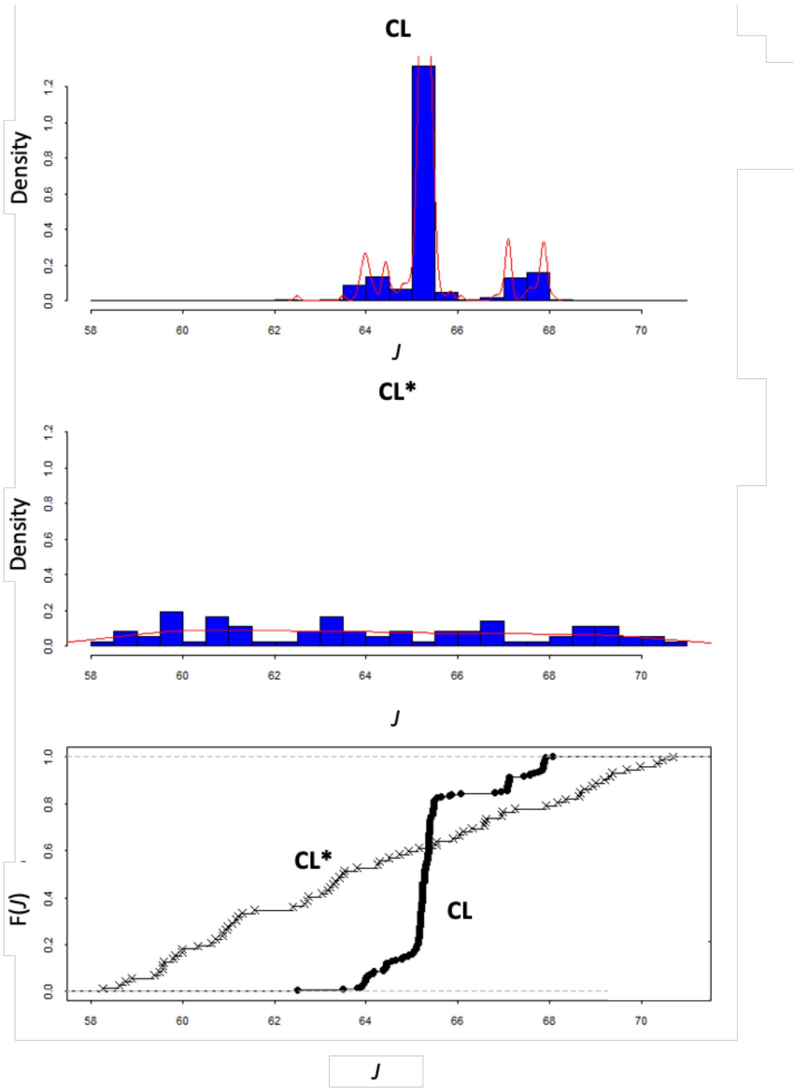


Figure 6.26 Comparison of the distribution of SS of BB50 for CL and CL* scenario

6.6.3 On conditions for factor fixing

In the preceding demonstration, the level of significance used for KS and DKW statistics was arbitrarily chosen as there still no governing threshold for the selection of the significant value. However, from the result of the factor fixing for scenarios CL, CB and CL*, a unique behavior can be observed regarding the relationship of the variance and the level of significance chosen. For example, the KS test performed for BB50 mix for CL, CB, CL* shows conflicting results. The influence measured by S_{Ti} value of the choice of aggregation method (A) for the three scenarios is suggestive that that it can be fixed to either LN or GM. For CB, however, despite having the lowest S_{Ti} for A amongst the three scenarios and for the same level of significance, KS and DKW test implies that fixing A would have a significant effect on *J*, which is counterintuitive.

To find resolution to this problem, the Eq. 5.6 and Eq. 5.7 in Chapter 5 was manipulated, as shown in Eq. 6.1 and Eq. 6.2. The distance D in Eq 6.1 becomes the maximum, D_{max}, as in Eq. 6.2, by removing the inequality sign for the significance level α. Dividing both sides of Eq. 6.2 by $\sqrt{\frac{g+h}{gh}}$ results into Eq. 6.3. The calculated D_{gh} for CL, CB and CL* following Eq. 6.3 is 1.4509, 2.2080, and 0.7496, respectively. To relate it to the distribution of J for each scenario, D_{gh} is be plotted against the variance of the distribution for BB50 (used as an example) as shown in Figure 6.27. The relationship of D_{gh} and the variance (VAR) is estimated by Eq. 6.4, which is the regressed function in Figure 6.27. Eq. 6.4 can then be back substituted to Eq. 6.3 to derive the expression for the minimum variance (VAR_{min}) for a level of significance α, which is expressed in Eq. 6.5.

$$D \leq D_{crit} = \sqrt{-\frac{1}{2}\ln(\alpha)}\sqrt{\frac{g+h}{gh}} \qquad \text{Eq. 6.1}$$

$$D_{max} = \sqrt{-\frac{1}{2}\ln(\alpha)}\sqrt{\frac{g+h}{gh}} \qquad \text{Eq. 6.2}$$

$$D_{gh} = \frac{D_{max}}{\sqrt{\frac{g+h}{gh}}} = \sqrt{-\frac{1}{2}\ln(\alpha)} \qquad \text{Eq. 6.3}$$

$$D_{gh} = 1.5296\,(VAR)^{-0.286} \qquad \text{Eq. 6.4}$$

$$VAR_{min} = 4.4195\left[\frac{1}{2}\ln(\alpha)\right]^{-1.7483} \qquad \text{Eq. 6.5}$$

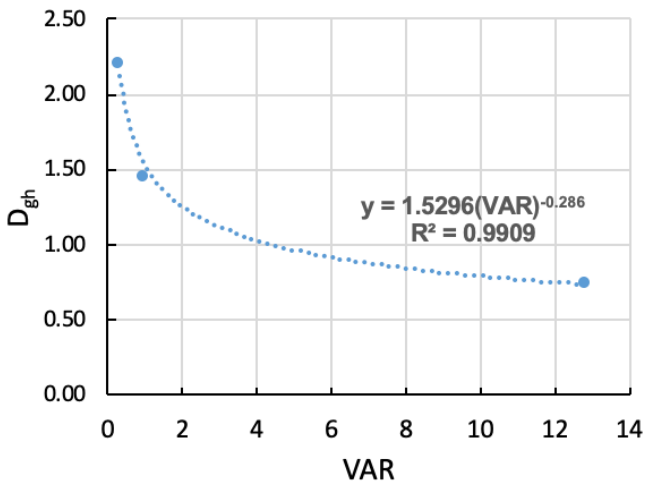


Figure 6.27 Plot of D_{gh} vs. the variance of the PDF of BB50 including the regressed equation

Figure 6.28 graphically illustrates Eq. 6.5, showing the minimum required variance of the distribution for factor fixing to be accepted (or the effect of factor fixing is statistically no significant) at the level of significance α. In the case of alpha = 0.01, the minimum required variance based on Eq. 6.5 is 1.03. For CL, the variance of BB50 the PDF is 0.98, which is very close to the estimated minimum variance. This is only reflective of the KS statistic $D = 0.176$ for CL of BB50 barely passing the $D_{crit} = 0.184$. For CB, the variance of BB50 is very small, equal to 0.32, compared to the minimum which would imply that factor fixing will have significant effect. While for CL*, the variance of BB50 is 12.85 which is well above the minimum, therefore, factor fixing will have no significant effect as discussed in Section 6.5.3. The idea of Eq. 6.5 is similar to the Horwitz trumpet function, which measures the reproducibility of an analytical experiment based on the concentration of an analyte using a relative standard deviation of reproducibility (RSDR) (see e.g., Thompson, 2004). In Horwitz trumpet, as the concentration of the analyte is reduced the RSDR increases. In other words, for measurement involving small values the uncertainty is higher. Similarly, as in Eq. 6.5, if variance of J is very small ($V(J) < VAR_{min}$), any small changes in the analytical structure would cause a significant impact on the result. The concept about variance presented in this subsection is critical to further the discriminate whether a factor is indeed non-influential to the analysis or not, based on its effect of the distribution of the sustainability scores. This method can later be generalized for other applications with larger data set and test values, so that both type 1 and type 2 errors can be avoided.

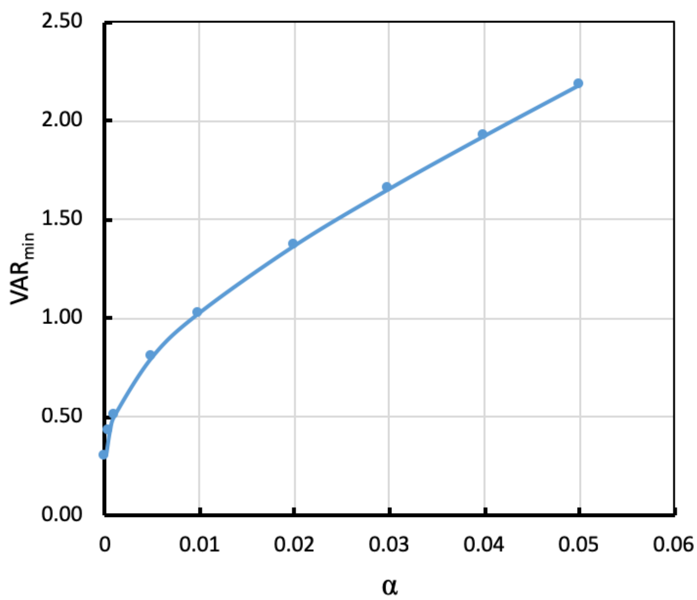


Figure 6.28 Plot of VAR_{min} vs. significance level α

6.7 Summary

The whole Chapter is dedicated on demonstrating the applicability of the multicriteria analytical sustainability evaluation framework under methodological uncertainties and the utilization of the SCMI framework. This was achieved by comparing the sustainability performance of six distinct concrete mixes prepared by manipulating the constituent material. The mixes vary in terms of their cement type (OPC, BB, and FA) and the water-to-cement ratio (approx. 0.40 and 0.50) as the primary material variables. The analytical flow proceeds by adopting the fundamental steps of the multicriteria analysis comprised of: indicator selection, normalization, weighting and aggregation. The methodological uncertainties were characterized by varying methodological approaches of each step of MA.

The indicator selection was varied by creating various sets of indicators from a relatively comprehensive initial set of *e* indicators by dropping one indicator at a time. The initial indicator set was formulated through the utilization of the SCMI framework. The normalization was allowed to vary between the methods: distance-to-a-reference and statistical standardization. Three weighting scenarios were considered comprised of: equal weighting, weighting by principal component analysis, and the weights from stakeholders. Lastly, linear sum and geometric mean were used as aggregation methods. The uncertainties from each step of MA were managed and captured by uncertainty and sensitivity analyses. The hierarchical ordering of the 6 mixes were determined by way of exceedance probabilities.

In addition to the consideration of methodological uncertainties, three evaluation scenarios have been created to represent the two important considerations for concrete sustainability: the effect of environmental conditions – captured by durability indicator value – and the condition of data unavailability. The durability is measured by the initiation of steel reinforcement corrosion. Missing data, on the other hand, is expressed by case deletion – removing indicators with no data. Following this, the scenarios considered are: CL – for a condition where chloride is the primary cause of corrosion and uses a relatively comprehensive indicator set; CB – for a condition where carbonation is the primary cause of corrosion and utilizing a comprehensive indicator set; and CL* – similar CL but uses a reduced indicator set due to missing data.

For the CL scenario, the presence of methodological uncertainty created a variation in the sustainability scores of the mixes. From the result of sensitivity analysis the primary cause of variability is the choice of weighting and normalization methods. The effect of indicator set inconsistency is not so prevalent, and the choice of aggregation method is the least influential in the analysis, implying that it can be fixed to either of the aggregation approach considered. KS and DKW test performed have shown that fixing the aggregation method to either linear or geometric aggregation have no significant effect on the resulting sustainability scores. The mixes were hierarchically ordered by the use of exceedance probability to capture the uncertainty in the sustainability scores. In this scenario the mixes using BB blended cement have been rank as the "most" sustainable mixes.

In the case of CB scenario, the methodological uncertainty created similar variation in the sustainability scores of the mixes. In this scenario the most influential source of uncertainty is the choice of normalization method explaining more the 60% of the total variance. In contrast, the aggregation method is the least influential, accounting only 4% of the total variance, implying that the aggregation method can be fixed to either of the two approaches considered. KS and DKW statistics, however, suggests the opposite, as the comparison of the empirical cumulative distributions after factor fixing and the original ECDF showed statistically significant difference. The hierarchical ordering of the mixes by probability of exceedance, however, produced the same ranks as the CL scenario.

The CL* scenario, similarly showed parallel effect with CL and CB on the sustainability scores of the mixes due to methodological uncertainties. The sustainability scores of the mixes showed different magnitudes of variabilities. The most influential source of uncertainty is still the normalization method, which accounts about 67% of the total variance based on the total effects. The least influential is again the choice of aggregation method, which explains about only 2% of the total variance based on the total effects, implying that aggregation could be fixed to either LN or GM. KS and DKW statistics validates that the aggregation method could be fixed as it was demonstrated that there was no significant effect on the sustainability scores of the mixes. The hierarchical ordering of the 6 mixes by probability exceedance matrix, however, showed significant rank reversals of the alternatives compared to CL, implying that the use of less indicator set could not substitute for a relatively comprehensive set as in CL scenario.

CL, CB and CL* scenarios reflect the effect of methodological uncertainties on the sustainability scores of the alternatives. It was also demonstrated that the use of UA and SA as part of the architecture of the sustainability analytical evaluation framework was beneficial in measuring quantitatively the influence of each methodological source of uncertainty, which discriminated each factor as influential or non-influential. The use of conditional statistics like KS and DKW further validates the condition for factor fixing, which could lead to the elimination of uncertainty from the non-influential sources of *methodological uncertainties*, making the evaluation more robust. The use of hierarchical exceedance probability matrix was also demonstrated to be effective at ordering the alternatives, leading to the identification of "best" sustainable options under the presence of uncertainties. Therefore, the demonstrations illustrated in this Chapter have confirmed the applicability of the multicriteria sustainability evaluation frameworks under methodological uncertainties for concrete materials sustainability decision problems.

Chapter 7
Exploratory works

7.1 Introduction

Defining the sustainability of concrete material quantitatively is important for the industry to select decisions and actions that are contributory to global sustainable development. Because of the multidimensional nature of concrete sustainability, it is often analyzed similar to a multicriteria decision problem (or multicriteria analysis). Multicriteria analysis consists of methodologies that condense the information of various indicators into a composite value (or sustainability score) (Munda and Figueira, 2005), summarizing the behavior of the system of interest. The method is usually used to make quantitative comparisons to rank or select the best in a set of alternatives or decisions (e.g., a set of concrete mixes) and is considered as the appropriate tool to perform assessments of sustainability (Cinelli et al., 2014).

The steps of MA have been elaborately extended and made robust in Chapter 5, by incorporating new analytical tools such as the uncertainty analysis and sensitivity analysis. However, despite its complexity, many areas of MA still needed more consideration and analysis to resolve other subjective and structural issues. In this Chapter, the other important issues relevant to the multicriteria analysis under methodological uncertainties are explored. In particular the Chapter explores in detail the area on indicator weighting, the limited exploratory power of the multicriteria analysis, and the use of different viewpoints to perform sustainability evaluation.

The issues on indicator weight assignment are diverse as presented in Chapter 5. Weights are marketed as indicator importance measure, but they most likely do not behave as such analytically within the structure of the multicriteria analysis. Inherent behavior of the data prevents the weights to be interpreted as importance and sometimes they could introduce bias in the analysis as they can compensate the behavior of indicators, thereby creating an imbalance between the indicator's contribution to the final sustainability score. This disparity between the interpretation of weight as importance and its structural function is explored in this Chapter in the form of Double Weighting (DW).

Another issue explored is the limitation of the multicriteria analysis to be used in exploratory works for material design. Multicriteria analysis is an effective tool to contrast distinct and seemingly equivalent sustainability options as what has been extensively demonstrated in Chapter 6. However, it has some limited applications for exploratory work specially when methodological uncertainties are accounted for. In this Chapter, the possibility of integrating MA with exploratory tools such as the response surface methodology (RSM) to extend the exploratory limits of MA is investigated.

The last issue examined in this Chapter is on the consideration of various perspectives in performing sustainability evaluation work – particularly in the concrete industry. Various stakeholders have different viewpoint about the sustainability of the concrete material and that the debates about which viewpoint should be taken as standard is far from resolved. Following this, the evaluation of concrete sustainability has been proposed to be restructured to account three important viewpoints in concrete: durability, cost and environmental performance. This is done by utilizing desirability analysis without departing from the concept of *methodological uncertainties* within the evaluation system. The following sub-sections provide the details on how each of the above-mentioned issues are tackled.

7.2 Use of double weights in indicator weighting process

7.2.1 Motivation of the work

Assigning weights to the different indicators, i.e., the SCMIs in Chapter 3, is one of the important steps in a multicriteria sustainability evaluation. Weights as discussed in Chapter 4 are usually interpreted as the indicator importance representing the preferences of the decision makers when comparing decision alternatives in terms of their sustainability performance. However, due to the methodological uncertainties (see Chapter 4) resulting from the plurality of preferences over the weighting approaches, no single set of weights is truly appropriate. Moreover, assigning weights directly without regard to the internal data variation and correlations of the indicators could result in double counting, magnifying of the effect of indicator(s) due to data overlap.

If weights should reflect the importance of indicators, such a phenomenon should be avoided (OECD, 2008) as this could introduce bias to the analysis, affecting the sustainability score of the alternatives and the subsequent stakeholder decisions. In addition, previous researches have shown (see e.g., Paruolo et al., 2013) that indicators weight could deviate from its relative strength in determining the ordering of the alternatives being compared due to correlations in the data structure. This is important to address as discussed in Chapter 4 since the SCMIs themselves are inherently related and that this would mean high degree of correlations between indicators. However, the full implications of indicator correlations and data structure are not yet fully understood mathematically in regard to the weighting process.

In this Section, to be sensitive to the data structure, the application of double weighting (DW) scheme to the multicriteria sustainability evaluation introduced in Chapter 5 is explored. DW is structured by combining the weight representing the desired indicator importance (or strength) and another weight accounting for the contribution of an indicator to the data variation. The use of double weighting has already been applied to some multicriteria evaluation in the past only if the indicators are structured hierarchically. To the knowledge of the author at the time of writing this manuscript, DW scheme has not yet been applied with similar function as discussed in the following subsections.

7.2.2 Methodological approach

(1) The concept of double weighting

Aggregating indicators with a high degree of correlation, even if, i.e., equal weighting is used, results in data overlap (OECD, 2008). Essentially, therefore, correction factors for data overlap need to be applied when aggregating indicators. In this vein, a double weighting scheme, such as shown in Eq. 7.1, is of practical value. In Eq. 7.1, w_i represents the normalized weight of an indicator over e indicators (i = 1, 2, …, e), which is a combination of w_{ai}, representing the weight representing the importance of an indicator and w_{bi} – the 'weight' accounting for data overlap (where $\sum w_i = 1$).

$$w_i = \frac{w_{ai} w_{bi}}{\sum_{i=1}^{n} w_{ai} w_{bi}} \qquad \text{Eq. 7.1}$$

Weights representing the relative importance of indicators are often applied to better reflect policy priorities (OECD, 2008; Henry and Kato, 2010). There are a number of ways weights can be assigned, e.g., by participatory approaches such as budget allocation process and the analytic hierarchy process (see e.g., Chapter 4 and 5 for examples of weighting techniques). Weighting in terms of the relative importance of indicators, however, is still heavily debated partly due to the multiplicity of weighting techniques and the due to the disagreements between stakeholders on priority preferences.

Weights accounting data overlap, on the other hand, are generally obtained by statistical analysis, e.g., principal component analysis (PCA) and factor analysis (FA), among others. Accordingly, the weights from PCA and FA intervene to correct for overlapping information between correlated indicators (OECD, 2008). For this reason, this exploratory work focused on using PCA as an example to obtain w_{bi}. PCA groups together individual indicators which are collinear and with the highest association to a principal component as discussed in Chapter 6 (see also Appendix B). The method from OECD (2008) to obtain w_{bi} from PCA is adopted.

7.2.3 Demonstration works

(1) Analytical set-up

The consequence of using DWs in multicriteria sustainability evaluation is demonstrated by comparing the sustainability performance of various concrete materials. The sustainability scores of 6 concrete mixes of similar compressive strength were compared based on 10 indicators. Additionally, two cases relevant to data structure were explored: Case 1, to represent a condition wherein all indicators uniformly contribute to the data variation and, Case 2, to represent the condition wherein indicators contribute to the data variation unequally.

The mix proportion of the concrete mixes is shown in Table 7.1, which was used in the calculation of the individual indicators value. The mixes are of similar compressive strength with the coefficient of variation of fc' equal to 7.06%. Notably, the mixes used 50% fly ash replacement to cement and some used recycled aggregates (RA) as replacements to natural aggregates (NA) at varying amounts. In the Table 7.1, S1 is be regarded as the reference mix.

Table 7.1 Mix proportions of the mixes for exploratory work on DW

Mixes	Proportion (kg/m^3)						fc' (MPa)
	W	C	FA	S	NA	RA	
S1	171	342	0	746	1015	0	43.5
S2	135	225	225	659	1067	0	46.9
S3	135	225	225	659	533	478	47.5
S4	135	225	225	659	0	957	41.3
S5	135	180	180	721	1095	0	40.4
S6	165	275	275	590	0	856	39.7

The indicators used for evaluating the sustainability scores are listed in Table 7.2. Two orderings of indicators, resembling their relative importance were used to simulate the differences in preference based on the perspectives of academics (Acad) and material engineers (Mat) adopted from Henry and Kato (2011). In the table, it is evident that there is already an inherent disparity between the indicators importance as viewed by academics and material engineers. The purpose using both orderings is for examine the effect of DW using various importance perspectives.

The weights w_{ai} based on the orderings in Table 7.2 were then obtained by randomly sampling 1000 sets of weights from a uniform distribution to reduce bias in assigning numerical values. Figure 7.1 shows the distribution of the weights assigned to each indicator. Depending on which ordering is viewed, the indicators with the highest rank (rank 1) is assigned with weights corresponding to the rightmost distribution in Figure 7.1. The weights of the other indicators are assigned based on their rank and the corresponding placement of the weight distribution starting from the rightmost distribution in Figure 7.1.

Table 7.2 Indicators used for the exploratory work on DW

Indicator		Order	
Symbol	Name	Acad	Mat
SCMI 1	Primary energy consumption	7	4
SCMI 3	Water consumption	9	6
SCMI 4.01	Pre-consumer recycled & waste material	8	5
SCMI 4.02	Post-consumer recycled & waster material	6	3
SCMI 20.1	Air Permeability	1	1
SCMI 28	Global warming potential	3	8
SCMI 30.02	Acidification potential – aquatic	4	9
SCMI 31.01	Eutrophication potential – terrestrial	2	7
SCMI 34	Human toxicity potential	5	10
SCMI 40	Production cost	10	2

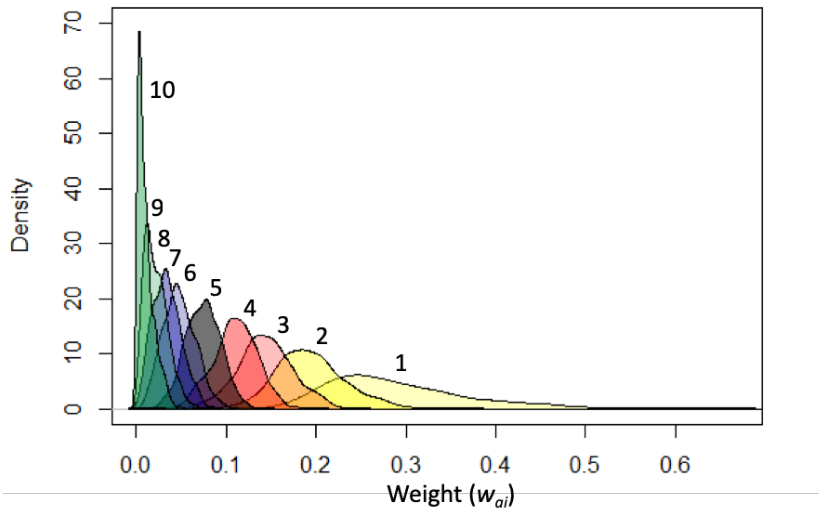


Figure 7.1 Distribution of the randomly sampled weights of the indicators according to the order of importance

For the calculation of the indicator's individual value, the methods discussed in Chapters 3, 4 and 5 were followed and the results are reflected in Table 7.3. The normalized indicator values using statistical standardization are also reflected in Table 7.3 shown in parenthesis. The Pearson's correlation between the indicators is shown in Table 7.4, showing the high degree of correlation between the indicators, which would require PCA to decorrelate them. In addition, Case 1 and Case 2 were developed using 3 and 1 principal components from PCA, respectively.

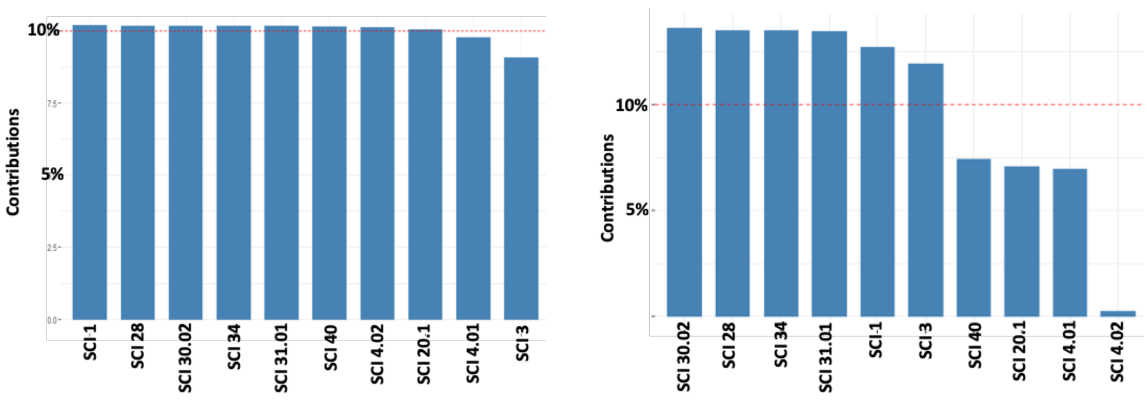
Table 7.3 Raw and normalized indicator values of indicators for DW

Mixes	Indicators									
	SCMI 1	SC135MI 3	SCMI 4.01	SCMI 4.02	SCMI 20.1	SCMI 28	SCMI 30.02	SCMI 31.01	SCMI 34	SCMI 40
S1	1.266 (0.334)	171 (0.340)	0 (0.287)	0 (0.407)	3.995 (0.338)	268 (0.315)	0.431 (0.310)	0.070 (0.314)	0.652 (0.314)	5804.95 (0.336)
S2	0.961 (0.536)	135 (0.570)	225 (0.541)	0 (0.407)	2.413 (0.654)	182 (0.539)	0.292 (0.539)	0.047 (0.543)	0.434 (0.542)	5510.14 (0.420)
S3	0.963 (0.535)	135 (0.570)	225 (0.541)	478 (0.524)	2.744 (0.588)	182 (0.539)	0.292 (0.540)	0.047 (0.539)	0.438 (0.539)	5101.62 (0.535)
S4	0.965 (0.534)	135 (0.570)	225 (0.541)	957 (0.641)	3.351 (0.466)	182 (0.539)	0.291 (0.541)	0.047 (0.535)	0.441 (0.535)	4695.04 (0.650)
S5	0.795 (0.647)	135 (0.570)	180 (0.491)	0 (0.407)	3.232 (0.490)	147 (0.631)	0.238 (0.627)	0.038 (0.631)	0.350 (0.631)	5031.20 (0.555)
S6	1.146 (0.414)	165 (0.379)	275 (0.598)	856 (0.616)	3.363 (0.464)	221 (0.437)	0.350 (0.444)	0.057 (0.438)	0.533 (0.439)	5209.97 (0.504)

Table 7.4 Pearson's correlation of the indicators used in DW

	SCMI 1	SC135MI 3	SCMI 4.01	SCMI 4.02	SCMI 20.1	SCMI 28	SCMI 30.02	SCMI 31.01	SCMI 34	SCMI 40
SCMI 1	1.00									
SCMI 3	0.91	1.00								
SCMI 4.01	0.50	0.50	1.00							
SCMI 4.02	-0.10	-0.01	0.58	1.00						
SCMI 20.1	0.60	0.74	0.66	-0.09	1.00					
SCMI 28	0.99	0.91	0.62	0.01	0.65	1.00				
SCMI 30.02	0.98	0.91	0.64	0.04	0.66	1.00	1.00			
SCMI 31.01	0.99	0.91	0.62	0.00	0.66	1.00	1.00	1.00		
SCMI 34	0.99	0.91	0.62	0.00	0.66	1.00	1.00	1.00	1.00	
SCMI 40	0.64	0.61	0.65	0.67	0.19	0.69	0.70	0.68	0.68	1.00

Figure 7.2 shows how individual indicators in each Case contribute to the total variance. In Figure 7.2a, all indicators almost uniformly contribute to the total variance, while in Figure 7.2b the indicators contribution are highly unequal. The PCA weights based on Case 1 and Case 2 representing the w_{bi} in Eq. 7.1 are plotted in Figure 7.3. From this figure, for Case 1 indicators, such as SCMI 28, 30.02, 31.01 and 34 received the highest weights based on PCA. The weights for Case 1 are fairly uniform, with SCMI 40.02 awarded the highest weight. The weight for Case 1 is just reflective of the degree of correlation between the indicators. The PCA weights for Case 2, on the other hand, almost directly correlates with the indicator's contribution to the output variance.



(a) Case 1 (b) Case 2

Figure 7.2 Contribution of indicators to the total variance.

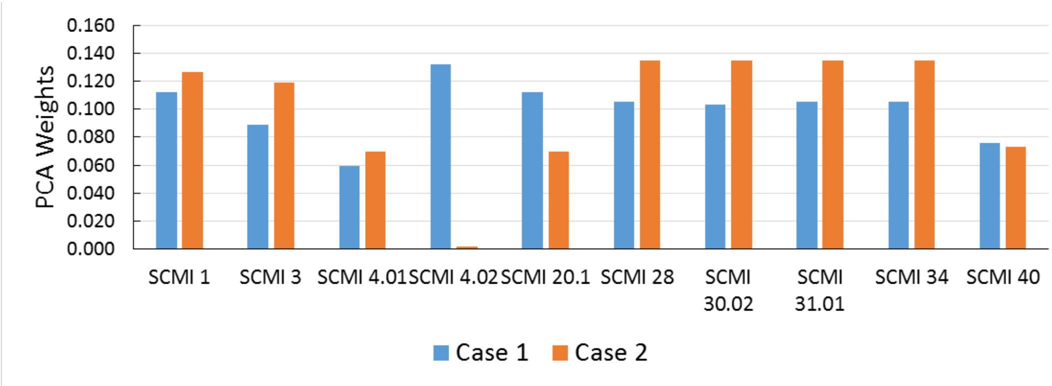


Figure 7.3 PCA weights calculated for Case 1 and Case 2

In the multicriteria analysis performed in this exploratory work, to isolate the effect of the use of DW, only one indicator set was used (Table 7.2), the normalization method was statistical standardization and the aggregation approach applied was linear sum. For the weighting, both single weighting (from stakeholders) and DW were used for comparative analysis.

(2) Discussion

DWs were obtained by multiplying the randomly sampled 1000 sets of weights in Figure 7.1 by the PCA weights in Figure 7.3 and then normalized as in Eq. 7.1. The results of the application of DW to both Case 1 and Case 2 in the multicriteria analysis are illustrated in Figure 7.4 for both Acad and Mat. Applying DWs for Case 1 barely affect the distribution of the sustainability scores for both Acad and Mat. This is supported by the small average Kolmogorov-Smirnov (KS) distance (Figure 7.4) in both Acad and Mat, meaning the corresponding distributions after applying DW are not significantly different. This result also suggests that when the indicators uniformly contribute to the total variance, there is no immediate need to compensate for the data structure. The sustainability scores of the mixes, in this case, is governed only by the importance order.

When DWs are applied to Case 2 (Figure 7.4), on the other hand, significant changes in the shape and spread on the distribution of the sustainability scores are observed. For some mixes in Case 2, the distribution shift substantially, i.e., S6 to S6DW in Figure 7.4 for Acad and Mat. This is further supported by a higher average KS distance in both Acad and Mat in Figure 7.4 than in Case 1. For Case 2, therefore, the sustainability scores are jointly governed by the effect of both importance and the application of PCA weights to compensate for data overlap.

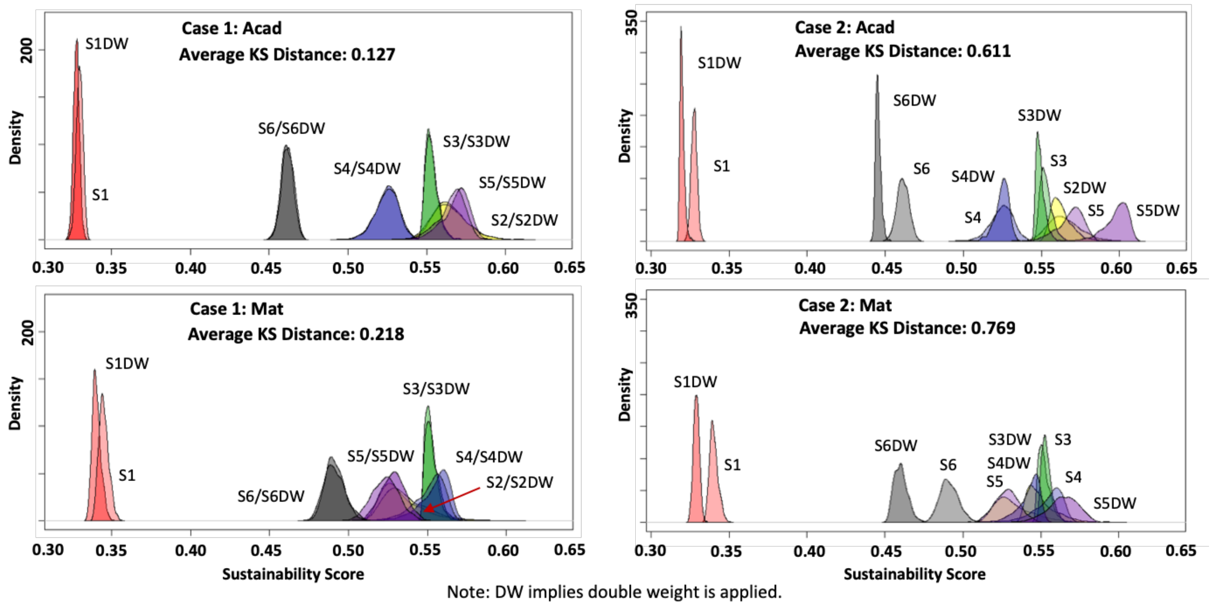


Figure 7.4 Distribution of the sustainability scores when applying DW for Acad and Mat in Case 1 and Case 2

7.2.4 Concluding remarks

The use of double weighting to compensate for the data structure in a multicriteria evaluation has been shown to have some effect on the resulting sustainability scores of the mixes being compared. This is beneficial for situations when high correlations between indicators cause data overlap. However, the effect of double weighting has varying effect, depending on the data structure – particularly on how the individual indicator contributes to the total variance. When the indicators' contribution is relatively uniform, the effect of double weighting seems not very significant. On the other hand, when there is an imbalance between the individual indicators' contribution to the total variance, the effect of double weighting becomes significant. Therefore, in such cases, applying double weighting for sustainability evaluation should be considered.

7.3 Application of modeling and decision tools for the design of sustainable concrete materials.

7.3.1 Motivation of the work

There are two caveats of the of multicriteria analysis that motivated this exploratory work: methodological multiplicity and its limited exploratory power. The first caveat refers to the menu of available multicriteria methods in literature – each with differing structural assumptions – to operationalize sustainability evaluations as presented in Chapter 6 and 7. This has been extensively addressed in the preceding Chapters – Chapter 5 in particular. The conventional multicriteria analysis, however, is very restrictive in that it could only investigate limited number of points (i.e., a number of concrete mixes as demonstrated in Chapter 6. Its exploratory power diminishes – the second caveat – when involving continuous variables (i.e., range of water-binder (W/B) ratio). Multicriteria analysis, for example, only ranks a number of concrete mixes in order based on the sustainability score so that the relatively "best" alternative(s) can be selected directly by decision makers. Since only few mixes are included in this ranking, there is a possibility that the true maximum (or minimum), or the optimum sustainability score, within the continuum of the analytical domain is missed.

In this Section, to tackle the two major caveats mentioned – especially the second – the use of an additional analytical tool is introduced – the application of response surface methodology (RSM) – to extend the concrete sustainability evaluation to an exploratory type of analysis. RSM is an appropriate approach to perform exploratory investigations because of its model fitting capability. RSM is combined with the multicriteria analysis under methodological uncertainties in this Section.

The results of the multicriteria analysis with UA for a number of concrete mixes are used as inputs to RSM to form emperical models that illustrate a continuous trend of sustainability scores within the domain of the variables investigated. Further, the RSM models allow making numerical inferences of the values of any point within the analytical domain, including the determination of optimum values, therefore, making concrete sustainability evaluation not only robust but also exploratory.

7.3.2 Methodological approach

Figure 7.5 shows the general analytical method employed followed in this Section. The multicriteria analysis under methodological uncertainty (Phase I) is performed first. The output of Phase I is used for response surface modeling (Phase II), wherein the empirical equations of the desired responses are generated (Phase III). These equations are then used for numerical optimization (Phase IV). The following discussions further detail Phases I and II, while Phases III and IV are illustrated in the demonstration.

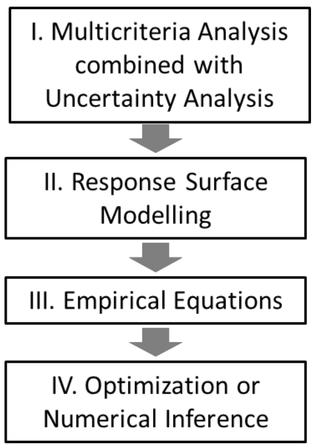


Figure 7.5 General analytical method

(1) Phase I

The multicriteria analysis used in this section have the same methodological approach discussed in Chapter 5. The structure followed in the below analysis is reflected in the methodological map in Figure 7.6. This figure maps all the considered methodological combinations representing *methodological uncertainty* in MA. The sustainability score is made stochastic by the propagation of the methodological uncertainties using uncertainty analysis. To propagate the uncertainties from these stages, multiple sustainability evaluations must be performed by using all possible methodological combinations in Figure 7.6 and returning the sustainability score of each concrete mix alternatives per evaluation.

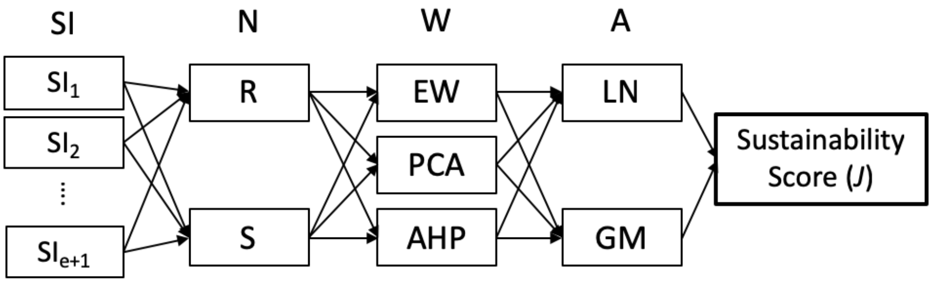


Figure 7.6 Map of methodological combinations

The values of J for each evaluation have been rescaled from 0 to 100 to neutralize the scale effect of the non-equivalent methods. A distribution of J values can then be obtained, which is used to create its probability density function (PDF) – the output of UA. Several statistics can then be computed from the PDF, such as measures of central tendency, measures of variability, and the probabilities. The following analysis, however, focus only on the minimum (J_{min}), average (J_{ave}), and maximum (J_{max}) sustainability scores, as well as the standard deviation (SD) of J obtained from the PDFs because these are the minimum requirements for making statistical inferences about the behavior of an exploratory point within the analytical domain.

(2) Phase II (and parts of II and IV)

Phase II can be performed using the architecture of response surface methodology. RSM consists of a series of mathematical and statistical techniques to devise an empirical equation (Simon, 2003) – a series of polynomial terms – of the response of interest (or the dependent variable, i.e., sustainability score) as a function of the factors (or independent variables, i.e., W/B and recycled aggregate replacements) for Phase II and III. This response model can be represented graphically as a surface, hence the name "response surface." Since the response is defined mathematically, numerical (or graphical) optimization is possible (Phase IV). RSM was performed using the Design Expert 11 software. Four response surfaces can be devised based on the PDFs generated from the results of UA by using the minimum (J_{min}), average (J_{ave}), maximum (J_{max}) and standard deviation (SD) values of each concrete mix. J_{min}, J_{ave}, and J_{max} define the range of the possible sustainability scores within the analytical space, while *SD* estimates the variability of *Y* at a particular point of interest.

7.3.3 Demonstration works

(1) Analytical Set-up

The data used to demonstrate how to perform exploratory sustainability evaluation with RSM under methodological uncertainty was sourced from (Henry and Kato, 2011), which investigates two experimental variables or factors: (1) effect of replacing natural aggregates with low-grade recycled aggregates (RA) at various percentages (0%, 50%, 100%), and (2) the effect of varying W/B (0.30, 0.375, 0.45). The mix proportion is reproduced in Table 7.5 for convenience. Ten concrete mixes (including the control) created from the combinations of RA and W/B were evaluated for sustainability by multicriteria analysis. In the source paper, time dependent values (i.e., compressive strength, Young's modulus, and air permeability) were reported at several curing periods (i.e., 28 and 91 days). In this analysis, however, only the 28-day curing period value of the time dependent properties was used, as this is the standard minimum curing period required to define concrete quality. The nomenclature used to identity the concrete mixes in the source paper is also adopted here for direct referencing of values.

Table 7.5 Mix proportion of concrete mixes for RSM exploratory work

Alternatives	Mix Proportion (kg/m^3)					
	W	C	FA	S	NA	RA
Control	171	342	0	746	1015	0
WB30-RA0	135	225	225	659	1067	0
WB30-RA50	135	225	225	659	533	478
WB30-RA100	135	225	225	659	0	957
WB375-RA0	135	180	180	721	1095	0
WB375-RA50	135	180	180	721	548	491
WB375-RA100	135	180	180	721	0	982
WB45-RA0	135	150	150	772	1103	0
WB45-RA50	135	150	150	772	552	500
WB45-RA100	135	150	150	772	0	999

On the other hand, the indicators used for sustainability evaluation were pre-selected from the list in Table A.1 in Appendix A. In summary, 18 sustainability indicators (Table 7.6) were utilized, which reflect a combination of mechanical performance, environmental emissions and impacts, and economic cost. The value of each indicator is computed for 1 m^3 functional unit of concrete, as described in Chapter 3 and Chapter 6 in this manuscript. Their indicator raw values are reported in Table 7.7.

Table 7.6 The selected indicators for RSM exploratory work

Indicator Name	Unit
SCMI 2	kg/m^3
SCMI 3	kg/m^3
SCMI 4	kg/m^3
SCMI 5	kg-CO_2/m^3
SCMI 6	kg-SOx/m^3
SCMI 7	kg-NOx/m^3
SCMI 8	kg-PM/m^3
SCMI 17.01	MPa
SCMI 17.04	N/mm^2
SCMI 23	Monetary
SCMI 25	Monetary
SCMI 28	Tons CO_2 eq.
SCMI 29	kg-C_2H_4 eq.
SCMI 30	kg-SO_2 eq.
SCMI 31	kg-PO_4 eq./m3
SCMI 34	kg 1.4-Dichlorobenzene eq.
SCMI 37	kN-m
SCMI 40	Monetary

Table 7.7 Raw values of the SCMI used in the RSM exploratory work

Mixes	SCMI																
	2	3	4	5	6	7	8	17.01	17.04	23	25	28	29	30	31	34	37	40
Control	2103	171	0	268	0.054	0.539	0.015	42.4	35.4	5805.0	0.0	268	0.018	0.431	0.070	0.652	41.02	5805.0
WB30-RA0	1951	135	225	182	0.041	0.359	0.011	47.5	33.2	4610.1	900.0	182	0.012	0.292	0.047	0.434	47.45	5510.1
WB30-RA50	1417	135	703	182	0.038	0.357	0.014	47.5	30.3	3905.3	1196.4	182	0.012	0.288	0.046	0.432	49.07	5101.6
WB30-RA100	884	135	1182	182	0.036	0.355	0.016	40.5	25.5	3201.7	1493.3	182	0.012	0.284	0.046	0.430	44.27	4695.0
WB375-RA0	1996	135	180	147	0.036	0.289	0.010	40.4	30.9	4311.2	720.0	147	0.010	0.238	0.038	0.350	41.09	5031.2
WB375-RA50	1449	135	671	147	0.033	0.287	0.012	31.8	26.5	3589.2	1024.4	147	0.010	0.234	0.037	0.348	33.21	4613.6
WB375-RA100	901	135	1162	147	0.031	0.286	0.015	31	23.9	2865.8	1328.8	147	0.009	0.230	0.037	0.346	33.55	4194.6
WB45-RA0	2025	135	150	124	0.033	0.243	0.009	27.4	27.5	4112.8	600.0	124	0.008	0.202	0.032	0.294	27.05	4712.8
WB45-RA50	1474	135	645	124	0.030	0.241	0.011	25.7	26.1	3385.5	906.9	124	0.008	0.199	0.031	0.292	25.63	4292.4
WB45-RA100	922	135	1139	124	0.027	0.239	0.014	23	22.8	2656.9	1213.2	124	0.008	0.195	0.031	0.290	22.86	3870.0

To operationalize the steps of the multicriteria analysis, the normalized values for R and S are computed as shown in Table 7.8 with values for S in parenthesis. For the R approach, the indicators value of the control mix was used as the reference for normalization. The corresponding average weights applied to each indicator are also reflected in Figure 7.7 for the three weighting approaches used. Appendix D shows the numerical values of the weights of each SCMI per indicator set.

By performing multiple sustainability evaluation following the methodological combinations in Figure 7.6, the uncertainties from the stages of multicriteria analysis are propagated. The concrete mixes were evaluated for sustainability using 19 *sets* of indicators created from 18 indicators by alternatively dropping one indicator-at-a-time (see Table 7.6) to simulate the natural inconsistency of indicator sets. Overall 228 methodological combinations were used for sustainability evaluation.

Table 7.8 Normalized values of the SCMI used in the RSM exploratory work

Mixes	Normalized SCMI values using R and S (in parenthesis)																	
	2	3	4	5	6	7	8	17.01	17.04	23	25	28	29	30	31	34	37	40
Control	1.00 (0.37)	1.00 (0.20)	1.00 (0.34)	1.00 (0.25)	1.00 (0.25)	1.00 (0.25)	1.00 (0.39)	1.00 (0.58)	1.00 (0.68)	1.00 (0.28)	1.00 (0.73)	1.00 (0.25)	1.00 (0.24)	1.00 (0.24)	1.00 (0.24)	1.00 (0.24)	1.00 (0.55)	1.00 (0.32)
WB30-RA0	1.07 (0.41)	1.21 (0.53)	1.11 (0.41)	1.25 (0.45)	1.25 (0.43)	1.33 (0.45)	1.26 (0.56)	1.12 (0.64)	0.94 (0.63)	1.21 (0.41)	0.84 (0.51)	1.32 (0.45)	1.32 (0.45)	1.32 (0.45)	1.33 (0.45)	1.33 (0.45)	1.16 (0.62)	1.05 (0.37)
WB30-RA50	1.33 (0.52)	1.21 (0.53)	1.33 (0.52)	1.29 (0.45)	1.29 (0.47)	1.34 (0.46)	1.11 (0.46)	1.12 (0.64)	0.86 (0.55)	1.33 (0.49)	0.79 (0.44)	1.32 (0.45)	1.33 (0.46)	1.33 (0.46)	1.34 (0.46)	1.34 (0.46)	1.20 (0.64)	1.12 (0.44)
WB30-RA100	1.58 (0.64)	1.21 (0.53)	1.56 (0.63)	1.34 (0.45)	1.34 (0.50)	1.34 (0.46)	0.95 (0.35)	0.96 (0.56)	0.72 (0.43)	1.45 (0.57)	0.74 (0.36)	1.32 (0.45)	1.34 (0.46)	1.34 (0.46)	1.34 (0.46)	1.34 (0.46)	1.08 (0.59)	1.19 (0.52)
WB375-RA0	1.05 (0.40)	1.21 (0.53)	1.09 (0.40)	1.34 (0.54)	1.34 (0.50)	1.46 (0.54)	1.36 (0.63)	0.95 (0.56)	0.87 (0.57)	1.26 (0.45)	0.88 (0.55)	1.45 (0.54)	1.44 (0.53)	1.45 (0.53)	1.46 (0.54)	1.46 (0.54)	1.00 (0.55)	1.13 (0.46)
WB375-RA50	1.31 (0.51)	1.21 (0.53)	1.32 (0.52)	1.39 (0.54)	1.39 (0.54)	1.47 (0.54)	1.20 (0.52)	0.75 (0.45)	0.75 (0.46)	1.38 (0.53)	0.82 (0.48)	1.45 (0.54)	1.45 (0.54)	1.46 (0.54)	1.47 (0.54)	1.47 (0.54)	0.81 (0.46)	1.21 (0.53)
WB375-RA100	1.57 (0.63)	1.21 (0.53)	1.55 (0.63)	1.44 (0.54)	1.44 (0.57)	1.47 (0.54)	1.04 (0.41)	0.73 (0.45)	0.67 (0.39)	1.51 (0.61)	0.77 (0.40)	1.45 (0.54)	1.47 (0.54)	1.47 (0.54)	1.47 (0.54)	1.47 (0.54)	0.82 (0.47)	1.28 (0.60)
WB45-RA0	1.04 (0.39)	1.21 (0.53)	1.07 (0.39)	1.40 (0.59)	1.40 (0.55)	1.55 (0.59)	1.43 (0.67)	0.65 (0.40)	0.78 (0.48)	1.29 (0.47)	0.90 (0.58)	1.54 (0.59)	1.53 (0.58)	1.53 (0.58)	1.55 (0.59)	1.55 (0.59)	0.66 (0.39)	1.19 (0.51)
WB45-RA50	1.30 (0.51)	1.21 (0.53)	1.31 (0.51)	1.45 (0.59)	1.45 (0.58)	1.55 (0.59)	1.27 (0.56)	0.61 (0.38)	0.74 (0.45)	1.42 (0.55)	0.84 (0.51)	1.54 (0.59)	1.54 (0.59)	1.54 (0.59)	1.55 (0.59)	1.55 (0.59)	0.62 (0.38)	1.26 (0.59)
WB45-RA100	1.56 (0.63)	1.21 (0.53)	1.54 (0.62)	1.50 (0.59)	1.50 (0.62)	1.56 (0.59)	1.10 (0.46)	0.54 (0.35)	0.64 (0.36)	1.54 (0.63)	0.79 (0.43)	1.54 (0.59)	1.55 (0.60)	1.55 (0.60)	1.56 (0.59)	1.56 (0.59)	0.56 (0.35)	1.33 (0.66)

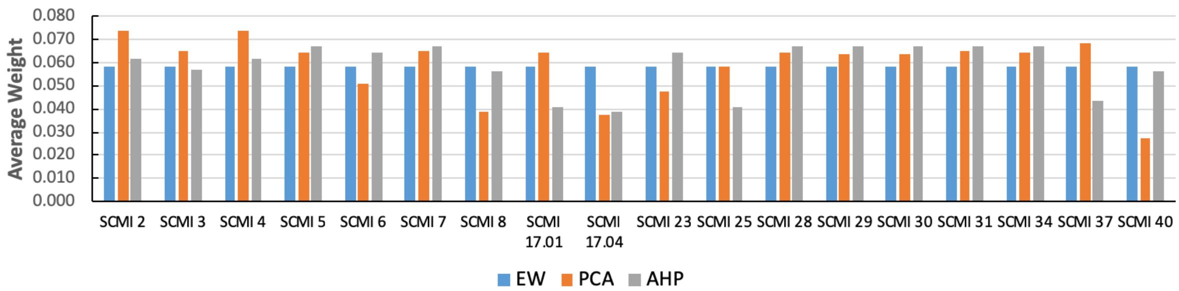


Figure 7.7 Average weights assigned to each indicator by EW, PCA and AHP approach

(2) Discussion

Figure 7.8 shows an example PDF of one of the mixes (WB30-RA50) generated by plotting the result of 228 multicriteria sustainability evaluation simulations. Each concrete mix will have a different PDF, which graphically explains the susceptibility of its sustainability score, *J,* to methodological uncertainties. Performing UA allows for the determination of the minimum and maximum values, which define the range of possible sustainability scores per concrete mix alternative. The summary statistics of the sustainability scores of the 10 concrete mixes after conducting UA is reflected in Table 7.9. From this result, it is clear that the sustainability scores of each concrete mix are not invariant to the methodological changes. The differences in the variance imply that methodological uncertainties affect each concrete mix's sustainability score unevenly, which could be attributed to the inherent disparity of the data of indicators between alternatives. The most affected is WB45-RA100 with sustainability score ranging from 51.26 to 60.85, while the least affected is WB375-RA50. Based on the sustainability scores, however, all alternatives are better than the control mix. The statistics in Table 7.8 were used as inputs for RSM computations.

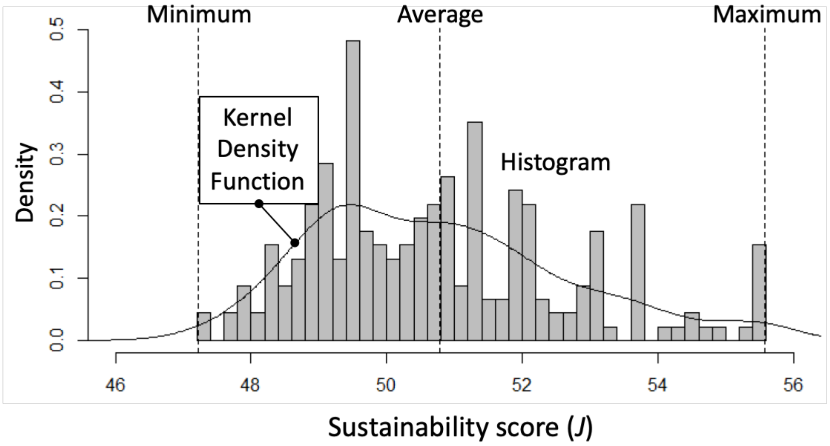


Figure 7.8 Distribution of J values for WB30-RA50

Table 7.9 Summary statistics of the sustainability scores of concrete mixes

Alternatives	Sustainability Score Statistics				
	Minimum	Average	Maximum	Variance	SD
Control	20.34	21.75	23.46	0.533	0.730
WB30-RA0	44.52	47.07	51.89	2.275	1.508
WB30-RA50	47.16	50.33	55.62	4.112	2.028
WB30-RA100	47.21	50.78	55.58	3.476	1.864
WB375-RA0	50.67	53.17	57.76	1.571	1.253
WB375-RA50	52.66	53.40	54.07	0.167	0.409
WB375-RA100	53.69	55.97	57.78	0.732	0.855
WB45-RA0	48.14	53.45	56.91	3.996	1.999
WB45-RA50	52.31	56.33	58.31	2.107	1.452
WB45-RA100	51.26	57.75	60.85	4.314	2.077

Using RSM, on the other hand, the models of the concrete sustainability score responses (J_{min}, J_{ave}, J_{max}) and the estimate model of the variability of sustainability scores, *SD,* are shown in Table 7.10. These models were obtained by adding (or removing) higher order terms from an initial polynomial model (usually linear) and performing f-statistic to measure the significance (p-value) of each term in the model. A term can be removed to simplify the model without substantially affecting the predicting power of the response model based on p-value (e.g., p-value > 0.05) of each term. The response model is accepted if $R^2 > 0.90$ and the adjusted $R^2 > 0.80$. Since these response models are empirical, they are valid only for the region of space being investigated (at RA = [0%, 100%] and W/B = [0.30, 0.45]), and their accuracy is dependent on the number of input points.

The response models in Table 7.10 allow numerical inference of the possible values of the minimum, average, maximum, and the standard deviation of the sustainability score at any point within the analytical space. They also illustrate graphically the trend of J as a function of RA and W/B, as in Figure 7.9, which shows the surface generated for J_{min}. The experimental points are reflected in the response surfaces as filled circular dots. From this surface, it is discernable that the true maximum point (marked with red square) is not part of the original concrete mixes investigated. This local maximum would normally be missed in point analysis. Exploratory analysis, therefore, provides better information so that the important points outside the original test set are identified, making the sustainability evaluation exploratory.

Table 7.10 Response surface models for sustainability scores and the standard deviation

Equation No.	Response	Equation	R^2
Eq. 7.2	J_{min}	$-57.969 + 0.088(RA) + 549.378(W/B) - 0.000585(RA)^2 - 694.519(W/B)^2$	0.9793
Eq. 7.3	J_{ave}	$-2.788 + 0.036(RA) + 251.222(W/B) - 277.630(W/B)^2$	0.9649
Eq. 7.4	J_{max}	$23.491 + 147.567(W/B) + 0.001848(RA)^2 - 160.723(W/B)^2 - 0.0399(RA)^2(W/B)^2 + 0.000021(RA)^3(W/B)^2 + 0.067684(RA)^2(W/B)^3$	0.9997
Eq. 7.5	SD	$5.044 + 0.037(RA) + 0.000651(RA)^2 - 47.779(W/B)^2 - 0.005404(RA)^2(W/B) - 0.3375(RA)(W/B)^2 + 0.010347(RA)^2(W/B)^2 + 364.719(W/B)^5$	0.9927

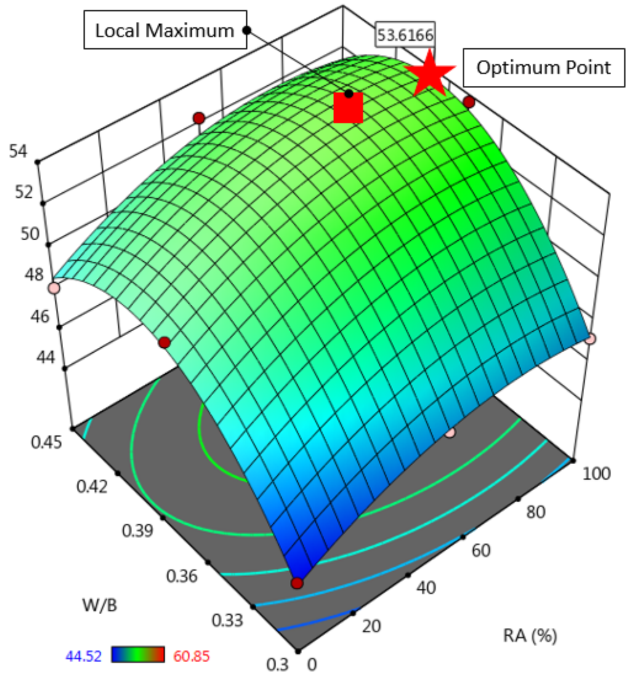


Figure 7.9 Surface plot of J_{min}

Figure 7.10 shows the contour plots of J_{ave}, J_{max}, and SD. Figures 7.9, and 7.10b demarcate the theoretical limits of J but may wrongfully estimate the mean if only both surfaces are used independently. The use of Figure 7.10a helps estimate the location of the mean (expected) value of J but is not enough to describe the randomness of the sustainability scores within the limits defined by J_{min} and J_{max}. Hence, Figure 7.10c, is also equally important to provide an estimate measure of variability or the spread of the J values from the mean of the distribution. Lower SD means that the sustainability scores tend to be close to the mean, while higher SD means the sustainability scores are spread in a much wider range. However, SD alone cannot provide an estimate of J, nor it can define the theoretical limits for J (the minimum or maximum). Therefore, Figures 7.9 and 7.10 should be used jointly to characterize more precisely the random behavior of sustainability score at a particular point, resembling the effect of *methodological uncertainty*.

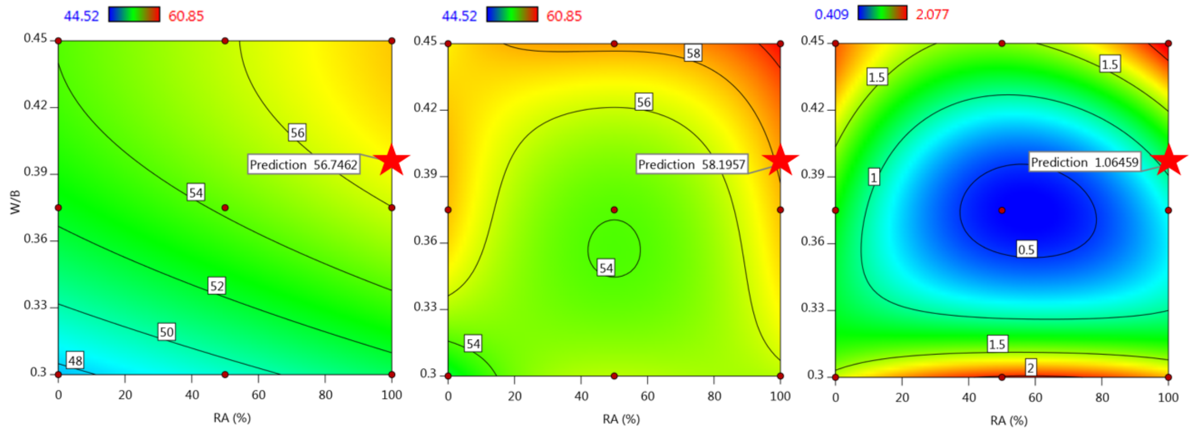


Figure 7.10 Contour plots of (a) J_{ave}, (b) J_{max}, and (c) SD

Important trends can also be observed using the response surfaces, directly linking the experimental variables to the behavior of the sustainability scores. In J_{min} surface (Figure 7.9), for example, it is observable that increasing use of recycle aggregate is beneficial for sustainability but only up to 80% then the benefit starts to diminish. In the same surface (or alternatively using Eq. 7.2), increasing W/B is beneficial only up to 0.38. On the other hand, based on average (Figure 7.10), both the increases in RA and W/B is beneficial for sustainability. For this exploratory investigation, the surfaces generated by Eq. 7.2 to 7.5 in Table 7.10 are highly important because they provide an idea of the randomness of the sustainability score of the concrete mix when the experimental variables are changed continually within the analytical domain.

By optimizing based on a certain predefined criterion, the most sustainable point(s) (or region in the analytical space) can be discovered. In this data set, for example, an analyst might be interested in what point(s) would satisfy if the criterion is to maximize the use of RA within the given range of W/B such that it produces the maximum sustainability score. A numerical optimization can be performed following this criterion because the response models are numerically defined (Table 7.10).

The desired optimization criteria are only applied to J_{min}, J_{ave}, and J_{max} since they estimate the sustainability scores and not to *SD,* as it was used only to describe the variability of J at the located optimum point. Table 7.11 summarizes the results of numerical optimization. The values within the parentheses in Table 7.11 indicate the optimum values of RA and W/B to obtain a maximum Y; otherwise, those without parentheses are the equivalent values of J_{min}, J_{ave}, J_{max}, and SD when the optimum values of RA and W/B are substituted to the other equations in Table 7.10 not used in optimization.

Table 7.11 Optimum points for each response surface models

Response used for Optimization	Numerical Values			RA (%)	W/B	SD
	J_{min}	J_{ave}	J_{max}			
J_{min}	(53.6116)	56.7462	58.1957	(100)	(0.3955)	1.0646
J_{ave}	51.5544	(57.6450)	60.7875	(100)	(0.4500)	2.0770
J_{max}	51.5544	57.6450	(60.7875)	(100)	(0.4500)	2.0770

Table 7.11 shows that, for the same optimization criteria, the optimum points will likely for different response. In this case, however, optimizing on J_{ave} and J_{max}, identified the same optimum point at RA = 100% and W/B = 0.45. Using this location, the equivalent minimum sustainability score is 51.5544, which is lower than the optimum value when using J_{min} with a score of 53.6166. To eradicate the possibility of obtaining a J value less than the optimal minimum value, optimizing using J_{min} surface (or Eq. 7.2) is more desirable. Another way to perform optimization using J_{min}, J_{ave}, and J_{max} is to apply desirability (see Section 7.4). However, for this exploratory work a simple optimization was followed to reduce the complexity of the analysis.

The optimization result (location and value) for J_{min} is marked with a 'star' in Figure 7.9 and 7.10, showing that the desired criteria is achieved by using RA = 100% and W/B = 0.3955. The response models infer the following statistics for this point: minimum = 53.6166, average = 56.7462, maximum = 58.1957, and SD = 1.0646. From these statistics, it is possible to estimate the distribution (similar to Figure 7.8) of this point by using, for example, a truncated normal distribution, as illustrated in Figure 7.11, without again performing multicriteria analysis and uncertainty analysis. Essentially, MA and UA could not be performed for this point because it has no real data in the first place. The normal distribution was selected because of its simplicity for this purpose and its close similarity to the distribution in Figure 7.8; however, other statistical distributions can also be applied (e.g., beta distribution) to obtain the idealized behavior of the sustainability score.

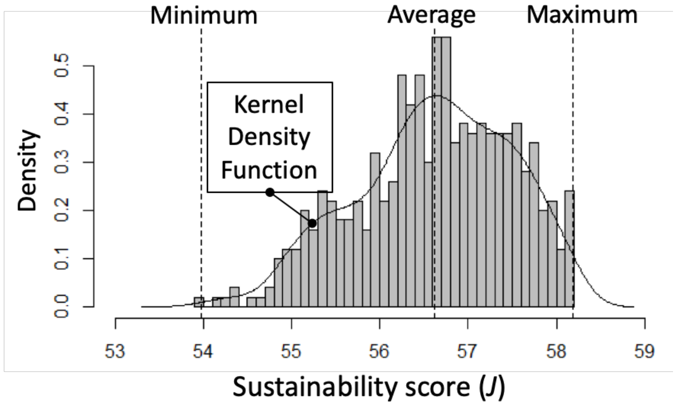


Figure 7.11 Estimated sustainability scores using truncated normal distribution

The estimation of this PDF is important because: (1) it provides the range and the randomness of the behavior of J values at the point of interest, (2) it can help guide future design of experiments and validate the experimental results and, (3) it provides quantitative information on locations without actual experimental data, which may be either too costly or takes longer time to collect to support immediate sustainability decisions.

7.3.4 Concluding remarks

Multicriteria analysis alone is not a robust exploratory method for problems involving continuous variables, such as those usually considered in concrete mix design (i.e., RA and W/B), as it only investigates distinct pre-selected points within the experimental domain. The combination of response surface methodology and uncertainty analysis together illustrates more clearly and continually the behavior of the concrete sustainability score within the experimental domain, leading to the discovery of important points, such as the local maximum or minimum. Numerical optimization is possible with RSM, which is important to locate point(s) that meet pre-determined sustainability criteria for concrete sustainability to guide future experimentations and support actions needing immediate decisions. The combination of multicriteria analysis, uncertainty analysis, and response surface methodology makes the quantitative concrete sustainability evaluation exploratory and robust.

7.4 The trilateral analyses of concrete sustainability

7.4.1 Motivation of the work

The concrete industry is not immune to conversations about sustainability; however, the integration of the concept of sustainability into concrete is still being debated. One of the arguments being put forward is the differences in perspectives on sustainability. Sustainability, for instance, is likely to be taken in the concrete and construction work from a trilateral viewpoint: durability, life cycle cost and resources and environmental impact (Yokota et al., 2016), which somehow mirrors the triple bottom line (TBL) of sustainable development – the environment, economy and society (see Chapter 2). Durability, for instance, presents the social aspect. The environmental impact relates to the environmental sustainability, while the cost represents the economy.

Designing for durability and minimizing concrete defects is one of the most effective way to improve sustainability, making concrete structures last longer (Hooton and Bickley, 2014). Greater durability, however, may also correspond to increases in both cost and environmental impacts (Hooton and Bickley, 2014). Strategies, therefore, are developed to make a compromise between these interrelated perspectives such as modifying the mix proportion by way of using supplementary cementing material (SCM) or recycled aggregates, among others. As a result, selecting the concrete mix that optimally reflects the trilateral viewpoint becomes a challenge.

The use of a composite sustainability index (CSI) is often beneficial in decision-making problems as has illustrated in the previous Chapters. In the case of concrete, for example, scores may be assigned to each viewpoint and then aggregated as a CSI, making comparison of the mix alternatives straightforward. However, defining the individual score of the viewpoints is challenging because of the inherent uncertainties in the estimation of their values. Defining durability, for instance, may be affected by randomly behaving variables (parametric uncertainty) such as construction error, environmental conditions, among others. The cost, itself, may be spatially and temporally dependent. Furthermore, defining the environmental impact is at times method-dependent. Therefore, to use CSI to compare mixes in a robust way, these uncertainties need to be considered.

In light of the above arguments, the objective of this Section is to present a CSI that optimally integrates the trilateral viewpoints on concrete by combing the use of uncertainty analysis (UA) and desirability analysis (DA). The aim of UA is to account the uncertainties in each viewpoint, while DA is used for optimization of multiple responses (King Hing Phoa, and Chen, 2017) – the CSI in this case. The effectiveness of the method in supporting concrete material selection problem is demonstrated by comparing six concrete mixes of similar performance.

7.4.2 Methodological approach

The general outline of the analysis in this Section is as shown in Figure 7.12, showing 3 analytical stages. The first stage concerns about the inputs of the analysis, i.e., the setting of the number of concrete mix alternatives to be compared and the collection of the relevant data for the analysis. The second stage is a trilateral analysis executed in tandem with uncertainty analysis, wherein the 3 viewpoints on concrete sustainability are examined: durability, environmental sustainability and cost. The last stage is the desirability analysis, which aggregates the result of the trilateral analysis to come up with the final CSI. The following subsections detail each analytical stage.

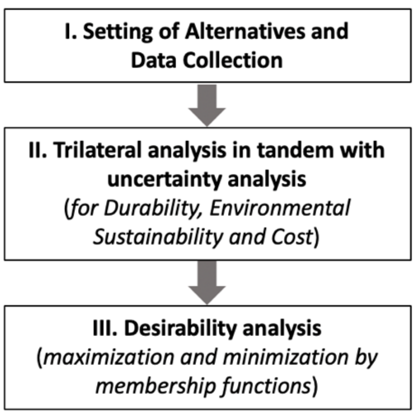


Figure 7.12 Analytical flow

Each of the analytical stages require different input data, in particular the environmental sustainability evaluation requires multiple indicators. The data need to be complete or with missing values imputed appropriately. For the uncertainty analysis, any associated uncertainties of the input (variables or otherwise) should also be defined adequately.

(1) Durability Performance (P_{50})

The durability performance of the concrete mixes is characterized in this analysis by the initiation of steel corrosion, which occurs when the critical threshold of chloride concentration, C_T, is exceeded, as defined by Eq. 7.6 (Akiyama et al., 2012):

$$dC = C_T - X_1\,(C) \qquad \text{Eq. 7.6}$$

Where C is the chloride concentration at a depth c (usually the concrete cover) after t years – usually taken as the designed life – from construction, given the surface chloride concentration, Co, and the chloride diffusion coefficient, D_k. The estimation of C follows the Fick's Law of diffusion, which is expressed in its modified form as in Eq. 7.7 (Akiyama et al., 2012). D_k is estimated using Eq. 7.8 (JSCE, 2017).

$$C{=}X_3Co\left\{1\text{-}\,erf\left(\frac{0.1c}{2\sqrt{X_2D_kt}}\right)\right\} \qquad \text{Eq. 7.7}$$

$$log_{10}D_k{=}\begin{cases}3.0(W/C)\text{-}1.8, & \text{OPC}\\ 3.2(W/C)\text{-}2.4, & \text{BB}\\ 3.0(W/C)\text{-}1.9, & \text{FA-B}\end{cases} \qquad \text{Eq. 7.8}$$

Both Eq. 7.6 and Eq. 7.7 are modified in a sense that they contain coefficients (X_1, X_2 and X_3 adopted from Akiyama et al., 2012), representing the uncertainties associated with the values that behave stochastically. X_1, for example, is the uncertainty associated with the estimation of C, while X_2, is the uncertainty related to D_k. Further, X_3 is the uncertainty associated with Co. The concrete cover, c, is also known to vary due to construction errors. C_T also varies due to several factors including the water-to-cement ratio (W/C) and the type of cement used, which can be estimated by Eq. 7.8 for 0.3 <W/C<0.55 (JSCE, 2017).

$$C_T{=}\begin{cases}\text{-}3.0(W/C)+3.4, & \text{OPC}\\ \text{-}2.6(W/C)+3.1, & \text{BB}\\ \text{-}2.2(W/C)+2.6, & \text{FA-B}\end{cases} \qquad \text{Eq. 7.8}$$

The random variables mentioned can be simplistically represented by a probability distribution function with parameters reflected in Table 7.12. In Table 7.12, Eq. 7.8 defines the mean of the distribution of C_T.

Table 7.12 Parameters of random variables (Akiyama et al., 2012)

Parameter	Distribution	Mean	COV
X_1	Lognormal	1.24	90.6%
X_2	Lognormal	1.89	184%
X_3	Lognormal	1.43	108%
C_T	Normal	See Eq. 7.8	37.5%
c	Normal	Specified + 8.5mm	16.5mm/ (specified + 8.5mm)

UA is concurrently performed to propagate the uncertainties to *dC*. UA in this part of the analysis is done by Monte Carlo experiment, performing *N* (10000 in this paper) number of evaluations of Eq. 7.6 and Eq. 7.7 by using the randomly sampled values of X_1, X_2, X_3, c, and C_T taken within the 95% confidence interval from the mean of the distribution. This limit is set to discount very large values that are reasonably unrealistic. For the succeeding analysis the specified cover is 50mm, Co = 4.5 kg/m^3 and the designed life t = 50 years. The *N* number of simulations create a distribution of *dC*. The final durability performance of concrete is then be expressed as a probability of exceedance defined as $P_{50} = P\,(dC < 0 \,/\, t = 50)$, which can be calculated from the distribution of *dC*. A small value of P_{50} ($0 < P_{50} < 1$) means better durability performance.

(2) Environmental Sustainability Performance (*J*)

The environmental sustainability performance of the concrete mix alternatives is evaluated using a multicriteria analysis (MA), wherein several indicators are used representing the environmental aspects relevant to concrete materials. In the case of the succeeding analysis, the indicators listed in Table 7.13 were used, which were selected from the list in Table A.1 in Appendix A. The calculation of each indicator values from the mix proportion data involves the use of inventory data which transforms, e.g., the amount to cement used to its equivalent global warming potential (GWP). For the detailed description of each indicator and the calculation of their values see Chapter 3 and 6.

Table 7.13 Environmental indicators

Indicator Name	Unit
Energy consumption	MJ/m^3
Raw materials	kg/m^3
Water consumption	kg/m^3
Recycled materials	kg/m^3
Global Warming Potential	Tons CO_2 eq.
Photochemical ozone creation potential	kg-C_2H_4 eq.
Acidification potential	kg-SO_2 eq.
Eutrophication potential	kg-PO_4 eq.
Human toxicity potential	kg 1.4-Dichlorobenze eq.

The MA performed here follows 4 general steps: indicator selection (SI), indicator normalization (N), weighting (W) and aggregation (A). The aim of MA is to assign an aggregated sustainability score (*J*) based on the indicators in Table 7.13 to each alternative. However, the existence of methodological uncertainties affects MA. The other methods considered representing the methodological uncertainty of each MA step are mapped in Figure 7.13.

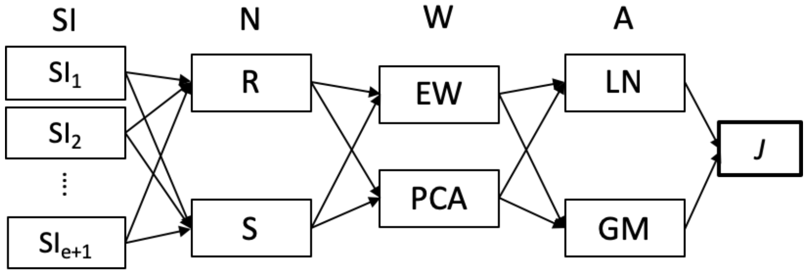


Figure 7.13 Map of methodological combinations

UA is performed for MA similar to a Monte Carlo experiment, in which the steps of MA are executed repeatedly and using a different combination of methods such as those shown in Figure 7.13 in every execution. Because the methods are structurally non-equivalent, the final J values are rescaled from 0-100% (or equivalently 0-1). Depending on the number of executions, a distribution of J is created – similar to that of dC. In the case of J, however, the final sustainability score of each alternative is equated to the mean of the distribution of J as measures of central tendencies (e.g., mean) are often used to represent a distribution as a single value (Barragues et al., 2014). For comparison purposes, it is assumed that the higher the value of J, the better is the environmental sustainability performance.

(3) Cost Performance (Pc)

Cost also plays an important role in the selection of concrete mix among the alternatives. However, cost also behaves randomly as it is affected by market movements such as inflation, affecting the constituent materials' cost. These sources of uncertainties can also be treated and analyzed using UA. In the following analysis, however, the uncertainties associated with unit cost estimation is not considered due to the lack of reliable data at the time of the analysis. In lieu of this, the unit production costs, P_u, for the alternatives from Yokota et al. (2016) were adopted.

The cost performance, P_c, for each alternative is then calculated using Eq. 7.9, which is the relative location of the alternative's unit cost within the theoretical minimum, P_{min}, and the maximum, P_{max}, unit cost. P_{min} and P_{max} is lower and the upper bound of normal distribution created using the mean and standard deviation of the unit costs of the alternatives. This is done because of the lack of reference value upon which to compare the costs. A lower P_c ($0 \leq P_c \leq 1$) implies better cost performance.

$$P_c = \frac{P_u - P_{min}}{P_{max} - P_{min}} \qquad \text{Eq. 7.9}$$

(4) Desirability Analysis

The outputs of the trilateral analysis (P_{50}, J and P_c) are combined by desirability analysis to produce a composite score, *CSI*, for each alternative. Desirability analysis works by transforming each output into their equivalent desirability values and then combines the individual desirability using a geometric mean as in Eq. 7.10.

$$CSI = \prod d_i^{w_i} \;\; ; \;\; i = \{P_{50}, J, P_c\} \qquad \text{Eq. 7.10}$$

The desirability of each trilateral output, d_i ($0 \leq d_i \leq 1$), can be obtained using a membership function which is selected based on the optimization criteria: minimization or maximization. Minimization assigns higher desirability when the output tends toward the minimum attainable value. On the other hand, maximization criterion assigns higher desirability when the output tends toward the maximum attainable value. In the case of P_{50}, J and P_c, the succeeding analysis used quadratic functions to decide the individual desirability of the mixes as shown in Figure 7.14. For both P_{50} and P_c a minimization criterion is used, while for J a maximization criterion is desired.

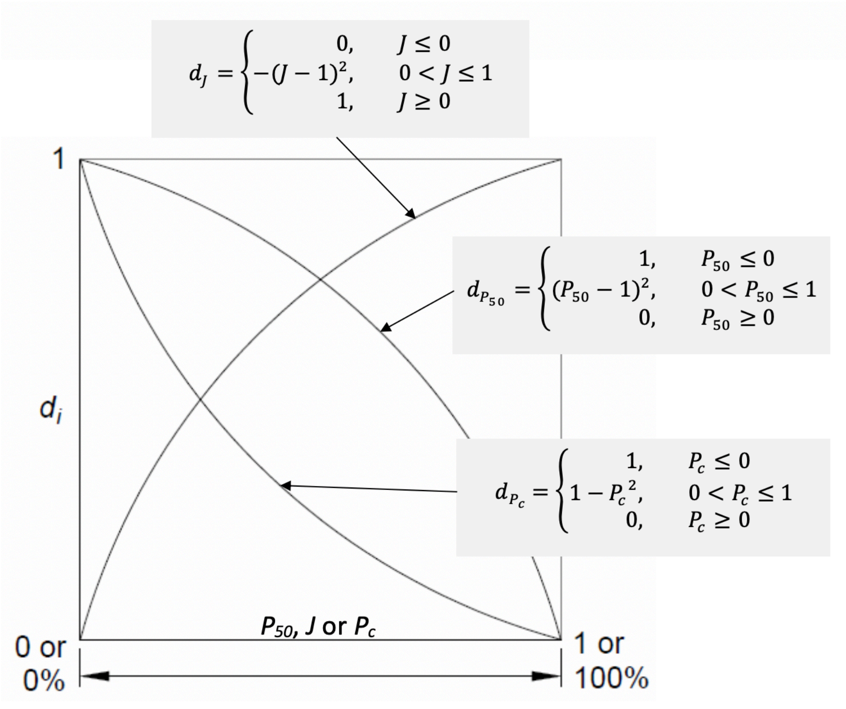


Fig. 7.14 Membership functions for d_i

The concavities of the membership function of P_{50} (upward) and P_c (downward) are different due to the fact that probability scale of P_{50} and the linear scale of P_c are also different. In this case, a slight improvement, or equivalently, a reduction in P_{50} could mean a higher impact on concrete's durability, particularly at the range of $0 \leq P_{50} \leq 0.5$. A small reduction P_c, on the other hand, improves the cost performance only slightly in the range of $0 \leq P_c \leq 0.5$. For, J, a concave downward curve is chosen as improvements in the range of $0.5 \leq J \leq 1.0$ only benefits environmental sustainability very slightly. It is important to note, however, that the selection of the membership functions depends on the goal of the analysis and the optimization criteria. Other curves such as linear, logistics, circular, error function, among others can also be used. The choice of quadratic function for this exploration is due to its simplicity and appropriateness in relation the behavior or the outputs of the trilateral analysis.

The weights assigned to d_i in Eq. 7.10 can be interpreted as importance, in such a way that higher value is assigned to a performance measure perceived as relatively more important than others. In any case $\sum w_i=1$. Since there are no established weights in concrete differentiating the importance of the performance measures, seven weighting scenarios were applied: one applies equal weights to all d_i, another three scenarios place strong emphasis on a particular d_i, and the other three scenarios place equally strong emphasis on two d_is simultaneously. Table 7.14 summarizes the weighting scenarios applied to Eq. 7.10.

Table 7.14 Weighting scenarios

Emphasize Performance	Weights		
	w_{P50}	W_J	w_{Pc}
Equal	0.333	0.333	0.333
P_{50}	0.750	0.125	0.125
P_c	0.125	0.125	0.750
J	0.125	0.750	0.125
$P_{50} = P_c$	0.438	0.125	0.438
$J = P_{50}$	0.438	0.438	0.125
$J = P_c$	0.125	0.438	0.438

The *CSI* ($0\leq CSI\leq 1$) for each weighting scenario can then be used to compare the overall performance of the alternatives. *CSI* that is very close to 0 means one or more performance measure behaves poorly, which is not an acceptable setting. On the other hand, when *CSI* is close to 1, then all performance measures reflect the ideal optimization criteria, implying a good compromise between the performance measures (King Hing Phoa, 2013). The *CSI* can also be used for the relative comparison of the alternatives.

7.4.3 Demonstration works

To demonstrate how the analytical method works, six ready-mix concretes prepared using ordinary Portland cement (OPC), JIS slag cement type B (BB), and JIS fly ash cement type A (FA) were compared. The mixes resemble two distinct groups: one with compressive strength (fc') equal to 30 MPa with water-to-cement ratio (W/C) of approximately 0.50, the other group is with fc' = 40 MPa and the W/C of approximately 0.40. The mix proportions of the mixes adopted from Yokota et al. (2016) is in Table 7.15. The mix proportions became the basis in defining the durability performance assessment, environmental sustainability and the cost. The succeeding analysis is based on 1 m^3 of concrete as the functional unit.

Table 7.15 Mix proportions for the trilateral analysis

Mix	fc'	Unit quantity (kg/m^3)				
		W	C	S	G	Ad
OPC50	30	157	328	783	1071	0.82
OPC40	40	162	411	688	1081	1.03
BB50	30	156	332	764	1076	0.83
BB40	40	156	419	672	1081	1.05
FA50	30	161	290	840	1065	2.90
FA40	40	149	379	735	1081	3.79

(1) Durability performance

The P_{50} of each alternative is evaluated from each distribution; e.g., the distribution for BB50 as shown in Figure 7.15. In this figure, P_{50} is the probability that dC falls within the portion of the distribution marked with yellow ($C_T < C$). For BB50, as an example, the probability that the threshold for chloride concentration for the initiation of steel corrosion will be exceeded within the 50-year designed life is P_{50} = 0.173. It is important to note, however, that there is no established acceptable threshold for P_{50}. The values of P_{50} of the other mixes are evaluated in the same way as BB50 and their values are reflected in Figure 7.16.

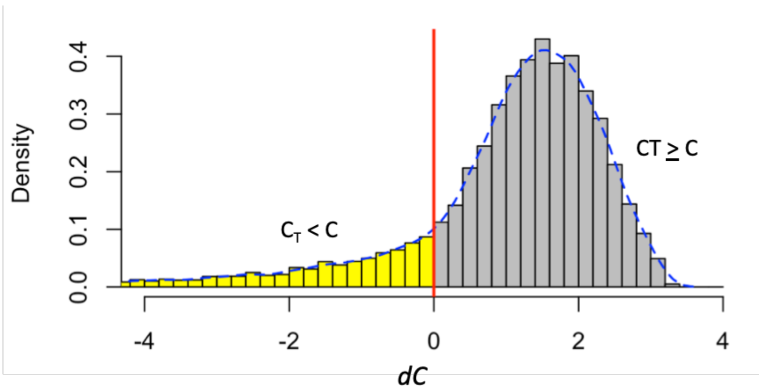


Figure 7.15 Distribution of *dC* for BB50

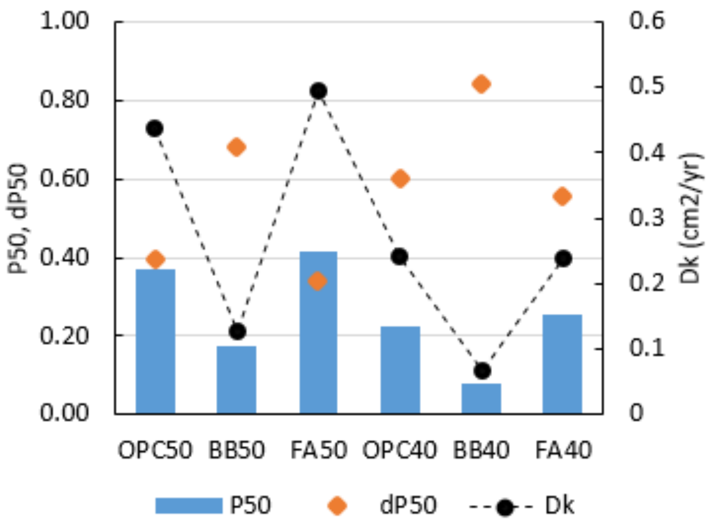


Figure 7.16 Durability performance

In Figure 7.16, it is clear that using different cement type and W/C will result in a different P_{50} values. Among the alternatives, BB40 has the lowest probability of exceeding the C_T in 50 years with P_{50} = 0.081. The differences in P_{50} values of the mixes can be attributed to the differences in their diffusion coefficient, D_k (also shown in Figure 7.16), which is again a function of W/C and cement type. Figure 7.16 further reflects the high correlation between P_{50} and D_k, which means that the influence D_k is high despite the presence of many other stochastic variables in the estimation of P_{50}.

In terms of the desirability score of the individual mixes (d_{P50}), the alternatives with very low P_{50} values are rated as more desirable than others. The desirability of BB40, for example, is the highest amongst the alternatives with d_{P50} = 0.845. This implies the inverse relationship between P_{50} and d_{P50} as a result of the minimization criterion used for the determination of the individual desirability.

(2) Environmental sustainability performance and individual desirability

MA coupled with UA results in a distribution of J; e.g., the distribution for BB50 as shown in Figure 7.17. It is clear from this figure that different methodological approach used for performing MA will result in a variable J. For BB50, the J is marked red in Figure 7.17 equal to 0.6397, which is equivalent to the arithmetic mean of the distribution. The values of the other distributions are obtained in the same way as BB50 and are reflected in Figure 7.18.

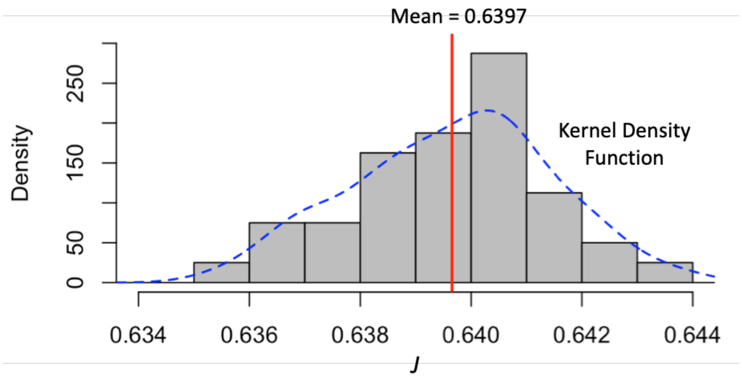


Figure 7.17 Distribution of *J* for BB50

The values of J behave fairly uniformly for the six concrete mixes, ranging from 0.3488 to 0.6397. There is, however, a distinguishable trend reflected between two concrete mix groups. In both groups, mixes using BB has the highest J, followed by mixes using FA-A blended cement, then the mixes using OPC. In the case of BB mixes, the high J values can be attributed to the huge reduction of OPC due to high replacement ratio. This reduction in cement content propagated across all other environmental indicators, particularly the global warming potential because of the high reduction of CO_2 emissions. For mixes using FA, the improvement in J is not solely due to the replacement of cement by fly ash, but because of the substantial reduction of the total cement type FA-A used in the concrete mix. For instance, the amount of cement for OPC50 is higher by 13% compared to FA50 (see Table 7.15). The effect of the reduction in the amount of cement used is also propagated to the other environmental indicators. Nevertheless, amongst the concrete mix alternatives, BB50 has the highest *J* value. In terms of the desirability scores of each concrete mix alternatives, the trend shown by the values of *J* is mirrored in the behavior of d_J, as a consequence of the maximization criterion used and the use of the membership function. There is, therefore, a direct relationship between d_J and *J* values.

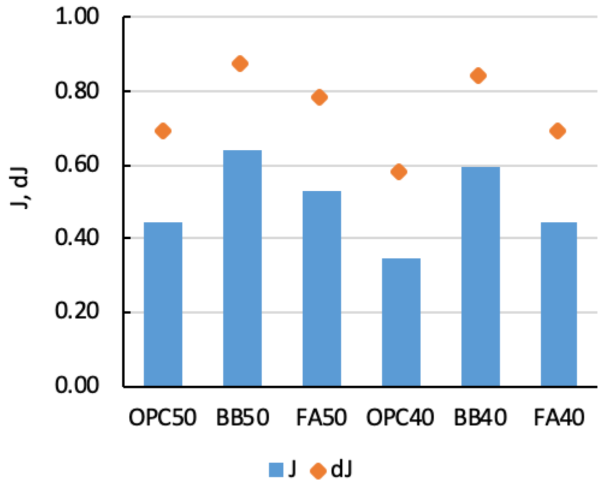


Figure 7.18 Environmental sustainability performance

(3) Cost performance and individual desirability

The relative cost performance of the alternatives is shown in Figure 7.19. In this figure, the distinction between the 30 MPa and the 40 MPa concretes is clear, with the concretes at 30 MPa have lower P_c values. This is only reflective of the difference in W/C ratios between the two groups as lower W/C values mean more cement is required in the matrix, therefore, the higher the cost. The desirability scores, d_{Pc}, on the other hand, shows an inverse trend due to the minimization criterion and the use of the membership function. OPC50 and FA50 are equivalently have good cost performance.

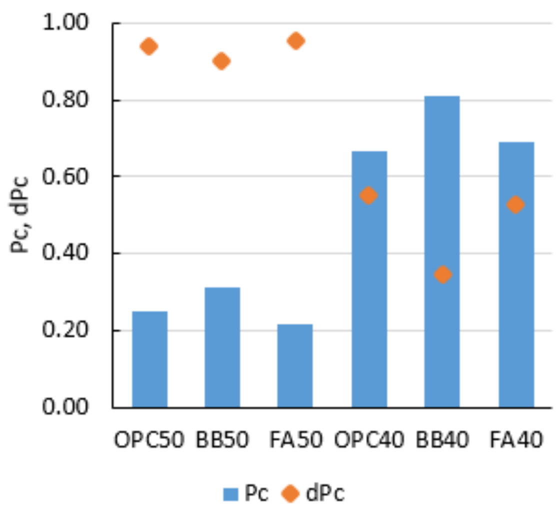


Figure 7.19 Cost performance

(4) Composite sustainability score

The composite sustainability score, CSI, of the alternatives summarized in Figure 7.20 integrates the three viewpoints on concrete sustainability considered in the analysis. Figure 7.20 also illustrates how the different weighting scenarios affect the overall desirability of the alternatives. By treating the P_{50}, J and P_c as equally important, BB50 is the most desirable material with CSI = 0.813, implying a good compromise between the different performance criteria. When placing a high emphasis on durability, BB40 seems to be the most desirable. This is because BB40 also obtained the highest performance in terms of the individual desirability score for durability. By considering different emphasis on assigning weights, BB50 is consistently rank the most desirable, except when durability takes the most weight. However, BB50 is still close to BB40 in that area.

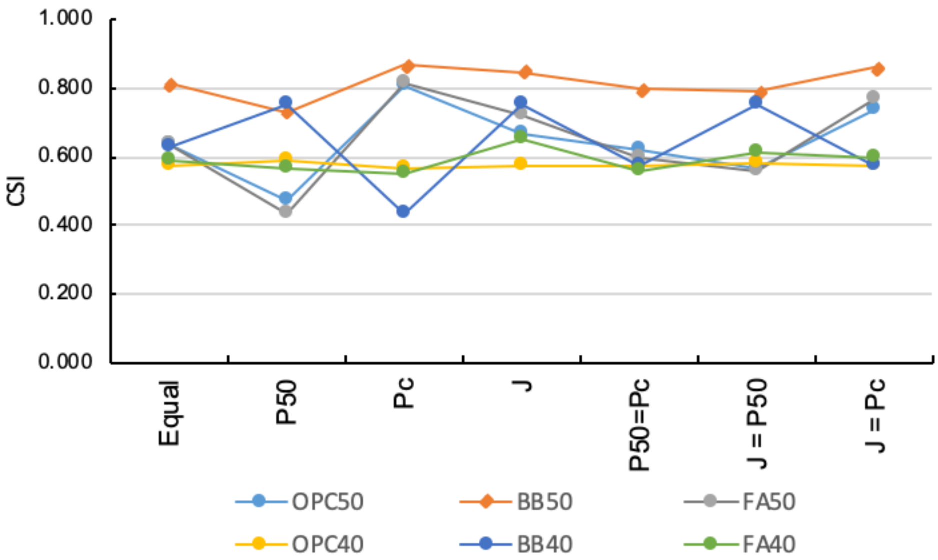


Fig. 7.20 Composite sustainability index

The OPC40 and FA40 is less affected by changes in the weighting scenarios due to their relatively equivalent performance across the three viewpoints. Finally, depending on the goal of the analysis and the perspective of the stakeholders on which weighting scenarios they will adopt, it is easily noticeable from Figure 7.20 that CSI can effectively distinguish the alternatives hierarchically from each other. This distinction ultimately supports the selection problem, whilst considering the uncertainties associated with each sustainability viewpoints, therefore, demonstrating the efficacy of the presented method.

7.4.4 Concluding remarks

Based on the above discussions, it was shown that using a trilateral viewpoint (durability, environmental sustainability and cost) is an effective way of integrating different areas of concern when performing comparative evaluation of the overall sustainability evaluation of concrete materials. By individually focusing on each viewpoint allows the uncertainties associated with their inputs be integrated thoroughly in the analysis. Both the stochastic form of uncertainty in durability performance and the methodological form in environmental performance evaluation were managed by incorporating uncertainty analysis. The use of a composite sustainability index (CSI) following the structure of desirability analysis is an efficient tool for optimization and selection problem. The effectiveness of CSI was fully demonstrated by comparing six mixes, wherein the mixes that provide a good compromise between the trilateral viewpoints are identified, thus supporting sustainable decision making.

7.5 Summary

This Chapter presented three exploratory work directly relevant to sustainability evaluation and multicriteria analytical framework under methodological uncertainties. Three exploratory areas were examined: (1) the use of double weighting as a new weighting approach for multicriteria analysis, (2) the integration of response surface methodology to expand the exploratory limits of the multicriteria analysis, and (3) the use of trilateral viewpoints (durability, cost, and environmental performance) to perform multicriteria analysis. While these works may seem diverse they are aimed to resolves specific issues relevant to the structure of multicriteria analysis in general and on concrete sustainability in particular.

The structure of double weighting (DW) has been shown to efficiently combine two different considerations in the indicator weighting process: the assignment of indicator importance and the data structure. The weights from the data structure have been extracted by principal component analysis, which acts as a correction factor for data overlap on the magnitude of highly correlated indicators. This weight would remove the tendency of double or multiple counting the contribution of an indicator to the final sustainability score, which would ideally provide a way for the importance weight to function as it should. The effect of double weighting has been investigated by considering two data case structures relevant to the total variance: Case 1: where individual indicators contribute fairly uniformly to the total variance, while the other case, Case 2, is where indicators have unequal contribution. It has been shown in the analysis that the effect of double weighting on the sustainability score is very minimal for Case 1, while it is prevalent in Case 2. Double weight, therefore, is found to effectively reflect the structure of the data and can significantly affect the resulting sustainability score of the alternatives.

Exploratory statistical tools such as the response surface methodology (RSM) have also been shown to work well with multicriteria analysis. The integration of RSM led to the identification of optimum points that would normally be missed by a conventional multicriteria analysis, which directly extends the exploratory limits of MA under methodological uncertainties. Inputs from MA and UA defining the variability of the sustainability scores of the alternatives where used in RSM to create spatial empirical models of the experimental variables (in this case the %RA and W/B). The models illustrated a clear continual trend between the sustainability scores and the experimental variables within the analytical domain, and from which critical design points can be extracted by the optimization capability of the RSM. The identification of these points is highly important in validating and designing experiments. Therefore, the integration of RSM to MA and UA makes concrete sustainability evaluation exploratory and robust for modeling applications.

The last exploratory work aimed to resolve various viewpoints about concrete sustainability by performing the sustainability evaluation process in a trilateral perspective. The evaluation was structured by combining three important viewpoints in concrete sustainability (durability, cost, and environmental performance) and their inherent uncertainties. The estimation of the values of these viewpoints is intrinsically uncertain, and thus uncertainty analysis was performed. Durability performance was estimated by considering various stochastic variables. The environmental performance followed the usual structure of multicriteria analysis under methodological uncertainties by considering only environmental related indicators. The cost performance, however, used single value despite being naturally uncertain to some extent due to lack of data. These viewpoints were effectively combined by desirability analysis which assigned a composite score to the alternatives. Few weighting scenarios were also considered, representing the various importance of the viewpoints. It was shown that the weighting scenarios also affect the ordering of the alternatives. This exploratory work has demonstrated that a trilateral viewpoint could be used effectively for sustainability evaluation without disregarding the uncertainties from each viewpoint.

Chapter 8
Limitations of the analytical framework and future directions

8.1 Limitations

8.1.1 Problem formation and forms of uncertainty

The limitations of the sustainability evaluation framework presented in this work in regard to uncertainty can be unfolded into three major areas. First, the framework and its results are ultimately dependent on how the whole analysis is framed – problem formation – involving the selection of methods to represent methodological uncertainties. This limitation is the natural result of the greater subjectivity committed by the researcher from problem formulation, the selection of data, and to the interpretation of the results (Martin, 2015). In the demonstration scenarios, for example, the formulation of the CL and CL* scenarios are is not restricted by the analytical structure, but instead both scenarios rely on the subjective decision, i.e., by the exclusion of some indicators due to data unavailability. The selection of different approaches for UA in general may eventually depend on the level of familiarity of the analyst to these methods (see e.g., Hodgett and Sajid, 2019; Maliene et al., 2018). Considering different approaches and framing assumptions may result in different definitions of the importance of the sources of uncertainty and sensitivity (Saltelli and Tarantola, 2002), affecting factor influence characterization so as to achieve reductions in total output uncertainty (Razavi and Gupta, 2015).

Second, the framework could not process all types of uncertainty analytically. While UA and SA demand that all sources of uncertainties that may lead to the risk of decision-making errors to be modeled explicitly (Paraulo et al., 2013; Zhu et al., 2018); however, this might not be possible with the current approach. The framework only covers model and parametric form of uncertainties that can be measured probabilistically – the reducible forms of uncertainty. Uncertainties arising from partial ignorance about the relevant mechanisms and outcomes or the ‘true uncertainty’, which cannot be measured by probabilistic methods (Ben-Haim and Demertzis, 2015) is not operable using the current framework. Sustainability decisions and policies designed under the assumption of probabilistically measurable uncertainty can lead to serious policy mistakes if the underlying uncertainty is non-probabilistic (Ben-Haim and Demertzis, 2015). Nevertheless, the consideration of uncertainty in the framework for sustainability evaluation will lead to better decisions in the long run than will ignorance of uncertainty (Reckhow, 1994).

The third is a corollary to both the first and second limitations which appertain to the probability measurements to support decisions. Probability measurements from the framework are also affected by knowledge uncertainty and variability over methodological choices. Since uncertainty quantification is fundamental to decision-making (Martin, 2015), imprecise probability measurements resulting from subjective choices may increase decision stakes. On the other hand, while probability provides a measure of uncertainty (Winkler et al., 2014), the probabilities obtained from the framework cannot deal with all sources of uncertainties (see e.g., Regan et al., 2002), hence there is a risk of overestimation or underestimation of the probability values. Therefore, analysts and decision-makers should be prudent about the utilization of sustainability evaluation process and update the inputs whenever new information becomes available.

8.1.2 Hierarchical indicator structure and the weighting process

The SCMI in Chapter 3 is presented in the form of a causal network, which hierarchically organized the indicators into 3 levels of causality. They are, however, used in the analysis linearly in a sense that they are treated within a single hierarchical level. Hierarchical ordering of the indicators such as when higher order latent variables are used, e.g., the use of the pillars or SDGs, will be challenging when directly applied to the analytical structure. This may require applying the analytical framework at various hierarchical level, which would complicate the analysis and may propagate and magnify the effect of uncertainties unintentionally to the higher hierarchical variables.

Hierarchical ordering of indicator may also affect the assignment of weights as this would have complex structural consequences. Assigning weights over to the Pillars or SDGs unequally is also counterproductive as this would mean substitutability between the pillars. Determining the data overlap between higher order indicators such as the pillars may also be difficult, as these are latent variables. Latent variables are not directly observed values but are inferred only from the measured indicators, as such, their values are inherently uncertain. One way to decipher this limitation would be to apply variable analysis such as the use of structural equation modeling tools.

8.2 Future directions

8.2.1 Concrete sustainability

(1) More robust indicator framework

While concrete sustainability is a global challenge for the industry as argued in Chapter 3, it might have regional qualities. Oftentimes regional and/or local solutions may be more effective than enforcing global values in regard to the sustainability. In this vein, the indicator framework for concrete should also be able to reflect regional needs, whilst reflecting the agenda of the global sustainable development. Future structures of an indicator-based concrete sustainability framework may consider the building of a global set of indicators that can be applied across different countries despite the disparity of their regional characteristics. The creation of this global sets of indicators may encourage a homogenized action towards sustainable development within the industry. However, this may require collaborations of various regional organizations on concrete (e.g., ACI, JCI) and related fields, to decide what will constitute this unified global sets of indicators.

On the other hand, countries with specific issues relevant to the sustainability of concrete materials may develop their own regional sets that should be reinforcing to the global set. This would free up some pressures from the local concrete industries in the practice of sustainability so that they can focus more on solving local immediate problems. For example, local industry can focus first on the issue of responsible sourcing of materials then later work on reducing the carbon emissions, rather than handling too many sustainability issues at one time which would economically burden the industry. Local industries may also be limited by the locally available technologies in the practice of sustainability. The creation of an adaptive indicator framework for concrete sustainability comprised of global and local set of indicators may propel a concerted action from various local industry that are ultimately contributory to global sustainable development.

(2) Predicting concrete structure sustainability from concrete material

Developing measurement framework for predicting the concrete structure sustainability from the property of concrete materials would be one direction that can be taken to boost the practice of sustainable development within the industry. Besides the sustainability of material, it is also important to clarify how materials would directly or indirectly contribute to structure sustainability. It may be intuitive, however, that using sustainable materials would naturally contribute to the overall sustainability of structures, but this should be defined in quantitative sense to support possible decision conflicts.

The challenge with the building of this overarching framework is the propagation of uncertainties because of systematic errors as materials and structures are two different systems. Systematic error is the difference between the quantity being measured and the quantity of interest (Morgan and Henrion, 1990). Concrete material sustainability evaluation is already overwhelmed by various sources of uncertainties that are difficult to reduce quantitatively. Using the result from materials could bequeath the structure sustainability evaluation with unwanted uncertainties. However, this type of framework is needed to be developed in the future to bridge the gap between material and structure sustainability evaluation. This will lead to a more comprehensive understanding of concrete material sustainability and may as well result to the formulation of a unified sustainability system for the concrete sector in particular and the construction industry in general.

(3) Setting of reference values

Setting of standardized reference values for concrete material sustainability would greatly help in the quantitative evaluation process. This would allow various actors of the industry to work together within solidly defined targets. For example, defining distinctively the reduction of associated CO_2 emissions from constituent material use (e.g. cement) could be one environmental reference value. Without such setting for concrete may invite additional uncertainties as stakeholders may doubt whether they are actually achieving some sustainability targets or not. On the other hand, the presence of standardize targets would encourage a sense of competition within various proponents of the industry, which could lead to innovations that are ultimately beneficial to sustainable development.

The setting of these standardized reference values for concrete could be derived from the intended nationally determined contributions to various international agreements (e.g., the Paris Agreement for GHG emissions) that are cascaded to different sectors. These values could also be internally determined by the concrete industry based on their level of technology and the consensus of various affected stakeholders, e.g., the cement production sector.

8.2.2 Sustainability evaluation

(1) Increase the robustness of the framework

While the framework introduced in this work is already robust in terms of the treatment of various uncertainties and in supporting decisions, there are still problem areas that needed to be addressed to further increase its robustness. Two areas relevant to the framework need further development: reducing input subjectivity and increase the reliability of probabilistic measurements. Reducing input subjectivity is important to uncertainty propagation and reduction. This, however, is a great challenge as subjectivity is systemic to sustainability. Input uncertainty is due to the lack of rigorous system for validating the applicability of various methodological approaches to be included in the analysis representing multiplicity. Creating a quantitative model validation system for sustainability quantification would be beneficial to reduce input uncertainty. One way to do this is by applying model sensitivities to measure the level of influence of the total output uncertainties.

Increasing the reliability of probabilistic measurements, on the other hand, will increase the robustness of the decision support component of the framework. The integration of state-of-the-art probability extraction approaches such as using Bayesian approaches may provide sharper measurements given the limited amount of input information used for sustainability evaluation. The presented HEPM resembles some Bayesian property as it enables updating the probability of exceedance based on various information. However, this probability measurement needs to be enhanced as it is still internally dependent.

(2) Integration of advanced analytical tools

Integrating new advanced analytical tools from the fields of machine learning (ML) and artificial intelligence (AI) is also one direction that the sustainability evaluation framework presented here can be taken forward. AI and ML algorithms have only been explored recently due to the advancements in these field. However, AI and ML is now slowly explored in various fields such as in natural resources, transportation, built environment, among others (see e.g. Fisher, 2016) to solve the convoluted sustainability problems. Machine learning techniques have the ability to process complex data structure – reminiscent of sustainability construct – and support decisions. Decision making typically involves nontrivial interactions between human and computation (Fisher, 2016) and that the integration of advanced analytics would elevate the robustness of the sustainability evaluation framework.

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Chapter 9
Conclusion

9.1 Thesis summary

The thesis centers on to two major works: the development of an indicator framework for sustainable concrete material and the formulation of a robust sustainability evaluation analytical framework under methodological uncertainties. The purpose of the indicator framework is to formalize in quantitative sense the idea of sustainable concrete to support sustainability evaluations and decision-making processes. The indicator framework helps define distinctively the constituency of sustainable concrete material. It was developed by first identifying potential indicators from various literatures. The characteristics and the inherent relationships between indicators helped the formation of the causal sustainable concrete material indicator framework. The indicators were also link to the global perspectives on sustainable development to make the indicator framework robust for sustainability evaluation purposes. The sustainability evaluation analytical framework, on the other hand, is a methodological approach to make quantitative assessments of sustainability. In order for the indicator framework to be operable, it should be used together with the sustainability evaluation analytical framework. The architecture followed in building the sustainability evaluation analytical framework is the multicriteria analysis under methodological uncertainties. This is to account for the multiplicity of approaches applicable to perform multicriteria analysis, introducing *methodological uncertainties*, which could produce divergent results. To resolve the issue on *methodological uncertainties* the analytics of the sustainability evaluation framework integrates both uncertainty and sensitivity analyses. The practical implementation of both frameworks was demonstrated in the selection problem of various sustainable concrete materials.

9.2 Objectives summary

9.2.1 Sustainable concrete material indicators framework

The first major objective of this research aims to bring down the concept of sustainable concrete into the language of civil engineering, so that it becomes more actionable for the different stakeholders of the concrete sector in particular, and for the construction industry in general. This led to the development of a sustainable concrete material indicators (SCMI) framework, which provides a clear and comprehensive outlook on what constitute sustainable concrete material viewed under the lens of the two global perspectives of sustainable development: the 3 pillars of sustainability and the sustainable development goals (SDGs).

This SCMI framework was built by aggregating the possible sustainability indicators from various literature. In total 65 SCMIs were identified which are all measurable entities. The SCMIs have disparate behavior and measurements (scale and unit), requiring various experimental and/or analytical data to determine their values for sustainability evaluation purposes. The SCMIs are also complexly interrelated, and this internal relationship was used to express them as a causal network comprising of the Driving-force, State, and Impact indicators. The causal form of the SCMI framework is beneficial for indicators selection for quantitative assessments of sustainability and for the identification of focus areas of improvement in regard to sustainable development.

The SCMIs were found to be inherently related to the two global perspectives of sustainable development. In the case of the 3 pillars of sustainability, it was found that there is an unequal distribution of indicators related to each pillar, with the environment pillar having the greatest number of representative indicators. There are also indicators that are multidimensional, in a sense that some SCMIs relate to two or all pillars of sustainability. Similar findings were observed in the case of the SDGs, with SDG 9, 11, and 12 are identified to be strongly associated with the SCMIs. The connection of the SCMIs to the two perspectives of sustainable development elevates their function for sustainable concrete material evaluation and sustainability decision-making processes. The applicability of the SCMI framework for sustainability evaluation was simplistically demonstrated by comparing the sustainability performance of various concrete material in the context of the pillars and the SDGs. The building of the SCMI framework informs various stakeholders of the diversity of sustainable concrete indicators available, providing stakeholders greater flexibility to tackle traditional tradeoffs between ensuring material performance and the practice of sustainability.

9.2.2 Multicriteria sustainability evaluation analytical framework under uncertainties

The second major objective of the research aims to develop a robust sustainability evaluation analytical framework to demonstrate in quantitative way that sustainability is operationalized. This is a challenge for sustainability because of its contextual component that entails various subjective judgements arising from the human values of sustainable development. The research argued that the most effective structure for sustainability evaluation is the multicriteria analysis (MA), which allows the concept of sustainability to be dealt with in mathematical way, whilst accommodating various levels of subjectivities. Therefore, MA was used as the structural backbone in developing the sustainability evaluation framework.

Multicriteria analysis is comprised of: indicator section, data treatment, normalization, weighting and aggregation. Indicator selection sets the extent of the analysis by identifying the relevant criteria (or indicators) for sustainability evaluation. Data treatment ensures the reliability and credibility of the indicator data. Normalization transforms the disparate indicators to a common unit and scale to make them structurally comparable. Weighting assigns importance values to the indicators based on policy preferences or stakeholder decisions. The aggregation stage summarizes the indicators to a composite value so that the analysis could be easily communicated to various stakeholders.

It is discussed in this work, however, that there is a considerable uncertainty – termed as *methodological uncertainty* in this work – with the use of multicriteria analysis because of the multiplicity of non-equivalent approaches to perform each stage, causing output uncertainty. Uncertainty analysis (UA) and sensitivity analysis (SA), therefore, was integrated into the analytical framework to manage and reduce (if possible) the *methodological uncertainties*. UA propagates the uncertainties from the steps of multicriteria analysis to the output, while SA measures the level of influence of the sources of uncertainties to the output. Additional stages such as factor prioritization and fixing were also included, which will determine the potential of a source of uncertainty to be eliminated from the analysis. This, however, must be used alongside statistical measurements such as the Kolmogorov-Smirnov statistics and the DKW inequality bounds to support uncertainty elimination.

The decision component of the analytical framework involves the use of a hierarchical exceedance probability matrix (HEPM) to make comparative assessments of the sustainability performance of various alternatives given the level of uncertainty present in the analysis. The combination of the various analytical components with the stages of MA comprise the multicriteria sustainability evaluation analytical framework under *methodological uncertainties* developed in this work. This evaluation framework can support decision-making and progress assessments in regard to the practice of sustainable development, despite the serious disagreements about methodological choices, making it a robust analytical framework for sustainability evaluation.

9.2.3 Demonstration studies

The last objective of the work is the practical implementation of the SCMI framework and the multicriteria sustainability evaluation analytical framework under methodological uncertainties, which was demonstrated through the comparative sustainability analysis of 6 concrete materials. These concrete mixes were prepared using various material manipulation strategies such as the use of blended cements with supplementary cementitious materials (SCM). The mixes were compared using sustainability a holistic set of indicators selected from the SCMI framework. Three scenarios were created to simulate the effect of environment – which will affect the value of durability indicator – and the issue on missing data. The scenarios are: CL (chloride environment); CB (carbonation environment); CL* (same as CL but with reduced indicators set). CL and CB used a relatively comprehensive indicators set, while CL represents a missing data scenario.

The multicriteria analysis under methodological uncertainties were effectively implemented for each scenario. The methodological uncertainties were characterized by using multiple approaches to each step of MA. The inconsistency of the indicator set was reflected by dropping one indicator at a time. The other steps of MA utilized 2 normalization method, 3 weighting schemes, and 2 aggregation methods. The highly influential sources of uncertainties were identified for each scenario, and in all scenarios, it is the choice of normalization and the weighting scheme. The least influential, on the other hand, is the choice of aggregation, making it a good candidate for factor fixing. Factor fixing was employed for each scenario by fixing the aggregation to either linear (LN) or geometric (GM). It was demonstrated that using KS and DKW statistics is an efficiently way to confirm statistically whether a non-influential source of uncertainty has no significant effect to the result of the analysis when fixed to a certain methodological approach.

The use of hierarchical probability exceedance matrix (HEPM) was also demonstrated to effectively contrast the sustainability performances of the alternatives in each scenario under the presence of uncertainties. CL and CB resulted in the same ordering of the mixes despite the minor differences in the absolute sustainability scores values. In CL vs CL*, some alternatives experienced rank reversal, implying that missing data would significantly affect the sustainability evaluation result. The use of the multicriteria analysis under uncertainties lead to the identification of the “best” sustainable option, which was determined using HEPM. The two frameworks, therefore, together comprise a robust structure in underpinning the theoretical construct of sustainable concrete material that is practical for stakeholders to reach homogenized conclusions and decisions for concrete material sustainability.

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Appendix A

List of sustainable concrete material indicators

Table A.1 The list of sustainable concrete materials indicators

I.D.	Indicator Name	Unit	Sustainability Pillar[a]	SDG		Inventory Data[b]	Expected Indicator Behavior[c]	Brief Description
				Relevant Targets	Most Relevant SDG			
1.01	Primary Energy Consumption (Non-Renewable)	MJ/m^3	All	7.3, 9.4, 12.c	7	Y-R		The amount of primary energy consumed for raw material extraction and manufacturing. The energy sources are disaggregated into non-renewable and renewable. The fuel type can be differentiated into coal, coke, natural gas, electricity, diesel, and waste derived energy sources.
1.02	Primary Energy Consumption (Renewable)	MJ/m^3	All	7.2, 7.3, 9.4	7	Y-R		
2	Consumption of Primary Raw Material	kg/m^3 concrete	All	8.4, 9.4, 12.2, 12.5	12	N		The amount of primary raw constituent materials excluding water, measured as mass per functional unit. The constituent material is differentiated into cement, aggregates (sand & gravel), and chemical admixtures.
3.01	Water Consumption (Material Extraction)	kg/m^3 concrete	All	6.3, 6.4, 8.4, 9.4, 12.2	6	Y-R		The amount of water used in raw material extraction and concrete production; measured in terms of mass of water used per functional unit of concrete.
3.02	Water Consumption (Concrete Production)	kg/m^3 concrete	All	6.3, 6.4, 8.4, 9.4, 12.2	6	N		
4.01	Recovered, Recycled, or Waster Material Content (Pre-consumer)	kg/m^3 concrete	All	6.3, 9.1 11.6, 12.2, 12.5	12	N		The quantity of recovered, recycled, or waste material used in the concrete matrix. Calculated as the total mass of recovered, recycled, or waste material content per functional unit of concrete. Pre-consumer materials may include by-products from other industrial processes such as slag, fly ash, silica fume, and rice-husk ash. Post-consumer materials may include glass and plastic or from demolition wastes such as recycled concrete, bricks and rubble, and may include the washing water. [34]
4.02	Recovered, Recycled, or Waster Material Content (Pre-consumer)	kg/m^3 concrete	All	6.3, 9.1 11.6, 12.2, 12.5	12	N		
5.01	CO_2 emissions (Production)	kg CO_2 equivalent	En	9.4, 13.1, 13.2, 14.3	9	Y-R		The mass of carbon dioxide associated with activities such as production and transportation. Production CO_2 emissions are determined by multiplying the quantity of each constituent materials with the corresponding inventory data and then summed. Transportation CO_2 emissions are dependent on fuel use in vehicles and transport time.
5.02	CO_2 emissions (Transportation)	kg CO_2 equivalent	En	9.4, 13.1, 13.2, 14.3	9	Y-R		

6	SOx emissions	kg SOx/ functional unit	EnSo	3.9, 11.6, 13.2	11	Y-R		Quantifies the sulfur oxides (SOx) emitted when burning fuels, such as coal, oil, heavy oil, kerosene, and natural gas for the operation of cement and concrete manufacturing equipment. It is calculated using inventory data considering the material, manufacture, production, and transportation activities.
7	NOx emissions	kg NOx/ functional unit	EnSo	3.9, 11.6, 13.2	11	Y-R		Quantifies the nitrogen oxides (NOx) emitted by automobiles, trucks and various non-road vehicles (e.g. construction equipment), as well as industrial sources such as power plants, industrial boilers, cement kilns, and turbines. It is calculated from the contributions from production, transportation, and construction activities related to concrete material.
8	Particulate Matter (PM) emissions	kg PM/ functional unit	En	3.4, 3.9, 11.6	11	Y-R		Quantifies the emissions of PM_{10} (inhalable particles with diameters that are generally 10 micrometers and smaller) and $PM_{2.5}$ (fine inhalable particles with diameters that are generally 2.5 micrometers and smaller) which is a mixture of solid particles, and liquid droplets found in the air due to concrete production sources. [61]
9	Other GHG emissions	kg GHG/ functional unit	En	12.4, 13.1, 13.2	12	Y-R		Quantifies other greenhouse gases emitted.
10	Other Acidifying agent emissions	kg/ functional unit	En	2.3, 12.4	12	Y-R		Quantifies other acidifying agents emitted.
11	Other Photochemical Ozone Creation Chemicals	kg/ functional unit	En	2.3, 12.4	12	Y-R		Quantifies other photochemical ozone creation chemicals.
12	Other Eutrophication Substances emissions	kg/ functional unit	En	2.3, 12.4	12	Y-R		Quantifies other nitrifying agents.
13	Other Ozone Depleting Substances	kg/ functional unit	En	12.4	12	Y-R		Quantifies other ozone depleting substances.
14	Toxicans emissions	kg/ functional unit	EnSo	3.9, 9.4, 12.4, 14.1	12	Y-R		Quantifies substances with an ecotoxic effect on species in the ecosystem.
15	Carcinogen content	kg/ functional unit	So	3.9, 12.4	12	Y-R		Quantifies the trace amounts of substances listed as carcinogens by National Toxicity Program (NTP), Occupational Safety and Health Administration (OSHA) and the International Agency for Research on Cancer (IARC).

								For example, IARC listed crystalline silica as a human known carcinogen, a potential trace level contaminant in Portland cement.
16	Ionizing Radioactive Materials Content	kg/ functional unit	So	3.9, 12.4	12	Y-R		Quantities the radioactive materials present in the concrete mix. Sandstone, concrete brick, natural stone, gypsum, and granite contain naturally occurring radioactive elements like radium, uranium, and thorium. The levels of radioactive materials found in building materials are generally very low. [62]
17.01	Mechanical Properties (Compressive Strength)	MPa	SoEc	9.1, 11.1, 11.2	9	N		Measures the mechanical properties of the resulting hardened concrete mix. These properties are relevant to the structural safety of the building elements they form part of. Their values can be obtained experimentally following standardized methodologies, e.g. ASTM and Japan Industrial Standard (JIS).
17.02	Mechanical Properties (Flexural Strength)	MPa	SoEc	9.1, 11.1, 11.2	9	N		
17.03	Mechanical Properties (Tensile Strength)	MPa	SoEc	9.1, 11.1, 11.2	9	N		
17.04	Mechanical Properties (Elastic Modulus)	MPa	SoEc	9.1, 11.1, 11.2	9	N		
18	Thermal Conductivity	W/m-K	So	7.3, 9.1	9	N		Measures the ability of concrete to conduct heat; is also a measure of concrete's thermal capacity; can be measured following BS EN ISO 8990:1996 and BS EN 1934:1998.
19	Specific Heat Capacity	J/kg-K	So	7.3, 9.1	9	N		Describes the concrete thermal property by determining how much mass is needed per unit for one unit increase in temperature of the material.
20.01	Durability (Resistance to Chloride Penetration)	kg/m^3 or Coulombs	SoEc	9.1, 11.1, 11.2, 11.b	11	N		These properties represent the ability of concrete to resist weathering action, chemical attack and abrasion while maintaining its desired engineering properties. The durability measurements are taken experimentally. Durability is the ability to a last long time without significant deterioration. [63]
20.02	Durability (Water Absorption)	kg/m^2-min	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.03	Durability (Resistance to Sulfates)	mm	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.04	Durability (Shrinkage Behavior)	Strain	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.05	Durability (Freeze-Thaw Resistance)	No. of cycles	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.06	Durability (Carbonation)	mm	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.07	Durability (Abrasion	% mass loss	SoEc	9.1, 11.1, 11.2, 11.b	11	N		

	Resistance)							
20.08	Durability (Porosity)	mg/L	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.09	Durability (Scaling)	kg/m^2	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.10	Durability (Air Permeability)	cm/s	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
20.11	Durability (Alkali-Silica Reaction)	-	SoEc	9.1, 11.1, 11.2, 11.b	11	N		
21	Pumpability	-	SoEc	7.3, 8.4, 9.4, 12.2	7	N		Defines the relationship between pressure and volumetric flow when pumping several batches of concrete mix. [64]
22.01	Workability (Slump Flow)	mm	SoEc	7.3, 8.4, 9.4, 12.2	12	N		Describe how easily freshly mixed concrete can be mixed, placed, consolidated and finished with minimal loss of homogeneity, which can be measured experimentally. [65]
22.02	Workability (Slump Loss)	mm	SoEc	7.3, 8.4, 9.4, 12.2	12	N		
23	Cost of Raw Materials	Monetary	Ec	8.4, 9.1, 9.4, 12.2	8	Y-R		Monetary equivalent of the primary raw materials used in the concrete matrix, computed per functional unit.
24	Energy Savings	Monetary	Ec	7.3, 9.4	7	Y-R		Translates the reduction in energy consumption in the production of concrete, due to alternative energy sources and new technology to monetary equivalent.
25	Cost of Waste Materials	Monetary	Ec	8.4, 9.1, 9.4, 12.5	8	Y-R		Monetary equivalent of the recycled, recovered, or waste materials utilized in the matrix.
26	Solid Waste Disposal Cost	Monetary	Ec	8.4, 11.6, 12.2, 12.5, 15.1	12	Y-R		The associated cost of disposing waste due to concrete production.
27.01	Abiotic Depletion Potential (Fossil Resources)	MJ	En	9.4, 12.4	12	Y-S		Assess the net quantity of each raw material used with the reserves of that raw material. [66]
27.02	Abiotic Depletion Potential (Non-fossil Resources)	kg-Antimony eq.	En	9.4, 12.4	12	Y-S		
28	Global Warming Potential (GWP)	tons CO_2 eq.	En	9.4, 13.1, 13.2, 13.a, 14.3	13	Y-S		Describes the integrated impact of different greenhouse gas emissions to global warming. [39]
29	Photochemical Ozone Creation Potential (POCP)	kg C_2H_4 eq.	En	3.4, 3.9, 11.6	11	Y-S		The estimated quantity of photo-oxidant formation in the formation of reactive chemical compounds such as ozone by the action of sunlight on certain primary air pollutants [39]
30.01	Acidification Potential (Terrestrial)	kg SO_2 eq.	En	12.4, 15.3	15	Y-S		Reflect the maximum acidification potential of a substance. Acidifying pollutants have a wide variety of impacts on soil, groundwater, surface waters, biological organisms,
30.02	Acidification Potential (Aquatic)	kg SO_2 eq.	En	6.3, 12.4, 14.1	14	Y-S		

								ecosystems and materials (buildings). [39]
31.01	Eutrophication Potential (Terrestrial)	kg PO_4 eq./m^3	En	2.3, 2.4, 12.4, 14.1, 15.3	2	Y-S		Cover all potential impacts of excessively high environmental levels of macronutrients, the most important of which are nitrogen (N) and phosphorous (P). [39]
31.02	Eutrophication Potential (Aquatic)	kg PO_4 eq./m^3	En	6.3, 12.4, 14.1	14	Y-S		
32	Ozone Depletion Potential (ODP)	kg. CFC-11 eq.	En	12.4, 13.1, 13.2	12	Y-S		Describes the integrated impact of an emission of substance on the ozone layer compared with CFC-11. [39]
33.01	Ecotoxicity Potential (Freshwater)	Kg. 1.4-Dichlorobenzene eq.	En	6.3, 12.4	6	Y-S		Cover the impact of toxic substances on aquatic, terrestrial and sediment ecosystems. The area of protection is the natural environment and natural resources. [39]
33.02	Ecotoxicity Potential (Marine)	Kg. 1.4-Dichlorobenzene eq.	En	12.4, 14.1	14	Y-S		
33.03	Ecotoxicity Potential (Terrestrial)	Kg. 1.4-Dichlorobenzene eq.	En	12.4, 14.1, 15.1, 15.3	15	Y-S		
34	Human Toxicity Potential	Kg. 1.4-Dichlorobenzene eq.	So	3.4, 3.9, 11.6	3	Y-S		Covers the impacts of human health of toxic substances present in the environment. [39]
35	Carcinogens Potential	Kg C_2H_3Cl eq.	So	3.4, 3.9	3	Y-S		Translates the potential to cause cancer of the trace amounts of carcinogens contained in the concrete matrix through inhalation of these substances or other modes of exposures. [39]
36	Ionizing Radiation	Bq C-14 eq.	So	3.4, 3.99.1, 11.1, 11.2, 11.b	3	Y-S		The potential to cause chemical changes in the cells and damage them by ionizing radioactive materials. Depending on the amount of these materials present, they may also cause small increases in radiation levels. [39]
37	Structural Safety	Unit less	So	9.1, 11.1, 11.2, 11.b	11	N		The relative strength of a structural member when using the concrete mix compared to a reference mix.
38	Fire Resistance	-	So	9.1, 11.1	11	N		Measures the effect of temperature increase from the surface of concrete during fire events. [67]
39	Designed Service Life	yrs.	So	9.1, 11.1, 11.2, 11.b	11	N		The expected service life of structure in years when using the concrete mix compared to a reference mix.
40	Production Cost of Concrete	Monetary	Ec	8.4, 9.1, 9.4, 12.2	8	Y-R		The cost of producing a functional unit of concrete.
41	Construction Cost	Monetary	Ec	8.4, 9.4, 12.2	8	Y-R		The estimated cost of using the concrete in actual construction, which may include special equipment, additional pumping effort, consolidation, etc.
42	Maintenance Cost	Monetary	Ec	8.4, 9.4, 12.2	8	Y-R		The relative cost in maintaining the concrete quality to last until the designed life of the structure.

Appendix B
Example of weight extraction by Principal Component Analysis

B.1 Computation environment

Principal component analysis (PCA) were performed in R Software version 3.4.4 using the package `factorextra` and `FactoMineR` authord by A. Kassambara (http://sthda.com) and the `psych` package authored by W. Revelle (https://personality-project.org/r/psych).

B.2 Inputs

In this example, the input use is the set of normalized values by standardization indicator Set 1 of CL scenario. Refer to Chapter 6 for the numerical values of the indicators.

B.3 Results of PCA

The output of PCA are the principal components (PC) associated with eigenvalues indicating the portion of the total variance explained by each component. Table B.1 is the result of PCA for indicator Set 1 for CL scenario. The table only shows 4 principal components, as these are enough to explain the total variance. The value of the eigenvalue was used as the basis for the selection of the number of principal components to be retained in the analysis. As a rule of thumb only those PC with eigenvalues more than 1 or PCs that explained at least 10% of the total variance is retained for rotation (see e.g., OECD, 2008). In this example, only PC1 and PC2 are retained.

Table B.1 Result of the principal component analysis

Principal Component	Eigenvalue	Percent Explained of Total Variance (%)	Cumulative (%)
PC1	12.1	75.8	75.8
PC2	3.32	20.7	96.5
PC3	0.34	2.15	98.6
PC4	0.22	1.35	100.0

B.4 Rotating Principal Components

The two selected PCs were rotated by *varimax* method using `psych` package in R to obtain the indicator loadings to the rotated components (RC). The result of this rotation is shown in Table B.2. Then the squatted of these loadings are calculated (also in Table B.2).

B.5 Computation of weights

Each SCMI is then associated to a single RC based on which rotated component the indicator is loading the most using the magnitude of the square of the loadings. For example, SCMI 1 is associated with RC1 only. After associating each SCMI with RC, the squared loadings of unused rotated components are set to zero. Then the retained loadings are normalized using the summation of the square of the loadings (see Table B.2) per RC, the result is shown in Table B.3. The final indicator weight is determined by dividing the normalized value of the associated RC with the total of the normalized loadings (see Table B.3) and multiplying it with the percentage explained by that RC (see Table B.2). The resulting set of weights is shown in Table B.3.

Table B.2 Result of the rotation of principal components

SCMI	Loadings		Squared Loadings	
	RC1	RC2	RC1	RC2
1	0.99	0.15	0.98	0.02
2	0.83	-0.56	0.69	0.31
3	0.32	0.84	0.10	0.71
4	0.56	-0.82	0.31	0.67
5	1.00	0.01	1.00	0.00
6	0.99	0.14	0.98	0.02
7	1.00	0.05	1.00	0.00
8	1.00	0.04	1.00	0.00
9	0.99	0.13	0.98	0.02
20	0.01	-0.92	0.00	0.85
28	1.00	0.01	1.00	0.00
29	1.00	0.06	1.00	0.00
30.02	1.00	0.06	1.00	0.00
31.01	1.00	0.05	1.00	0.00
34	1.00	0.05	1.00	0.00
40	0.31	0.85	0.10	0.72
TOTAL			12.14	3.34
Percentage			78%	22%

Table B.3 Normalized retained loadings and the SCMI weight

SCMI	Normalized retained loadings per associated RC		SCMI weight
	RC1	RC2	
1	0.081		0.066
2	0.057		0.046
3		0.212	0.052
4		0.202	0.049
5	0.082		0.067
6	0.081		0.066
7	0.082		0.067
8	0.082		0.067
9	0.081		0.066
20		0.254	0.062
28	0.082		0.067
29	0.082		0.067
30.02	0.082		0.067
31.01	0.082		0.067
34	0.082		0.067
40		0.217	0.053
TOTAL	0.958	0.883	1.000

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Appendix C

Numerical values of weight for CL, CB and CL* scenarios

C.1 CL scenario

(1) Equal Weights

Table C.1 Weights of SCMIs by equal weighting approach for CL scenario

Indicator Set	SCMI weight																Sum
	1	2	3	4	5	6	7	8	9	20	28	29	30.02	31.01	34	40	
1	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	1.000
2		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
3	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
4	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
5	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
6	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
7	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
8	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
9	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
10	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
11	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	0.067	1.000
12	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	0.067	1.000
13	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	0.067	1.000
14	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	0.067	1.000
15	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	0.067	1.000
16	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		0.067	1.000
17	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067		1.000
Average	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(2) PCA Weights

Table C.2 Weights of SCMIs by PCA approach for CL scenario

Indicator Set	SCMI weight																Sum
	1	2	3	4	5	6	7	8	9	20	28	29	30.02	31.01	34	40	
1	0.066	0.046	0.052	0.049	0.067	0.066	0.067	0.067	0.066	0.062	0.067	0.067	0.067	0.067	0.067	0.053	1.000
2		0.050	0.056	0.052	0.072	0.071	0.072	0.072	0.071	0.066	0.072	0.072	0.072	0.072	0.072	0.056	1.000
3	0.071		0.050	0.047	0.072	0.071	0.072	0.072	0.071	0.061	0.072	0.072	0.072	0.072	0.072	0.053	1.000
4	0.070	0.043		0.059	0.070	0.070	0.070	0.070	0.070	0.067	0.070	0.070	0.070	0.070	0.070	0.059	1.000
5	0.066	0.052	0.063		0.070	0.067	0.069	0.069	0.067	0.072	0.070	0.069	0.069	0.069	0.069	0.061	1.000
6	0.071	0.049	0.055	0.053		0.071	0.072	0.072	0.071	0.066	0.072	0.072	0.072	0.072	0.072	0.057	1.000
7	0.071	0.050	0.056	0.052	0.072		0.072	0.072	0.071	0.066	0.072	0.072	0.072	0.072	0.072	0.056	1.000
8	0.071	0.050	0.055	0.053	0.072	0.071		0.072	0.071	0.066	0.072	0.072	0.072	0.072	0.072	0.057	1.000
9	0.071	0.050	0.055	0.053	0.072	0.071	0.072		0.071	0.066	0.072	0.072	0.072	0.072	0.072	0.057	1.000
10	0.071	0.050	0.056	0.052	0.072	0.071	0.072	0.072		0.066	0.072	0.072	0.072	0.072	0.072	0.056	1.000
11	0.070	0.049	0.060	0.054	0.071	0.070	0.071	0.071	0.070		0.071	0.071	0.071	0.071	0.071	0.061	1.000
12	0.071	0.049	0.055	0.053	0.072	0.071	0.072	0.072	0.071	0.066		0.072	0.072	0.072	0.072	0.057	1.000
13	0.071	0.050	0.055	0.053	0.072	0.071	0.072	0.072	0.071	0.066	0.072		0.072	0.072	0.072	0.057	1.000
14	0.071	0.050	0.055	0.053	0.072	0.071	0.072	0.072	0.071	0.066	0.072	0.072		0.072	0.072	0.057	1.000
15	0.071	0.050	0.055	0.053	0.072	0.071	0.072	0.072	0.071	0.066	0.072	0.072	0.072		0.072	0.057	1.000
16	0.071	0.050	0.055	0.053	0.072	0.071	0.072	0.072	0.071	0.066	0.072	0.072	0.072	0.072		0.057	1.000
17	0.069	0.043	0.059	0.058	0.070	0.070	0.070	0.070	0.070	0.068	0.070	0.070	0.070	0.070	0.070		1.000
Average	0.070	0.049	0.056	0.053	0.072	0.070	0.071	0.071	0.070	0.066	0.072	0.071	0.071	0.071	0.071	0.057	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(3) ST Weights

Table C.3 Weights of SCMIs by stakeholder approach for CL scenario

Indicator Set	SCMI weight																Sum
	1	2	3	4	5	6	7	8	9	20	28	29	30.02	31.01	34	40	
1	0.089	0.089	0.008	0.149	0.015	0.042	0.042	0.042	0.042	0.117	0.015	0.042	0.023	0.069	0.004	0.209	1.000
2		0.098	0.009	0.156	0.017	0.049	0.049	0.049	0.049	0.120	0.017	0.049	0.026	0.082	0.004	0.224	1.000
3	0.098		0.009	0.155	0.017	0.049	0.049	0.049	0.049	0.120	0.017	0.049	0.026	0.082	0.004	0.224	1.000
4	0.090	0.090		0.156	0.012	0.041	0.041	0.041	0.041	0.121	0.012	0.041	0.020	0.069	0.004	0.223	1.000
5	0.110	0.110	0.009		0.017	0.050	0.050	0.050	0.050	0.154	0.017	0.050	0.026	0.083	0.004	0.220	1.000
6	0.091	0.091	0.009	0.154		0.041	0.041	0.041	0.041	0.120	0.014	0.041	0.020	0.069	0.004	0.222	1.000
7	0.091	0.091	0.009	0.154	0.017		0.045	0.045	0.045	0.122	0.017	0.045	0.026	0.069	0.004	0.221	1.000
8	0.091	0.091	0.010	0.152	0.018	0.045		0.045	0.045	0.121	0.018	0.045	0.027	0.069	0.004	0.220	1.000
9	0.091	0.091	0.009	0.153	0.017	0.045	0.045		0.045	0.121	0.017	0.045	0.026	0.069	0.004	0.222	1.000
10	0.091	0.091	0.009	0.155	0.017	0.044	0.044	0.044		0.122	0.017	0.044	0.026	0.069	0.004	0.220	1.000
11	0.110	0.110	0.009	0.155	0.017	0.050	0.050	0.050	0.050		0.017	0.050	0.026	0.083	0.004	0.220	1.000
12	0.091	0.091	0.009	0.155	0.014	0.041	0.041	0.041	0.041	0.121		0.041	0.020	0.069	0.004	0.221	1.000
13	0.091	0.091	0.009	0.157	0.017	0.044	0.044	0.044	0.044	0.123	0.017		0.026	0.068	0.004	0.221	1.000
14	0.091	0.091	0.009	0.155	0.017	0.041	0.041	0.041	0.041	0.122	0.017	0.041		0.069	0.005	0.222	1.000
15	0.090	0.090	0.009	0.155	0.017	0.049	0.049	0.049	0.049	0.121	0.017	0.049	0.026		0.004	0.223	1.000
16	0.090	0.090	0.004	0.154	0.012	0.041	0.041	0.041	0.041	0.121	0.012	0.041	0.020	0.069		0.222	1.000
17	0.110	0.110	0.009	0.221	0.017	0.050	0.050	0.050	0.050	0.155	0.017	0.050	0.026	0.082	0.005		1.000
Average	0.095	0.095	0.009	0.158	0.016	0.045	0.045	0.045	0.045	0.125	0.016	0.045	0.024	0.073	0.004	0.221	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

C.2 CB scenario

(1) Equal Weights

Table C.4 Weights of SCMIs by equal weighting approach for CB scenario

Indicator Set	SCMI weight															Sum
	1	2	3	4	5	6	7	8	9	28	29	30.02	31.01	34	40	
1	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	1.000
2		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
3	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
4	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
5	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
6	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
7	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
8	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
9	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000
10	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	0.071	1.000
11	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	0.071	1.000
12	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	0.071	1.000
13	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	0.071	1.000
14	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	0.071	1.000
15	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		0.071	1.000
16	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071		1.000
Average	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(2) PCA Weights

Table C.5 Weights of SCMIs by PCA approach for CB scenario

Indicator Set	SCMI weight															Sum
	1	2	3	4	5	6	7	8	9	28	29	30.02	31.01	34	40	
1	0.070	0.049	0.060	0.054	0.071	0.070	0.071	0.071	0.070	0.071	0.071	0.071	0.071	0.071	0.061	1.000
2		0.054	0.063	0.058	0.076	0.075	0.076	0.076	0.075	0.076	0.076	0.076	0.076	0.076	0.065	1.000
3	0.073		0.058	0.051	0.076	0.073	0.076	0.076	0.075	0.076	0.075	0.075	0.076	0.076	0.060	1.000
4	0.075	0.040		0.080	0.073	0.075	0.073	0.073	0.075	0.073	0.073	0.073	0.073	0.073	0.073	1.000
5	0.068	0.060	0.085		0.072	0.068	0.071	0.071	0.068	0.072	0.071	0.071	0.071	0.071	0.083	1.000
6	0.075	0.053	0.063	0.059		0.075	0.076	0.076	0.075	0.076	0.076	0.076	0.076	0.076	0.066	1.000
7	0.073	0.054	0.064	0.058	0.076		0.076	0.076	0.075	0.076	0.076	0.076	0.076	0.076	0.065	1.000
8	0.075	0.053	0.064	0.058	0.076	0.075		0.076	0.075	0.076	0.076	0.076	0.076	0.076	0.065	1.000
9	0.075	0.053	0.064	0.058	0.076	0.075	0.076		0.075	0.076	0.076	0.076	0.076	0.076	0.065	1.000
10	0.073	0.054	0.064	0.058	0.076	0.075	0.076	0.076		0.076	0.076	0.076	0.076	0.076	0.065	1.000
11	0.075	0.053	0.063	0.059	0.076	0.075	0.076	0.076	0.075		0.076	0.076	0.076	0.076	0.066	1.000
12	0.075	0.053	0.064	0.058	0.076	0.075	0.076	0.076	0.075	0.076		0.076	0.076	0.076	0.065	1.000
13	0.075	0.053	0.064	0.058	0.076	0.075	0.076	0.076	0.075	0.076	0.076		0.076	0.076	0.065	1.000
14	0.075	0.053	0.064	0.058	0.076	0.075	0.076	0.076	0.075	0.076	0.076	0.076		0.076	0.065	1.000
15	0.075	0.053	0.064	0.058	0.076	0.075	0.076	0.076	0.075	0.076	0.076	0.076	0.076		0.065	1.000
16	0.073	0.039	0.073	0.080	0.073	0.075	0.073	0.073	0.075	0.073	0.073	0.073	0.073	0.073		1.000
Average	0.074	0.051	0.065	0.060	0.075	0.074	0.075	0.075	0.074	0.075	0.075	0.075	0.075	0.075	0.066	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(3) ST Weights

Table C.6 Weights of SCMIs by stakeholder approach for CB scenario

Indicator Set	SCMI weight															Sum
	1	2	3	4	5	6	7	8	9	28	29	30.02	31.01	34	40	
1	0.110	0.110	0.009	0.155	0.017	0.049	0.049	0.049	0.049	0.017	0.049	0.026	0.082	0.005	0.221	1.000
2		0.126	0.011	0.161	0.020	0.059	0.059	0.059	0.059	0.020	0.059	0.031	0.101	0.005	0.231	1.000
3	0.126		0.010	0.161	0.019	0.058	0.058	0.058	0.058	0.019	0.058	0.030	0.102	0.005	0.235	1.000
4	0.113	0.113		0.160	0.014	0.049	0.049	0.049	0.049	0.014	0.049	0.023	0.084	0.005	0.231	1.000
5	0.142	0.142	0.011		0.020	0.060	0.060	0.060	0.060	0.020	0.060	0.031	0.101	0.005	0.230	1.000
6	0.113	0.113	0.010	0.161		0.048	0.048	0.048	0.048	0.016	0.048	0.023	0.084	0.005	0.234	1.000
7	0.113	0.113	0.010	0.162	0.020		0.053	0.053	0.053	0.020	0.053	0.030	0.083	0.005	0.233	1.000
8	0.113	0.113	0.011	0.159	0.020	0.053		0.053	0.053	0.020	0.053	0.030	0.083	0.005	0.232	1.000
9	0.114	0.114	0.011	0.162	0.020	0.053	0.053		0.053	0.020	0.053	0.030	0.083	0.005	0.231	1.000
10	0.113	0.113	0.011	0.160	0.020	0.053	0.053	0.053		0.020	0.053	0.031	0.083	0.006	0.231	1.000
11	0.093	0.093	0.010	0.160	0.016	0.043	0.043	0.043	0.126		0.043	0.023	0.069	0.005	0.232	1.000
12	0.092	0.092	0.011	0.162	0.020	0.047	0.047	0.047	0.125	0.020		0.030	0.068	0.005	0.237	1.000
13	0.093	0.093	0.010	0.160	0.019	0.043	0.043	0.043	0.126	0.019	0.043		0.069	0.005	0.235	1.000
14	0.093	0.093	0.011	0.161	0.020	0.053	0.053	0.053	0.125	0.020	0.053	0.031		0.005	0.231	1.000
15	0.093	0.093	0.005	0.161	0.013	0.043	0.043	0.043	0.125	0.013	0.043	0.023	0.069		0.233	1.000
16	0.112	0.112	0.011	0.231	0.020	0.054	0.054	0.054	0.161	0.020	0.054	0.031	0.083	0.005		1.000
Average	0.109	0.109	0.010	0.165	0.019	0.051	0.051	0.051	0.085	0.019	0.051	0.028	0.083	0.005	0.232	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

C.3 CL* scenario

(1) Equal Weights

Table C.7 Weights of SCMIs by equal weighting approach for CL* scenario

Indicator Set	SCMI weight					Sum
	2	3	4	20	40	
1	0.200	0.200	0.200	0.200	0.200	1.000
2		0.250	0.250	0.250	0.250	1.000
3	0.250		0.250	0.250	0.250	1.000
4	0.250	0.250		0.250	0.250	1.000
5	0.250	0.250	0.250		0.250	1.000
6	0.250	0.250	0.250	0.250		1.000
Average	0.240	0.240	0.240	0.240	0.240	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(2) PCA Weights

Table C.8 Weights of SCMIs by PCA approach for CL* scenario

Indicator Set	SCMI weight					Sum
	2	3	4	20	40	
1	0.230	0.208	0.186	0.092	0.283	1.000
2		0.345	0.253	0.102	0.300	1.000
3	0.258		0.208	0.236	0.298	1.000
4	0.341	0.302		0.109	0.248	1.000
5	0.257	0.263	0.208		0.273	1.000
6	0.260	0.294	0.210	0.236		1.000
Average	0.269	0.282	0.213	0.155	0.280	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

(3) ST Weights

Table C.9 Weights of SCMIs by stakeholder approach for CL* scenario

Indicator Set	SCMI weight					Sum
	2	3	4	20	40	
1	0.089	0.038	0.259	0.154	0.460	1.000
2		0.064	0.270	0.143	0.523	1.000
3	0.063		0.273	0.146	0.518	1.000
4	0.147	0.065		0.266	0.523	1.000
5	0.143	0.062	0.271		0.525	1.000
6	0.143	0.061	0.525	0.272		1.000
Average	0.117	0.058	0.320	0.196	0.510	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

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Appendix D

Numerical values of weight for Exploratory work Section 7.3

D.1 Equal Weights

Table D.1 Weights of SCMIs by equal weighting approach

Indicator	SCMI weight																			Sum
Set	1	2	3	4	5	6	7	8	17.01	17.04	23	25	28	29	30	31	34	37	40	
1	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	1.000
2		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		1.000
3	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
4	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
5	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
6	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
7	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
8	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
9	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
10	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
11	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
12	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
13	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000
14	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	0.059	1.000
15	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	0.059	1.000
16	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	0.059	1.000
17	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	0.059	1.000
18	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	0.059	1.000
19	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059		0.059	1.000
Average	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

D.2 PCA Weights

Table D.2 Weights of SCMIs by PCA approach

Indicator	SCMI weight																			Sum
Set	1	2	3	4	5	6	7	8	17.01	17.04	23	25	28	29	30	31	34	37	40	
1	0.070	0.062	0.070	0.061	0.048	0.061	0.036	0.061	0.036	0.045	0.055	0.061	0.060	0.060	0.061	0.061	0.065	0.026	0.070	1.000
2		0.065	0.076	0.064	0.048	0.064	0.036	0.069	0.040	0.051	0.064	0.064	0.063	0.063	0.064	0.064	0.072	0.032		1.000
3	0.074		0.074	0.067	0.052	0.067	0.036	0.060	0.039	0.049	0.059	0.067	0.066	0.066	0.067	0.067	0.064	0.024	0.074	1.000
4	0.076	0.066		0.064	0.050	0.065	0.038	0.068	0.039	0.049	0.061	0.064	0.063	0.063	0.065	0.065	0.072	0.031	0.076	1.000
5	0.075	0.067	0.075		0.050	0.064	0.039	0.067	0.038	0.047	0.058	0.064	0.063	0.063	0.064	0.064	0.070	0.029	0.075	1.000
6	0.074	0.064	0.074	0.064		0.064	0.037	0.065	0.039	0.048	0.058	0.064	0.062	0.063	0.064	0.064	0.069	0.028	0.074	1.000
7	0.075	0.066	0.075	0.064	0.050		0.039	0.066	0.039	0.048	0.058	0.064	0.063	0.063	0.064	0.064	0.071	0.029	0.075	1.000
8	0.074	0.062	0.073	0.064	0.049	0.064		0.062	0.040	0.048	0.058	0.064	0.062	0.062	0.064	0.064	0.066	0.025	0.074	1.000
9	0.074	0.060	0.073	0.068	0.054	0.068	0.037		0.040	0.048	0.056	0.068	0.067	0.067	0.068	0.068	0.061	0.020	0.074	1.000
10	0.072	0.065	0.072	0.064	0.051	0.064	0.039	0.063		0.045	0.055	0.064	0.063	0.063	0.064	0.064	0.067	0.027	0.072	1.000
11	0.072	0.066	0.072	0.064	0.052	0.064	0.041	0.064	0.035		0.055	0.064	0.063	0.063	0.064	0.064	0.068	0.028	0.072	1.000
12	0.074	0.068	0.073	0.064	0.053	0.065	0.042	0.064	0.038	0.045		0.064	0.064	0.064	0.065	0.065	0.069	0.025	0.074	1.000
13	0.075	0.067	0.075	0.064	0.050	0.064	0.039	0.067	0.038	0.047	0.058		0.063	0.063	0.064	0.064	0.070	0.029	0.075	1.000
14	0.075	0.066	0.075	0.064	0.050	0.064	0.039	0.066	0.039	0.048	0.059	0.064		0.063	0.064	0.064	0.070	0.029	0.075	1.000
15	0.075	0.066	0.075	0.064	0.050	0.064	0.039	0.066	0.039	0.048	0.059	0.064	0.063		0.064	0.064	0.070	0.029	0.075	1.000
16	0.075	0.066	0.075	0.064	0.050	0.064	0.039	0.066	0.039	0.048	0.058	0.064	0.063	0.063		0.064	0.071	0.029	0.075	1.000
17	0.075	0.066	0.075	0.064	0.050	0.064	0.039	0.066	0.039	0.048	0.058	0.064	0.063	0.063	0.064		0.070	0.029	0.075	1.000
18	0.075	0.062	0.075	0.070	0.055	0.070	0.038	0.060	0.016	0.048	0.061	0.070	0.068	0.069	0.070	0.070		0.025	0.075	1.000
19	0.072	0.063	0.071	0.063	0.050	0.064	0.038	0.061	0.037	0.045	0.055	0.063	0.062	0.063	0.064	0.064	0.065		0.072	1.000
Average	0.074	0.065	0.074	0.065	0.051	0.065	0.039	0.064	0.037	0.047	0.058	0.065	0.063	0.064	0.065	0.065	0.068	0.027	0.074	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

D.3 AHP Weights

Table D.2 Weights of SCMIs by AHP approach

Indicator Set	SCMI weight																			Sum
	1	2	3	4	5	6	7	8	17.01	17.04	23	25	28	29	30	31	34	37	40	
1	0.058	0.054	0.059	0.063	0.061	0.064	0.053	0.039	0.037	0.061	0.038	0.063	0.063	0.064	0.064	0.064	0.041	0.054	0.058	1.000
2		0.058	0.062	0.067	0.065	0.068	0.057	0.041	0.039	0.065	0.041	0.067	0.067	0.067	0.068	0.068	0.044	0.057		1.000
3	0.062		0.062	0.067	0.064	0.068	0.057	0.041	0.039	0.064	0.041	0.067	0.067	0.067	0.068	0.068	0.043	0.057	0.062	1.000
4	0.062	0.058		0.067	0.065	0.068	0.057	0.041	0.039	0.065	0.041	0.067	0.067	0.067	0.068	0.068	0.044	0.057	0.062	1.000
5	0.062	0.058	0.062		0.065	0.068	0.057	0.041	0.039	0.065	0.041	0.068	0.068	0.068	0.068	0.068	0.044	0.057	0.062	1.000
6	0.062	0.058	0.062	0.067		0.068	0.057	0.041	0.039	0.065	0.041	0.067	0.068	0.068	0.068	0.068	0.044	0.057	0.062	1.000
7	0.062	0.058	0.063	0.068	0.065		0.057	0.042	0.039	0.065	0.041	0.068	0.068	0.068	0.068	0.068	0.044	0.057	0.062	1.000
8	0.061	0.057	0.062	0.067	0.064	0.068		0.041	0.039	0.064	0.041	0.067	0.067	0.067	0.068	0.068	0.043	0.057	0.061	1.000
9	0.061	0.056	0.061	0.066	0.063	0.066	0.056		0.038	0.063	0.040	0.066	0.066	0.066	0.066	0.066	0.043	0.056	0.061	1.000
10	0.060	0.056	0.061	0.066	0.063	0.066	0.056	0.040		0.063	0.040	0.066	0.066	0.066	0.066	0.066	0.043	0.056	0.060	1.000
11	0.062	0.058	0.062	0.067	0.065	0.068	0.057	0.041	0.039		0.041	0.067	0.068	0.068	0.068	0.068	0.044	0.057	0.062	1.000
12	0.061	0.056	0.061	0.066	0.063	0.066	0.056	0.041	0.038	0.063		0.066	0.066	0.066	0.066	0.066	0.043	0.056	0.061	1.000
13	0.062	0.058	0.062	0.068	0.065	0.068	0.057	0.041	0.039	0.065	0.041		0.068	0.068	0.068	0.068	0.044	0.057	0.062	1.000
14	0.062	0.058	0.063	0.068	0.065	0.068	0.057	0.042	0.039	0.065	0.041	0.068		0.068	0.068	0.068	0.044	0.057	0.062	1.000
15	0.062	0.058	0.063	0.068	0.065	0.068	0.057	0.042	0.039	0.065	0.041	0.068	0.068		0.068	0.068	0.044	0.057	0.062	1.000
16	0.062	0.058	0.063	0.068	0.065	0.068	0.057	0.042	0.039	0.065	0.041	0.068	0.068	0.068		0.068	0.044	0.057	0.062	1.000
17	0.062	0.058	0.063	0.068	0.065	0.068	0.057	0.042	0.039	0.065	0.041	0.068	0.068	0.068	0.068		0.044	0.057	0.062	1.000
18	0.061	0.057	0.061	0.066	0.063	0.067	0.056	0.041	0.038	0.063	0.040	0.066	0.066	0.066	0.067	0.067		0.056	0.061	1.000
19	0.062	0.057	0.062	0.067	0.064	0.067	0.056	0.041	0.039	0.064	0.041	0.067	0.067	0.067	0.067	0.067	0.043		0.062	1.000
Average	0.061	0.057	0.062	0.067	0.064	0.067	0.056	0.041	0.039	0.064	0.041	0.067	0.067	0.067	0.067	0.067	0.043	0.057	0.061	1.000

Note: Blank value per set refers to the indicator excluded in that particular set.

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