Robust building design optimization using the robust optimality criterion

by

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Abstract

Design exploration is a fundamental part of the building design process that aims to identify the best-performing solution that satisfies the preferences of the stakeholders and the requirements of the regulations. Building performance simulation (BPS) can act as a quantitative guide for this 'explorative' process, its potential however being restricted by the various sources of uncertainty which reduce the confidence in BPS results, hence jeopardising robustness in decision-making. Although some building design studies may have focused on the integration of uncertainty analysis (UA) into BPS, optimization and UA are still most commonly treated as separate procedures. Coupling these two methods is however essential in the context of robust decision-making, as optimization can ensure the identification of solutions that minimise the objective functions, and UA can improve the confidence in the optimality of solutions by evaluating their performance under possible uncertain conditions.

Additional studies are hence needed to show how uncertainties should be quantified, and how robustness should be assessed in the context of building design exploration. The literature review uncovers the need for a more flexible definition of robustness that enables the articulation of any stakeholder preferences. It also reveals the need to extend such a definition to multi-objective problems, as building design solutions are most commonly assessed with respect to only one or two criteria due to the associated computational complexity, this however restricting the number of optimization trade-offs and consequently the exploration of the design space.

This thesis introduces a robust building design optimization framework for handling building design problems that are exposed to uncertain conditions, hence supporting building design exploration and decision-making under uncertainty. The framework comprises five principal steps, which are applied to a single-zone building and a real-world building: a) uncertainty quantification; b) exhaustive search; c) BPS; d) robust optimization; and e) solution analysis.

Uncertainty quantification refers to the two principal categories of uncertainty which are found in the literature: a) the *epistemic* uncertainty in the choice of an optimum solution (that is, the choice of form, construction and systems); and b) the *aleatoric* uncertainty in the predicted performance of the selected solution (due to the natural variability in the behaviour of any uncertain conditions, such as the weather). Robust optimization combines *multi-objective optimization* (to efficiently explore the design space and reduce the uncertainty in the selection of an optimum design solution), and *robustness assessment* (to ensure the optimality of the selected solution under possible uncertain conditions).

Robust building design optimization is performed in this thesis using a novel robust optimality criterion, which states that *a robust solution is one that remains optimal regardless of the uncertainty in the predicted building performance*. Through its application to the design optimization of a single-zone building, the robust optimality criterion is found to be able to support building design exploration and decision-making under uncertainty, as it can provide the stakeholders with a set of optimized design solutions which are insensitive to the behaviour of any uncertain conditions, while accounting for their (risk) preferences. Its application to the design optimization of a real-world building shows that the adoption of the novel criterion in the design practice can assist the different stakeholders in gaining a better understanding of the relationship between solutions and objectives and ultimately designing buildings that are optimal in the defined objectives and robust to the inherent uncertainties.

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Chapter 1

Introduction

1.1 General background and problem statement

The goal of the building design process is to produce a solution that responds to the needs of the client while meeting the requirements of the building regulations such as the Building Regulations Part L (UK Government 2013a), or the Passivhaus Standard (International Passive House Association 2018). Design exploration is a vital part of this process that can result in the identification of a satisfactory solution through the generation and evaluation of design alternatives. Rules of thumb and the experience of the designers have traditionally played a significant role in the evaluation of alternative design options. Even though designers' judgement is essential for the integration of qualitative criteria (such as aesthetics and functionality) which cannot be quantified in a direct and general manner (Geyer 2009), the reliance on common rules of thumb and the intuition of the designers should be treated with caution (Hillier *et al.* 1972), as the entailed subjectivity increases the risk that well-performing design solutions will be eliminated and a sub-optimum solution will be chosen.

Building performance simulation (BPS) can support the identification of a satisfactory solution by providing rapid, quantitative feedback on the performance of alternative design options (Clarke and Hensen 2015). However, the commonly-used trial-and-error process of identifying an 'optimum' design solution may be misleading and time-consuming (mainly in the case of a large design space), this revealing the need for a more efficient exploration method (Wang *et al.* 2005). Such a need has resulted in the integration of optimization into building design exploration over the last few years, as it supports the identification of solutions that best satisfy the considered objective and constraint functions (Machairas *et al.* 2014). Optimization is therefore described as the process of identifying the best solution – or set of solutions – with respect to one or more objective and constraint functions. Nevertheless, this process may prove to be (computationally) complex due to the plethora of functions which need to be defined to reflect the multi-dimensionality of real-world problems (Deb and Saxena 2005).

The potential of BPS and optimization is also susceptible to parameter uncertainty, as – even small – perturbations in input data can affect performance prediction and shift nominal optimal solutions to sub-optimal, or even infeasible solutions (Ben-Tal *et al.* 2009). As the search for robust designs may return solutions that are different from those of the deterministic Pareto set (that is, the nominal optimal solutions, which do not incorporate uncertainty) (Avigad and Branke 2008), including uncertainty in BPS and optimization is critical for uncovering the consequences of decisions with more confidence (Gokhale 2009). However, the majority of building performance analysis studies use deterministic simulations that neglect possible variations in any uncertain parameters, this entailing the risk of sub-optimality for the optimized solutions, and thus of misguided decisions for the decision-makers (DMs) (Van Gelder *et al.* 2014).

Robust design optimization couples optimization and uncertainty analysis, acting as a decision support tool that accounts for the possibility that the deterministic/ nominal values of uncertain parameters may never occur, as a result of the randomness in their nature (Hopfe 2009). Although robust optimization may have been used over the last few years in other fields such as structural design (Doltsinis and Kang 2004, Martinez-Frutos *et al.* 2016), it is still not widely used in building energy studies, this revealing the need for further investigation into its significance and implementation in building design optimization problems (Nguyen *et al.* 2014).

It is hence still ambiguous how to quantify uncertainty and assess robustness, which is revealed by the existence of multiple definitions of robustness in the literature and the discrepancy in the types of uncertainty that are accounted for as well as their handling (Walsh *et al.* 2013). The majority of existing studies adopt a probabilistic handling of uncertainty, assuming that the probability of each uncertain value occurring is known and evaluating solutions upon the probability density functions of their performance indicators (Van Gelder *et al.* 2014). These probabilistic formulations of robustness are however infeasible if there is no sufficient information on the probability of occurrence of each uncertain input value, this being the case for uncertainties such as the weather. Existing formulations of robustness may also not be comprehensible to a non-specialist audience (Huang and Du 2007), or may have not been extended to problems where multiple objective functions need to be minimised due to the associated computational complexity (Rysanek and Choudhary 2013). Finally, existing robustness indicators may be conservative (Ehrgott *et al.* 2014), thus calling for a more flexible definition of robustness that is able to support the articulation of the customised (risk) preferences of the DMs.

1.2 Aim and objectives

This thesis aims to develop a new robust building design optimization framework for handling building design problems that are exposed to uncertain conditions, therefore supporting building design exploration and decision-making under uncertainty. This will be accomplished by meeting the following objectives:

- To investigate the different sources of uncertainty during the building design process and how they are quantified.
- To investigate existing robustness indicators and how they assess robustness.
- To develop an approach to formulating a multi-objective design problem that is exposed to uncertain conditions – this referring to the definition of design solutions, uncertain conditions, design objectives and constraints.
- To develop a new indicator for evaluating the robustness of design solutions and identifying optimum solutions that are insensitive to the behaviour of the considered uncertain conditions, while supporting the articulation of the (risk) preferences of the DMs.
- To explore the behaviour of the new robustness indicator.
- To demonstrate the potential of the new robustness indicator in a real-world context.

1.3 Thesis outline

This thesis consists of six chapters. An outline of the chapters is provided below:

- Chapter 2 carries out a literature review on robust optimization in the context of building design exploration. The chapter investigates the different sources of uncertainty during the design process and how these are quantified. It also investigates existing robustness indicators, with the objective of showing how robustness is currently assessed in the presence of such uncertainties.

- Chapter 3 presents the methodology of this thesis. The chapter describes the steps of the robust building design optimization framework, which can lead to the identification of robust solutions that perform well under uncertainty, while satisfying the requirements of the building regulations and the preferences of stakeholders. It also defines the experiments that will be performed in chapters 4 and 5 using a test cell and a real-world building, respectively.

- Chapter 4 describes the application of the framework to a ‘test cell’ (that is, a single-zone office building located in London), with the objective of exploring the behaviour of the new robustness indicator.

- Chapter 5 describes the application of the framework to a real-world building (that is, a new community centre that will be constructed in London), with the objective of demonstrating the potential of the new robustness indicator to support design exploration and decision-making under uncertain conditions in a real-world context.

- Chapter 6 includes the final discussion and conclusions of this thesis. It also summarises any limitations and suggestions for future research.

Chapter 2

Literature review

Chapter 2 explicates the role of robust optimization in the building design exploration process. The exploration of the design space during the concept and developed stages of the building design process is firstly discussed, this flagging up the lack of specific steps to generate design solutions and assess their performance. The role of building performance simulation and optimization in identifying a solution with a satisfactory performance, is then discussed. As this is subject to several uncertainties, uncertainty categorisation and quantification are described. The role of robustness assessment in ensuring performance and optimality despite such uncertainties, is finally discussed.

2.1 The building design process

The increased requirements for the successful completion of contemporary building projects has led to the involvement of a wide range of stakeholders[1], this converting the design and construction industry into a more complex landscape. This complexity is intensified by the distinctive characteristics of each project, which complicate the identification of generalised patterns. Nevertheless, despite the unique character of each project, a number of key stages are suggested by the Royal Institute of British Architects (RIBA) (Sinclair 2013), in an effort to organise the procedure of briefing, designing, constructing and operating buildings. With the design exploration process being under the microscope of this work, this section will briefly introduce the key stages of building projects and then focus on the steps to explore the design space in order to obtain a successful solution during the concept and developed design stages.

[1] According to the RIBA Plan of Work (Sinclair 2013), the core roles of a building project include the client, project leader, lead designer, architect, building services engineer, civil and structural engineer, cost consultant, construction leader, contract administrator as well as health and safety adviser.

2.1.1 Key stages of building projects

The RIBA Plan of Work (Sinclair 2013) aims to provide the stakeholders which are involved in the design and construction industry with the tasks and outputs that are required within the context of the design, construction and operation of buildings. This document was originally published in 1963 in order to ‘provide a model procedure for methodological working by the design team’ (Duffy and Hutton 2004), while its up-to-date version was launched in 2013 (Sinclair 2013). According to the latest version, building projects can be divided into eight stages denoted by numbers (from 0 to 7), as displayed in figure 2.1: 0) Strategic Definition; 1) Preparation and Brief; 2) Concept Design; 3) Developed Design; 4) Technical Design; 5) Construction; 6) Handover and Close Out; and 7) In Use.

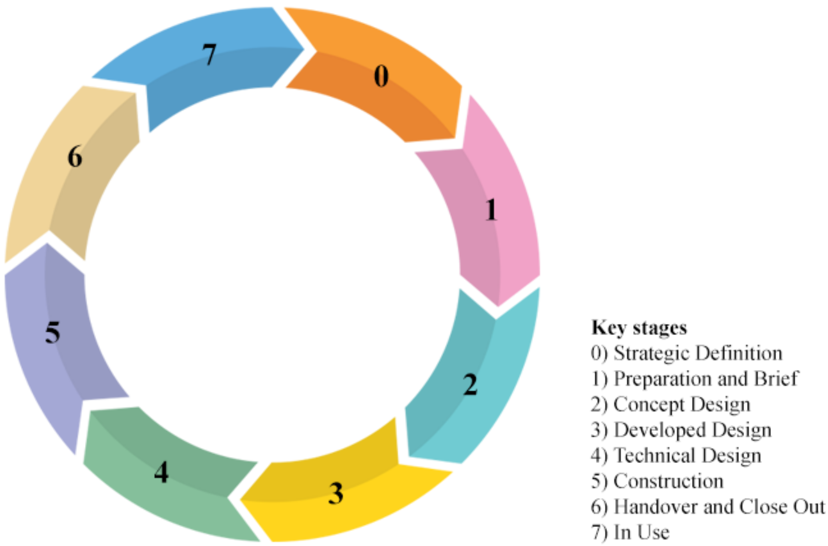

Figure 2.1. The key stages of a building project according to the RIBA Plan of Work (Sinclair 2013) (adapted from Sinclair 2013).

At each of these eight stages, the importance of assembling a successful collaborative project team is emphasised. Collaboration is vital for achieving a sustainable design solution, this also being one of the cornerstones of the integrated design process that was introduced in the 1990s, as a holistic approach to building design (Zimmerman 2006). Contrary to the traditional design process, the integrated approach is inclusive as it encourages the active participation of stakeholders at all design stages. Section 2.1.2 will focus on how stakeholders can explore the design space during the concept and developed building design stages, in order to identify a satisfactory solution.

2.1.2 Exploration during concept and developed design stages

Zooming in on the concept and developed building design stages, the RIBA Plan of Work (Sinclair 2013) suggests that these 'may require a number of iterations of the design', without however providing further guidance about the steps that should be followed by stakeholders. Design exploration is iterative (Rezaee *et al.* 2015) as it is powered by a 'constant search for a design direction' (Ochoa and Capeluto 2009). The adoption of a design direction (also called concept) at the early design stages has been described by Darke (1979) as the 'primary generator' of the design process (as shown in figure 2.2). Its significance has also been underlined by Rowe (1991), who proposed the '*a priori* use of an organising principle or model to direct the decision-making process'. In the architectural world, this organising principle is also known as 'parti'[2] and is associated with the sketches that the students of the French School of Arts had to prepare in only a few hours – and then elaborate (Gargus 1994).

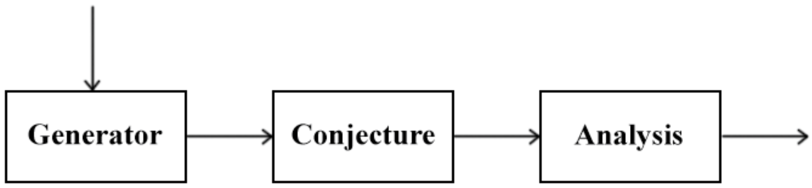

Figure 2.2. The map of the design process (adapted from Darke 1979).

As mentioned by Mitchell *et al.* (1988), several renowned architects and artists such as Villard de Honnecourt, Leonardo da Vinci and Albrecht Dürer had implemented a similar design strategy to translate the general massing they had conceived into fully-developed drawings. In the context of the building design process, massing refers to the three-dimensional form of the building. Massing does not however only influence the form of the building, but also its layout and circulation. Given that a building is an aggregation of zones accommodating different uses, massing is able to strengthen the relationship between individual zones, thus also influencing occupant experience. Due its critical role in the building design process, form is part of the exploration process in this thesis (section 3.2). However, note that, the exhaustive generation and aesthetic evaluation of alternative forms are not within the scope of this work, this requiring the continual interaction of the design team with the process (Turrin *et al.* 2011).

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[2] 'Parti' is derived from the French verb partir, which means to depart.

As stated in the Green Overlay to the RIBA Outline Plan of Work (Gething 2011), influential design parameters[3] referring to construction and operation must also be explored and defined early in the design process to ensure satisfactory performance, with no specific steps being, however, determined. As highlighted by Laseau (2001), this iterative process commonly involves the following five steps:

1. Definition of the problem;
2. Generation of alternatives;
3. Evaluation;
4. Selection; and
5. Communication.

The first step of this process is the formulation of the design problem, this referring to the definition of design objectives, constraints and variables. To be able to define these details, attention must be paid by the project team to the initial brief that was agreed with the client during stage 1 (i.e. Preparation and Brief) of the RIBA Plan of Work (Sinclair 2013). The next step is to generate viable design alternatives, the performance of which will then be evaluated with respect to the defined objectives and constraints. Based on such evaluation results, a satisfactory design will be selected to be refined during the upcoming detailed stages. Prior to refinement, the selected solution must be carefully communicated to all team members to make sure the project will move in a direction that aligns with the requirements of the client.

The use of parameters or variables to express a building during the design process is based on algorithmic thinking and is known in the literature as parametric design (Jabi 2013). Its goal is ‘to produce a complete and consistent design model, which satisfies the given requirements’ (Motta 1998). In the late 1990s, a few computer-aided tools which supported the generation of design variations were launched. However, these did not offer a sophisticated interface (Hernandez 2006), hence discouraging designers from using them in a systematic way (Monedero 2000). Utilising parametric design to solve a building design problem was just popularised over the last few years with the

[3] Section 2.4.1.1 will present the design parameters that greatly influence performance prediction and should hence attract the attention of stakeholders when developing design alternatives.

release of more sophisticated tools which support the generation of several parametric design alternatives and therefore increase the efficiency of the search process (Oxman and Gu 2015). Grasshopper 3D (Rutten and Robert McNeel & Associates 2007) is a popular example, this being a graphical algorithm editor integrated with Rhinoceros 3D (Robert McNeel & Associates 1998). Building Information Modelling (BIM) tools, such as Autodesk Revit (Autodesk 2020), are also based on parametric design thinking, although these are characterised by a component-based – rather than a form-finding – approach. Despite their great potential to generate design variations, parametric design tools still need to improve their interoperability with BPS tools to better support the performance-based evaluation of design alternatives, with tools such as Ladybug and Honeybee (Roudsari and Pak 2013) being promising to this end.

Section 2.2 will cast light on the performance-based evaluation of design alternatives which takes into account the requirements of the building regulations, with the final selection of a suitable design solution being also dependent on the preferences of the different stakeholders. Note that, although the decision-making process may be here discussed, the focus of this thesis is primarily on the design exploration process – that is, the generation and evaluation of alternative designs – and not on the selection of the (single) design that will be refined later on in the design process.

2.2 Performance-based building design

As emphasised by Laseau (2001), evaluating the performance of design alternatives with respect to the defined objectives and constraints is an indispensable part of the design exploration process, which is also necessitated by the rising energy costs and environmental concerns (Elbeltagi *et al.* 2017). The goal of the explorative process is hence to identify a good configuration for the defined design variables depending on their economic and environmental performance (Geyer 2009). Building performance simulation (BPS) can support the identification of a sustainable solution by providing rapid feedback on the performance of design alternatives (Clarke and Hensen 2015). Section 2.2.1 will discuss the beneficial role of BPS. Section 2.2.2 will focus on the indicators and metrics for quantitatively comparing candidate design solutions.

2.2.1 The role of BPS in the design process

Integrating BPS in building design exploration can support the designers in meeting the requirements of the brief that has been agreed with the client, but also complying with the Building Regulations Part L that includes the energy efficiency requirements for all buildings in England[4]. As described in the Green Overlay to the RIBA Outline Plan of Work (Gething 2011), Part L assessment is one of the principal sustainability checkpoints of the conceptual and design development stages. This can be completed with the assistance of an energy modelling tool that is approved by the Department for Communities and Local Government (DCLG). Two Approved Documents (L1A (UK Government 2013b) and L2A (UK Government 2013a)) are able to provide practical guidance about how to meet the requirements of the Building Regulations in the case of new dwellings and new commercial buildings, respectively. In the case of existing dwellings and existing buildings other than dwellings, the Approved Documents L1B (UK Government 2013c) and L2B (UK Government 2013d) can respectively assist the design team in ensuring compliance with the Building Regulations.

As highlighted in the CIBSE Guide F (CIBSE 2012), Part L assessment can increase the energy efficiency of buildings by setting limits on their design flexibility, quality of construction and operation. Building energy efficiency has been the focus area of many institutions of architecture across the world, which have established energy and environmental policies to highlight the critical issue of climate change and encourage sustainable development. One of the cornerstones of those policies is the Declaration of Interdependence for a Sustainable Future, published in 1993 by the International Union of Architects (IUA) in order to 'place environmental and social sustainability at the core of the professional responsibilities of architects' (IUA 1993). This policy has been adopted by the Royal Australian Institute of Architects (RAIA), recognising 'the responsibility of the architectural profession to embrace an integrated approach to ecological, social and economic sustainability' (RAIA 1993).

The Climate Change Act that was launched in 2008 by the UK Government was also an effort to tackle climate change, declaring that 'the net UK carbon account for the year 2050 needs to be at least 80% lower than the 1990 baseline' (UK Government

[4] This thesis focuses on the Regulations in England, as the examined buildings are located in London.

2008), with a recent announcement requiring carbon to be brought to net zero by 2050 (Priestley 2019). Given that buildings greatly contribute to the high level of greenhouse gases and hence to global warming, integrating BPS in the building design process can play an important role in achieving this significant drop (Hong *et al.* 2000). After the first applications in the 1960s, several researchers have supported the beneficial effects of using BPS tools (Augenbroe 2002, de Wilde *et al.* 2002, Bleil de Souza 2009, Clarke and Hensen 2015). These are referred to as ‘a piece of software that accommodates three-dimensional representations of the building and that predicts something useful about its performance’ (Milne 1991). They are also described as ‘design environments that allow designers to reach a good compromise between contradictory requirements’ (Morel and Faist 1993), such as energy efficiency and aesthetics (Appelbaum 2015).

SBEM (Simplified Building Energy Model) (BRE 2018) is the software program developed by BRE (Building Research Establishment) for DCLG in order to predict the performance of non-domestic buildings and ensure compliance with the Building Regulations Part L. In the case of dwellings, SAP (Standard Assessment Procedure) (BRE 2012) is used to quantify performance with respect to space heating, domestic hot water, lighting and ventilation to satisfy the energy efficiency requirements of the Building Regulations. PHPP (Passive House Planning Package) (Passivhaus Institut 2015) is used when aiming for a Passivhaus building ‘to ensure a high level of energy efficiency and comfort’ (International Passive House Association 2018).

Instead of using one of these tools that carry out steady state calculations, designers can use dynamic modelling to predict the performance of the preferred design before developing it (Gething 2011). Several building energy performance simulation tools are commercially available, the capabilities of which have been contrasted to reveal the main features but also the limitations of each software tool (Crawley *et al.* 2008). Among them, EnergyPlus (U.S. Department of Energy 2016a) is a simulation engine that has been validated using the tests included in the ANSI/ASHRAE Standard 140-2001, these enabling the identification of differences in predictions that are caused by software errors (Henninger and Witte 2004). EnergyPlus (U.S. Department of Energy 2016a) can hence support the accurate prediction of the (energy and thermal comfort) performance of design alternatives (Maile *et al.* 2007) using the metrics described in 2.2.2, which aim to ensure compliance with building regulations and guides.

2.2.2 Performance indicators and metrics

As recommended by the Green Overlay to the RIBA Outline Plan of Work (Gething 2011), the project team must update the building model as design develops and check its performance against targets (Gething 2011). The CIBSE Guide L (Cheshire and Grant 2007) also discusses the need for the project team to identify an appropriate set of design objectives (or performance indicators) and targets. The literature review on building design exploration and decision-making (Attia *et al.* 2013, Chardon *et al.* 2016, Huang and Niu 2016, Østergård *et al.* 2016, Touloupaki and Theodosiou 2017, Kheiri 2018, Longo *et al.* 2019) reveals that the objectives that are most commonly considered by the project team when exploring the performance of design alternatives, are the following: a) energy use; b) cost; and c) thermal comfort. In case optimization is used to explore the design space, the defined design objectives also act as the goals of the optimization process. The requirements of the regulations and the needs of the client will inform the selection of objectives and the identification of relevant targets (Cheshire and Grant 2007).

In particular, in the case of buildings other than dwellings, to ensure compliance with the Building Regulations Part L that sets the legal minimum standards with respect to energy efficiency, the designers must calculate the annual energy use of the proposed building and compare it with the energy use of a comparable ‘notional’ building (UK Green Building Council 2007). Both calculations make use of the standard data sets that are included in the National Calculation Method (NCM), as have been mandated by the Energy Performance of Buildings Directive (EU Parliament 2010). These sets can limit the design flexibility, quality of construction and operation of the building (CIBSE 2012), to make sure that it will meet the limiting fabric and building services parameter values and ultimately the carbon dioxide targets. In the case of dwellings, the minimum performance requirements are differentiated, these however not being the focus of this thesis.

To ensure compliance with the Passivhaus Standard, heating energy demand must be less than or equal to 15 kWh/m^2.yr (International Passive House Association 2018). In climates where active cooling is required, cooling energy demand must similarly not exceed the limit of 15 kWh/m^2.yr. Thermal comfort is also a critical performance indicator which can be quantified with the help of the percentage of hours per year that the internal temperature is over 25 ℃. To guarantee comfort in warm conditions, no more than 10 % of hours must exceed that temperature limit (International Passive House Association 2018). Although the PHPP (Passivhaus Institut 2015) estimates the percentage of discomfort hours, using a dynamic modelling tool is recommended for comfort calculations, as it is more likely to lead to a realistic prediction compared with a steady state tool (UK Green Building Council 2007).

In particular, dynamic tools such as EnergyPlus (U.S. Department of Energy 2016a) can provide a more accurate prediction of temperatures in spaces and consequently a better estimate of thermal comfort (Maile *et al.* 2007). Nevertheless, several metrics are available in the literature for quantifying the performance of design alternatives with respect to thermal comfort (Bleil de Souza and Tucker 2015), and providing designers with 'realistic and measurable targets' (Cheshire and Grant 2007). Some of the most prevalent metrics are displayed in table 2.1. As proposed by the ASHRAE Standard 55-2013 (ASHRAE 2013), for a mechanically conditioned building, the comfort zone is defined as 'conditions falling within and including PMV[5] levels from -0.5 to +0.5'.

For a naturally ventilated building, the ASHRAE Standard 55-2013 (ASHRAE 2013) states that the thermal environment should be considered as acceptable if it meets the 80% acceptability limit – that is, when the indoor operative temperature is no greater than 3.5 ℃ from the comfort temperature that is based on the daily average outdoor temperatures of the previous 30 days. Based on the British Standard 15251:2007 (BS EN 2007), the operative temperature must be no greater than 3.0 ℃ from the comfort temperature, which is based on the weighted average of the outdoor air temperature of the previous 7 days. Additional metrics for evaluating comfort performance can be found in the literature, this revealing the uncertainty in the definition of performance indicators and metrics that should be further investigated in the future.

[5] That is, the Predicted Mean Vote based on Fanger's comfort model (Fanger 1970).

Table 2.1. Metrics for evaluating the thermal comfort performance of buildings based on their ventilation type and applied comfort model.

Ventilation type	Applied method	Metric	Reference
Mechanical	Deterministic thermal comfort model	-0.5 ≤ PMV ≤ +0.5	ASHRAE Standard 55-2013 (ASHRAE 2013)
Natural	Adaptive thermal comfort model	Operative temperature - Comfort temperature ≤ 3.5 °C (80% acceptability)	ASHRAE Standard 55-2013 (ASHRAE 2013)
		Operative temperature - Comfort temperature ≤ 3.0 °C (Category II)	BS EN 15251:2007 (BS EN 2007)

2.3 Multi-objective optimization

As discussed in section 2.2, BPS can assist designers in meeting the defined objectives and constraints. However, the commonly-used trial-and-error process of identifying an ‘optimum’ design solution may be misleading and time-consuming (mainly in the case of a large design space), this revealing the need for a more efficient exploration method (Wang *et al.* 2005). This need has resulted in the integration of optimization into the building design process over the last few years, as it can support the identification of solutions that best satisfy objective and constraint functions (Machairas *et al.* 2014). Optimization is hence described as the process of identifying the best solution (i.e. combination of design parameter values) – or set of solutions – with respect to one or more objective and constraint functions. Nevertheless, this process may prove to be complex due to the plethora of objective functions (multi-objective optimization) and the uncertainty in the representation of input data – which will be further discussed in section 2.5.2.2 that focuses on robust optimization. Section 2.3.1 will discuss relevant benefits and limitations. Section 2.3.2 will present common optimization algorithms.

2.3.1 Benefits and limitations

By evaluating the performance of two algorithms in the context of a building design problem that aimed to minimise the annual energy consumption of an office building, Wetter and Wright (2003) demonstrated that simulation-based optimization can lead to a great reduction in energy use (up to 32% (depending on the location) for the case study building) and hence yield considerable economic gains. Optimization is used to replace the tedious trial-and-error process of identifying a suitable design solution as, when coupled with a thermal simulation tool, it enables the efficient exploration of the design space (for a pre-defined problem) (Wang *et al.* 2005). It can therefore facilitate the comparison of several design alternatives with respect to prevalent performance indicators, such as energy use, cost or thermal comfort (Attia *et al.* 2013, Chardon *et al.* 2016, Huang and Niu 2016, Østergård *et al.* 2016, Touloupaki and Theodosiou 2017, Kheiri 2018, Longo *et al.* 2019).

Equation 2.1 represents a single-objective optimization problem that aims to optimise – and, in particular, to minimise – an objective function $f(x)$, subject to a constraint $g(x) \leq b$ (if applicable) (Caramia and Dell´Olmo 2008):

$$\min f(x) \text{ subject to } g(x) \leq b \tag{2.1}$$

Nevertheless, multi-objective optimization is recommended to support green building design (Wang *et al.* 2005), with designers therefore needing to account for more than one performance indicator when comparing design alternatives. Prowler (2008) also highlights the importance of considering multiple objectives to achieve a successful solution. This is similarly suggested by the integrated design approach (described in section 2.1.1), which highlights the need to explicitly define all objectives early on to inform decisions and prevent critical conflicts. Lawson (1997) also states that building design solutions should be 'an integrated response to a complex, multi-dimensional problem', with the multi-dimensionality of real-world problems calling for solutions that meet several, often-conflicting objectives.

There are two main methods to resolve various conflicting objectives in optimization problems: the weighted-sum method and Pareto optimality (Evins 2013). In the case of the weighted-sum method for multi-objective optimization, the various objectives must be combined to form a single objective function – that will then be optimized as described in equation 2.1. Equation 2.2 reveals the need to assign a weight w_i to each objective $f_i(x)$ in order to define this aggregate function (Marler and Arora 2010):

$$\sum_{i=1}^{k} w_i \, f_i(x) \tag{2.2}$$

where k is the total number of objectives (prior to aggregation).

However, as the choice of these weights affects optimization results (Emmerich and Deutz 2006), this method is suitable for design stages where stakeholder preferences are already consolidated and hence their *a priori* articulation is desirable (Marler and Arora 2010). On the other hand, determining scalar weights is not compulsory in the case of Pareto optimization, which can therefore support the *a posteriori* articulation of preferences. A solution is called Pareto optimal, if it is not dominated by any other solution (Branke *et al.* 2008). Mathematically, x^* (that is, a feasible combination of design variable values in X) is Pareto optimal, 'if there exists no feasible x, which would decrease some criterion without causing a simultaneous increase in at least one other criterion' (Coello *et al.* 2007):

$$\begin{gathered} f_i(x) > f_i(x^*) \text{ for at least one } i \in I, I = \{1, \dots, k\} \\ \forall\, x \in X, X = \{x_1, \dots, x_m\} \end{gathered} \tag{2.3}$$

where m is the total number of feasible solutions in the feasible region X.

As revealed by the review conducted by Evins (2013), optimization is applicable to various fields of sustainable building design such as envelope design (this referring to form and construction) (Al-Homoud 1997, Caldas and Norford 2002, Coley and Schukat 2002, Wetter and Polak 2005, Diakaki *et al.* 2008, Wright and Mourshed 2009, Tuhus-Dubrow and Krarti 2010, Leskovar and Premrov 2011); configuration and control of building systems (Wang and Jin 2000, Chow *et al.* 2002, Wright *et al.* 2002, Lu *et al.* 2005, Fong *et al.* 2006, Zhang *et al.* 2006, Cassol *et al.* 2011, Yang and Wang 2012); and renewable energy generation (Charron and Athienitis 2006, Li *et al.* 2006, Kumar *et al.* 2008, Ren *et al.* 2009, De Ridder *et al.* 2011, Bornatico *et al.* 2012, Milan *et al.* 2012, Vetterli and Benz 2012).

Multi-objective optimization can bring all these fields together, therefore enabling a holistic approach to building design (Bichiou and Krarti 2011, Chantrelle *et al.* 2011, Hamdy *et al.* 2011). Accounting for multiple objectives can consequently moderate the decision bias that characterises the conventional one- and two-objective problem formulations, via providing the DMs with additional trade-offs that can increase the understanding of the consequences of decisions (Kollat *et al.* 2011). Such trade-offs are visualised in figure 2.3 for a bi-objective problem, with rhombuses indicating the non-dominated design solutions that form the two-dimensional Pareto optimal front (highlighted with a dashed line). However, in the case of a multi-dimensional Pareto front, calculating and visualising trade-offs proves to be challenging (Kotireddy *et al.* 2018). This is due to the difficulty in, firstly, calculating a multi-dimensional Pareto optimal surface and, secondly, disseminating it to the DMs in a user-friendly manner (Deb and Saxena 2005). Accounting for uncertain factors (e.g. weather variations, occupant behaviour and randomness of thermal properties) increases the complexity of calculating and visualising trade-offs (Tian *et al.* 2018), which are also vulnerable to the capabilities of the selected optimization algorithm (Evins 2013).

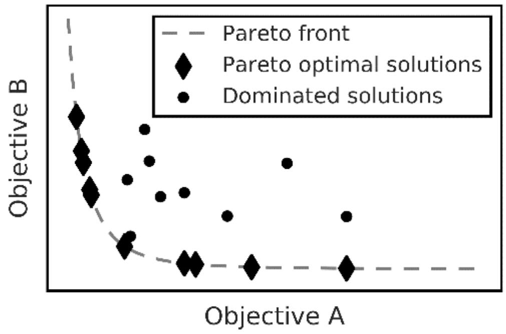

Figure 2.3. The Pareto front for a (hypothetical) bi-objective problem.

2.3.2 Search and optimization algorithms

Given that the capabilities of optimization algorithms can affect the optimized trade-offs (Wetter and Wright 2003), selecting a suitable algorithm is important to finding the Pareto optimal front for a given problem. Suitability is however case-sensitive, as it depends on the characteristics of the problem that needs to be solved, such as the size of the design space (Machairas *et al.* 2014). Choosing an optimization algorithm is also reliant on the desirable trade-off between computational run-time and solution quality, as less accurate results may require less computational time but may possibly fail to find the global optimum (Brownlee and Wright 2015).

Optimization algorithms are commonly subdivided into two categories: deterministic and probabilistic (or stochastic) (Bartz-Beielstein and Zaefferer 2017). Deterministic optimization algorithms can guarantee convergence to the true Pareto front, but at the cost of increased computational time (Emmerich and Deutz 2006). Exhaustive search is a simple deterministic approach to optimization that can result in the identification of the global optimum (for the defined problem) by evaluating all possible solutions

(Barhen *et al.* 1997). In contrast to probabilistic optimization algorithms, this search method is independent of the number of objective and constraint functions and it also supports the post-processing of results – without the need to reformulate the problem (ur Rehman *et al.* 2017).

On the contrary, probabilistic optimization algorithms are not guaranteed to find the global optimum (Brownlee and Wright 2015) as the discontinuity and/or ruggedness of the fitness landscape may obstruct their convergence (Emmerich and Deutz 2006). However, such algorithms require less computational time, especially in the case that a high level of confidence in convergence is not necessary (Wetter and Wright 2004). Evolutionary algorithms can result in a satisfactory approximation set to the globally optimal solution set in a single execution (Fleming *et al.* 2005). By working with a population of solutions and employing Darwin's theory of the survival of the fittest, they can search for several Pareto optimal solutions in one run, and provide the DMs with a set of options (Branke *et al.* 2008). There are several evolutionary algorithms available in the literature, with NSGAII (Deb *et al.* 2000) being more widely applied (Reed *et al.* 2013, Kerdan *et al.* 2017). Note that, ε-NSGAII has extended NSGAII to adjust the population size based on the problem complexity (Kollat *et al.* 2008).

Being also stochastic in nature, surrogate models (or metamodels) such as Kriging (van Beers and Kleijnen 2003) have been used over the last decades for accelerating the search process and therefore improving run-time performance (Bartz-Beielstein and Zaefferer 2017). Metamodels replace the original, time-intensive models with simpler and faster models, thus being computationally inexpensive to run (Van Gelder 2014). In other words, they are fit to original data, but have a different parametric structure (Eisenhower *et al.* 2012b). Although metamodels decrease computational run-time, they increase the risk of errors in optimization (Nguyen *et al.* 2014). Their behaviour within uncertain optimization problems must also be further investigated (Ramallo-González *et al.* 2015), as metamodels were originally applied to such problems only a few years ago (Marijt 2009), yet with limitations on the considered uncertainties.

2.4 Uncertainty analysis

Being a concept generation procedure that involves the interaction between several stakeholders, the building design process is characterised as an 'uncertain exchange of information' (Gray and Hughes 2001). In addition to any design parameter variations, the building design process is also susceptible to environmental parameter variations, which can remarkably affect building performance prediction (Goh and Tan 2009) and Pareto optimality (Avigad and Branke 2008). Uncertainty analysis (UA) is essential for dealing with this complex process as it allows the 'determination of the uncertainty in results that derives from uncertainty in inputs' (Helton *et al.* 2006). This section will reveal why UA must be part of the building design process and will categorise common sources of uncertainty that affect BPS and optimization results (as discussed in chapter 1). The most influential sources will be presented, this being beneficial to the definition of building design solutions and uncertain conditions. Their quantification will also be described, this being vital for populating the thermal model.

2.4.1 Classification of uncertainties

Even though BPS can support the building design exploration process, its potential is restricted by the uncertainties that are inherent in the definition of all building design problems (Clarke 2001), these affecting the accuracy of performance prediction and being able to cause a gap between predicted and actual performance (Demanuele *et al.* 2010). As recommended by Hopfe and Hensen (2011), taking into consideration these uncertainties can strengthen the confidence in the BPS outcomes, and hence improve design support and boost decision-making. As also emphasised by Sun *et al.* (2014), the UA of building performance can assist the decision-makers (DMs) in taking risk-conscious decisions, and therefore increase the robustness of performance prediction (Clarke 2001). Despite its benefits though, it is not yet regarded as standard practice in building design exploration (Tian *et al.* 2018), which can be partly attributed to the lack of tools that deal with the various sources of uncertainty and thus eliminate any associated risks in decision-making (Martani 2015).

The appropriate treatment of uncertainties is crucial in analysing complex problems and informing decisions (Helton *et al.* 2010), this however being a great challenge due to the presence of different types of uncertainty in real-world problems. Kennedy and

O'Hagan (2001) classify the uncertainties that are generally associated with the use of computational models into the following six main categories: parameter uncertainty; parametric variability; model inadequacy; observation error; residual variability; and code uncertainty. *Parameter uncertainty* derives from the lack of knowledge about the value of a model input – this being considered as an unknown parameter. *Parametric variability* stems from the incapability to control an input – with its value thus varying according to a defined distribution. *Model inadequacy* is due to the fact that there is no perfect model and thus there is always an inconsistency between the predicted and real values. *Observation errors* are considered in the case that the model configuration is based on real-world observations, these being part of the *residual variability*, i.e. the variability that is associated with unrecognised conditions. Finally, *code uncertainty* arises from the fact that, in practice, the actual relationship between input and output is only known after the successful running of a code, this being questionable in the case of several inputs of interest that result in an increased computational effort.

Focusing on engineering problems, Faber (2005) divides input uncertainties into the following three categories: inherent; model; and statistical. *Inherent uncertainties* are due to the fact that nature is not deterministic – or even if it is, our knowledge about it remains incomplete. There is therefore an inherent natural variability, which cannot be eliminated with the collection of additional data. In contrast, *model uncertainties* and *statistical uncertainties* can be reduced with the update of available information as they arise from the lack of knowledge about input parameter values, this affecting the setup and level of detail of the model as well as the sampling and exploration of the design space, respectively.

In the context of building design problem-solving, de Wit (2001) acknowledges the subsequent four principal types of uncertainty: scenario; numerical; modelling; and specification. *Scenario uncertainties* derive from the uncontrolled behaviour of the 'external' conditions the building is exposed to, these referring to the outdoor climate, the internal heat gains from people, lighting and equipment, and the control of the windows, solar shadings and the HVAC system. *Numerical uncertainties* are caused by errors in simulation, these however being eliminated – and consequently ignored – in the case of an appropriate specification of discretisation and timesteps. *Modelling* *uncertainties* stem from the simplifications and assumptions that are entailed in the development of each building model (due to the difficulty in representing complex physical processes). *Specification uncertainties* emerge from the lack of sufficient information on the properties of the building, these being related to its geometry and construction materials.

A similar categorisation is introduced by MacDonald (2002), who casts light on the quantification of the effects of the following predominant sources of uncertainty: the *stochastic processes* that refer to the assumptions on the weather, as well as on the occupancy and operation of the building; the *simulation program capabilities* and, in particular, the algorithms for the various heat and mass transfer processes; the *model realism* that is related to the quality of the representation of reality by the model; the values of the *input parameters* that are used in case there are no measured data; and the *design variations* that are caused by changes in the various design aspects.

Although the detailed classification of the different sources of uncertainty may vary from case to case and/or from scholar to scholar due to the fact that there is still not a widely-applied categorisation, their analysis is commonly (Paté-Cornell 1996, Dessai and Hulme 2004, Helton *et al.* 2006, Der Kiureghian and Ditlevsen 2009) performed on the basis of their reducibility (i.e. their capability of being reduced). In this way, uncertainties are divided into the following two principal categories: epistemic; and aleatoric. In more detail, 'uncertainties are characterised as *epistemic*, if the modeller sees a possibility to reduce them by gathering more data or by refining the model, and as *aleatoric*, if he/she does not foresee the possibility to reduce them' (Der Kiureghian and Ditlevsen 2009). Since epistemic uncertainty emerges from the lack of knowledge about design parameter values and it can thus be eliminated with the update of the available information, it is also characterised as subjective and reducible (Helton *et al.* 2010). On the contrary, aleatoric uncertainty is referred as stochastic and irreducible uncertainty, as it arises from the natural variability in the behaviour of any external conditions, which cannot be mitigated by gathering additional information.

In this way, the uncertainties that are detected in the formulation of building design problems and the use of BPS for design support can be divided – depending on their capability of being reduced or not, respectively – between epistemic and aleatoric (table 2.2). Epistemic uncertainties emerge from the lack of detailed information on the form and construction of the building, this eventually resulting in a high number of unknown design parameters and potential values, and therefore in a broad range of possible performance outcomes. However, while proceeding to the final stage of the building design process, the amount of detailed design information increases thanks to the decisions that are taken by the DMs in an effort to successfully complete the design project. In this way, as the design progresses, the size of the design space – that is, the number of alternative design options that need to be explored – decreases, this resulting in the gradual elimination of epistemic uncertainties.

Table 2.2. Categorisation of common sources of uncertainty in building design problems on the basis of their reducibility.

Main categories	Cause	Reducibility	Subcategories
Epistemic	The lack of detailed design information.	Reducible	Form Construction Systems and operation
Aleatoric	The natural variability in the behaviour of external conditions.	Irreducible	Weather Occupancy Construction (actual performance) Systems and operation (actual performance)

On the contrary, the increase in the design detail does not necessarily result in the elimination of aleatoric uncertainties, which emerge from the assumptions that need to be taken with respect to the weather, as well as the occupancy and operation of the building. As highlighted by Clarke (2001), weather is stochastic and hence inherently uncertain, this jeopardising the accuracy of the BPS outcome. Another obstacle to the accuracy of the performance prediction is the difficulty in accounting for any micro-climate phenomena, this being commonly attributed to the unavailability of on-site measurements. As a result, the adjustment of the data that is collected from a nearby meteorological station is required in order to also take into consideration the urban surroundings of the building, a process that however commonly results in intensive computations and is therefore being skipped (Sun *et al.* 2014). The weather-based uncertainties that are associated with the prediction of the future performance of the building and the influence of climate change on it are similarly frequently ignored in the favour of simplicity (Rastogi and Andersen 2016).

Occupant-related uncertainties are also commonly disregarded due to the difficulty in controlling the random and unpredictable variability in occupant behaviour (O'Brien 2013). In this way, general – and often unreliable – assumptions are taken in order to describe the presence and activity of occupants, as well as their control actions that affect the operation of the building in an effort to improve its indoor environmental conditions (thermal; air quality; light; and noise) (Hoes *et al.* 2009). As indicated by Soebarto and Williamson (2001), these assumptions may however have significant implications in building performance prediction, as they determine the density and schedule of occupancy, and thus the energy needs for lighting, equipment, heating, cooling, ventilation and hot water. However, in case occupants cannot interfere in the control of the HVAC system, the uncertainties that are associated with the undecided operation of the system (e.g. the selection of the thermostat setpoint temperature, air supply rate etc.) are considered as epistemic (table 2.2).

Finally, although the uncertainties that are associated with the selection of building materials can be eliminated within the design process and are therefore considered as epistemic, the uncertainties that stem from the specification of their thermophysical properties cannot be removed and are thus characterised as aleatoric. In particular, the values of the thermophysical properties of materials (thickness, thermal conductivity, density and heat capacity, as well as vapour permeability, roughness, emissivity and absorptivity) cannot be accurately predicted due to the influence of several, randomly varying factors that cannot be controlled by the designers (Hopfe and Hensen 2011). These factors are most commonly related to the moisture content, temperature and age of the materials (Huang *et al.* 2015); the quality of workmanship during installation (Salonvaara *et al.* 2001); and any probable errors in measurement (MacDonald 2002), with the overall uncertainty leading to deviations from initial design specifications and should thus be considered during design exploration (Malkawi and Augenbroe 2004).

Similarly, even though the uncertainty that is related to the selection of infiltration rate can be eliminated during the design process, its inherent variability – and hence its actual performance – cannot be accurately predicted. In particular, the factors that commonly affect the unintended leakage of air through the building fabric are: the quality of construction; the usage of the building (such as the opening and closing of windows); and the weather (including local micro-climate phenomena) (MacDonald 2002). The infiltration rate of the building is also a function of its age, this possibly causing cracks at the joints (Heo *et al.* 2012). However, there is not adequate data for making a generalisation about the correlation between infiltration rate and age – or any other building feature (Persily 1998, 1999).

2.4.1.1 Influential design parameters

Given the presence of several sources of epistemic uncertainty, the identification of the most influential parameters among them can indicate the principal areas of focus during the design exploration process and thus minimise time and effort. Considering the impact of any unknown parameters on performance prediction can hence inform decisions throughout the building design process, and especially at the early design stages where the majority of parameters have not been finalised yet, this providing a greater potential for creating a best-performing solution (Farrar-Nagy *et al.* 2002). In addition to this, at early design stages, it is more important to determine the ranking of the importance of the different properties of the building, rather than their accurate values (Malkawi and Augenbroe 2004).

Even though the precise ranking of the impact of any unknown design parameters on building performance prediction may differ from case to case, an extensive literature review can reveal the elements that are most commonly responsible for variations in BPS outcomes and should thus be part of design exploration. Note that, the reported cases focus on the impact of different sources of epistemic uncertainty on energy use, cost and thermal comfort, these being the most prevalent objectives (Attia *et al.* 2013, Chardon *et al.* 2016, Huang and Niu 2016, Østergård *et al.* 2016, Touloupaki and Theodosiou 2017, Kheiri 2018, Longo *et al.* 2019). Sensitivity analysis (section 2.4.2) may be used during design exploration to enable a customised list of influential design parameters (based on the mapping from analysis inputs to analysis outputs).

In general, energy consumption is concluded to be higher in non-domestic buildings (compared with residential buildings), with the highest rates being observed in retail, offices, hotels and restaurants (Pérez-Lombard *et al.* 2008). Building *typology* is thus a fundamental factor (Moran *et al.* 2012) as it affects not only the use and operation of the building, but also its *form*, this defining the total surface area that is subject to both heat losses and solar gains (Chiras 2002). The importance of form is verified in the literature by the high sensitivity of performance prediction to form-related design parameters, which are commonly the following: *total floor area* (Firth *et al.* 2010, Cheng and Steemers 2011, Hopfe and Hensen 2011, Hygh *et al.* 2012, Wei *et al.* 2016); *number of floors* (Hygh *et al.* 2012, Wei *et al.* 2016); *storey height* (Firth *et al.* 2010); *total length and width* (Yildiz *et al.* 2012); *aspect ratio*[6] (Hygh *et al.* 2012, McKeen and Fung 2014); *window area* (Hopfe and Hensen 2011, Ballarini and Corrado 2012, Yildiz *et al.* 2012); *window-to-wall ratio* (WWR) (Hygh *et al.* 2012, Yang *et al.* 2016); and *solar shading* (Ballarini and Corrado 2012).

Regarding the epistemic uncertainties that stem from the undecided (at an early stage) *construction* of the building, the most influential sources are generally related to the thermal transmittance of the elements that the building envelope consists of, this also being known as U-value. In more detail, energy consumption is highly sensitive to the *U-value* of walls, roof and windows (de Wilde and Tian 2009, Demanuele *et al.* 2010, Firth *et al.* 2010, Cheng and Steemers 2011, Tian and de Wilde 2011, Ballarini and Corrado 2012), as this expresses the rate of heat transfer through the building skin (measured in Watts per m^2 of construction and Kelvin of temperature difference across it). *Air permeability* is another influential factor (de Wilde and Tian 2009, Heiselberg *et al.* 2009, Breesch and Janssens 2010, Demanuele *et al.* 2010, Hopfe and Hensen 2011, Tian and de Wilde 2011, Tian and Choudhary 2012, Kim *et al.* 2014, Heo *et al.* 2015), which represents the volume of air leakage through the building envelope (measured in m^3 of air per hour and m^2 of envelope, commonly at 50 Pa differential pressure between inside and outside the building).

With respect to the epistemic uncertainties that are associated with the *operation* of the HVAC system, the *outdoor air supply rate* is one of the most influential design parameters (Lam and Hui 1996, Heiselberg *et al.* 2009, Tian and Choudhary 2012, Rasouli *et al.* 2013), as it defines the amount of fresh air that flows to the conditioned

[6] Aspect ratio interprets the building's footprint as a ratio of length to width.

building zone(s). The *thermostat setpoint temperature* for both heating and cooling (when applicable) are also concluded to significantly influence building performance prediction (Lam and Hui 1996, Lam *et al.* 2008, Brohus *et al.* 2009, Demanuele *et al.* 2010, Firth *et al.* 2010, Cheng and Steemers 2011, Tian and Choudhary 2012, Wright *et al.* 2012, Daly *et al.* 2014), as they control the zone air temperature.

The *specific fan power* of the air distribution system is another influential parameter (Heiselberg *et al.* 2009), this expressing the total amount of electrical power that is provided to the supply and extract fans, divided by the design air flow rate through the system (most commonly expressed in Watts of power per litre of air and second) (UK Government 2013e). The type and characteristics of the selected heating and cooling system(s) are also very important factors (Hamdy *et al.* 2011). In particular, building performance prediction is found to be sensitive to the *efficiency* of the system (Firth *et al.* 2010, Cheng and Steemers 2011, Tian and de Wilde 2011, Moran *et al.* 2012, Heo *et al.* 2015), this representing (in %) the useful energy output divided by the energy input (i.e. fuel or electricity) delivered to the system, as determined by the appropriate test methods for that type of system (UK Government 2013e). Additional factors that are related to the different components of the HVAC system (such as the *hot water temperature* of the heating system, the *coefficient of performance* of the chiller etc. (Eisenhower *et al.* 2012a)) should be considered for the correct sizing of the system, this however being out of the scope of this thesis.

2.4.1.2 Uncertain conditions

Ramallo-González *et al.* (2015) acknowledge three main types of aleatoric uncertainty that should be considered in robust building design problem-solving: environmental; behavioural; and workmanship and the quality of building elements. Environmental uncertainty refers to the uncertainty in the weather prediction and in particular, the use of synthetic data to express a real year and the influence of climate change. Behavioural uncertainty includes any parameters that are related to human behaviour. Uncertainty in workmanship and the quality of building elements expresses possible variations in the U-values of materials and the infiltration rate of the building. The consideration of all these uncertainties can be facilitated by the development of scenarios, these being possible future states that represent plausible conditions (Mahmoud *et al.* 2009).

In more detail, BPS tools contain simplifications about the actual weather, as they make use of standard weather data sets that are based on historic data and will thus be different from the actual conditions during the operation of the building (Cheshire and Menezes 2013). As the unpredictable nature of weather conditions can result in great differences between predicted and real performance values, taking into consideration possible *weather* variations is essential for reinforcing the robustness of BPS results (Wang *et al.* 2012). Designers should hence test the performance of candidate design solutions using different weather data sets that represent possible weather scenarios (Cheshire and Menezes 2013). Given the potential consequences of climate change on the building and its occupants (such as discomfort and reduced productivity) (de Wilde and Coley 2012), designers should also assess the resilience of the building to possible future changes in climate (Gething 2011). They should thus consider climate change scenarios to enable the quantification of the influence of climate change on building performance prediction (Holmes and Hacker 2007, Wan *et al.* 2011, Roetzel and Tsangrassoulis 2012, Wang *et al.* 2012, McLeod *et al.* 2013, Nik and Kalagasidis 2013, Karimpour *et al.* 2015, Rastogi and Andersen 2016). Since determining the likelihood of these scenarios is difficult due to the natural variability in the behaviour of the weather, the selection of scenarios can be informed by the attitude of the client and the project team towards risk (Hacker *et al.* 2009).

Occupant density is another source of aleatoric uncertainty, which cannot be reduced due to the uncontrollable nature of occupant behaviour (Tian *et al.* 2018). Occupant behaviour is an important contributor to the overall uncertainty of BPS (Macdonald and Strachan 2001, Clevenger and Haymaker 2006, Hoes *et al.* 2009, Guerra-Santin and Itard 2010, Virote and Neves-Silva 2012, Wang *et al.* 2012, O’Brien 2013, Mavrogianni *et al.* 2014, Silva and Ghisi 2014, Yan *et al.* 2015, Hong *et al.* 2016, Gaetani *et al.* 2017, Sun and Hong 2017). In addition to occupant density, the control of the windows, solar shadings, artificial lighting, equipment and the HVAC system are also occupant-related uncertain aspects – if the users of the building can however interfere in the control of its different systems (Gaetani *et al.* 2017).

In addition to any uncertainties in weather and occupancy, designers should also take into consideration possible variations in the *actual performance of construction* and, particularly, in the U-value of different building elements and the infiltration rate of the building envelope (Ramallo-González *et al.* 2015). Such variations can be caused by both measurement errors and environmental conditions (such as moisture), which can affect the thermophysical properties of materials (such as thermal conductivity, density and heat capacity) (Tian *et al.* 2018). BPS tools do not, however, capture such uncertainties, this eventually resulting in incorrect assumptions and hence misleading performance values (Li *et al.* 2015). Due to their impact on performance prediction (MacDonald 2002, Corrado and Mechri 2009, Breesch and Janssens 2010, Hopfe and Hensen 2011, Silva and Ghisi 2014), these uncertainties must be included in building performance analysis. Chapter 3 will suggest how all the aforementioned uncertainties can be integrated into the building design exploration process.

2.4.2 Uncertainty quantification

As stated in section 2.4.1.1, any influential design parameters (e.g. the glazing area, shading strategy, level of thermal mass etc.) must be explored and specified early on in the design process to ensure satisfactory performance (Gething 2011). However, in real practice, the detailed information about those parameters may not be available at the early design stages, this hindering the accurate population of the thermal model and thus the confidence in its performance prediction. As stated in the CIBSE Guide L about sustainability (Cheshire and Grant 2007), legislation (building regulations) and client requirements are the two main drivers of building projects that should be considered from the very beginning to avoid unexpected prerequisites and hence save time, effort and money later on. For buildings located in England, energy efficiency requirements are incorporated in four Approved Documents[7] that provide guidance for ensuring compliance with the Building Regulations. Table 2.3 displays the limiting values for different fabric parameters as obtained from the Approved Document L2A about the conservation of fuel and power in new buildings other than dwellings (UK Government 2013a). The table also displays the limiting values for compliance with the Passivhaus Standard (International Passive House Association 2018).

[7] L1A (new dwellings); L1B (existing dwellings); L2A (new buildings other than dwellings); and L2B (existing buildings other than dwellings).

Table 2.3. Limiting values for different fabric parameters according to the Passivhaus Standard and Building Regulations Part L.

Fabric parameter	Limiting value: Passivhaus Standard (International Passive House Association 2018)	Limiting value: UK Building Regulations (UK Government 2013a)
Wall	0.15 W/m^2K	0.35 W/m^2K
Roof	0.15 W/m^2K	0.25 W/m^2K
Window	0.80 W/m^2K	2.20 W/m^2K
Infiltration rate	0.60 ac/h at 50 Pa	10 m^3/hm^2 at 50 Pa

By increasing the amount of available information and limiting the design parameter values, building regulations can assist the design team in eliminating the (epistemic) uncertainties that arise from the lack of detailed knowledge and excluding infeasible design choices. Quantifying these sources of uncertainty is required for ameliorating the confidence in simulation (Macdonald *et al.* 1999). As stated by Tian *et al.* (2018), there are two principal methods for quantifying uncertainties in building performance assessment: forward and inverse methods. Forward uncertainty quantification aims to predict building performance by making use of thermal models with input variations, while inverse uncertainty quantification aims to quantify any unknown parameters by making use of measurement data that has been collected from existing buildings.

In forward UA, assigning deterministic values to the design parameters of the model would ignore the (aleatoric) uncertainties that are related to the inherent variability in the behaviour of any external conditions (such as the weather), this jeopardising the confidence in the predicted values of key performance indicators (Hopfe *et al.* 2013). As stated by Tian *et al.* (2018), there are two main methods for treating uncertainties: probabilistic and non-probabilistic. In probabilistic analysis, the probability of each uncertain value occurring is assumed to be known and candidate design solutions are evaluated upon the probability density function of key performance indicators (Van Gelder *et al.* 2014). In non-probabilistic analysis, the probability of occurrence of each uncertain input value is unknown, this obstructing the probabilistic treatment of output distributions (Rysanek and Choudhary 2013).

The probabilistic approach can be subdivided into sampling-based and non-sampling methods (Xiu 2009). Sampling-based methods such as Monte Carlo are characterised as ‘external’ methods because the simulation engine is treated like a black box, with the model being run several times with different samples (Macdonald and Strachan 2001). The analysis of the differences in performance predictions is then required to draw conclusions on the effect of uncertainties (MacDonald 2002). On the other hand, non-sampling methods such as stochastic differential equations are characterised as ‘internal’ methods. Parameters are here represented as a function of uncertainty, this meaning that the underlying algorithm of the simulation engine has to be altered so that uncertainty is included at all stages (MacDonald 2002).

Regarding the sampling-based methods for uncertainty analysis (UA) and sensitivity analysis (SA), the following five steps are commonly recommended in the literature for their successful implementation (Helton *et al.* 2006):

1. Definition of probability distributions to characterise all uncertain input data;
2. Generation of samples in accordance with the defined distributions;
3. Propagation of sampled inputs;
4. Presentation of UA results; and
5. Determination of SA results.

In more detail, the first step towards the implementation of a sampling-based method for UA and SA is to specify the distributions that characterise the uncertainty in each unknown input element. This is the most significant part of the procedure, as it will determine the uncertainty in the simulation output and its sensitivity to each element. The next step is to generate samples in line with the specified distributions following the principles of the selected sampling strategy, with random sampling, importance sampling and Latin hypercube sampling being some of the most prevalent methods. That is succeeded by the propagation of samples to produce a mapping from analysis inputs to analysis outputs, this commonly being the most computationally demanding part of the process. Displaying the UA results will then reveal the distributions of performance indicators – as resulted from the distributions of uncertain inputs – that are usually presented via probability density functions. Exploring the mapping from analysis inputs to analysis outputs will finally determine the SA results and disclose the impact of individual uncertain input elements on performance indicators.

Hence, prior to analysing the probability density functions of performance indicators, all uncertain input data need to be expressed mathematically (Haldar and Mahadevan 2000). If they are normally distributed, as it is most commonly assumed for aleatoric uncertainties (de Wilde and Tian 2009, Fennell *et al.* 2017), their range can be defined by their mean plus and minus three standard deviations ($\mu \pm 3\sigma$). The probability that a variable value lies in this range is 99.7%, which indicates that the associated error is marginal. If the bounds are decreased to $\mu \pm 2\sigma$, 95.4% of data are included, while if $\mu \pm 1\sigma$ bounds are applied, 68.3% of variable values are considered. To calculate the probability $P(x_1 \leq x \leq x_2)$ of a variable x having a value between x_1 and x_2, the area under the density curve and between these two limits needs to be calculated, as expressed by equation 2.4. Note that, the probability density function of variable x is represented by $f_x(x)$:

$$P(x_1 \leq x \leq x_2) = \int_{x_1}^{x_2} f_x\,(x)dx \tag{2.4}$$

As suggested by Gang *et al.* (2015), the quantification of aleatoric uncertainties (such as occupant density) should consider the maximum possible values of the examined unknown parameters – despite the fact that according to building operation examples, the real values of these parameters are very likely to be lower. The upper and lower bounds of uncertain inputs can be informed by historic data (if however available) or confidence intervals (Hussain *et al.* 2016). For instance, Li *et al.* (2015) have used $\mu \pm 1\sigma$ to quantify the range in the U-values of solid brick and stone walls that stems from the uncertainty in heat flux plate measurements. Heo *et al.* (2012) suggest using the 95.4% confidence interval (that is, $\mu \pm 2\sigma$) to define the minimum and maximum possible values of the thermal properties of different building materials. Focusing on the uncertainty that arises from modelling approximations, Marijt (2009) proposes to use a range of $[-3\sigma, 3\sigma]$, so that the probability that a value lies in the defined range is 99.7%. To achieve robust buildings that are not sensitive to aleatoric uncertainties, designers can hence calculate the 'six-sigma capability' of uncertain input elements (Tuohy 2009), which can lead to an 'error-free' prediction (Pyzdek and Keller 2003).

Aleatoric uncertainties can be similarly quantified in non-probabilistic UA, although performance outputs cannot be subsequently treated as probabilistic distributions due to the absence of certainty in the probability of each uncertain input value occurring (Tian *et al.* 2018). Scenario analysis could hence be used to cope with the unknown probabilities of occurrence of these values (Kotireddy *et al.* 2018). Scenarios are 'a common and easy way to describe uncertain factors in deterministic status', with the only problem then lying in how to reduce the large number of possible states (Xiang *et al.* 2016). A worst-case approach may then be selected, this encouraging the DMs to investigate the performance of candidate solutions under the impact of the defined worst-case scenarios (El Ghaoui *et al.* 2003). Based on this approach, a robust solution will be one that leads to a satisfactory performance outcome under the worst possible realisation of the modelled uncertainty set (Xiang *et al.* 2016). However, as extreme scenarios have a low probability of occurring (Gang *et al.* 2015) and thus a high level of conservatism (Hussain *et al.* 2016), a more flexible definition of robustness should be determined, so that it is able to articulate the customised (risk) preferences of the DMs. As highlighted by Tian *et al.* (2018), additional studies are needed to uncover how uncertainties should be quantified as well as how robustness should be assessed in building performance analysis, this being discussed in 2.5. Chapter 3 will describe how scenario analysis is adopted by the suggested robust optimization framework.

2.5 Robustness assessment

In order to make sure that the predicted (as resulted from the thermal simulation tool) performance of candidate solutions will meet the defined performance requirements and not violate any constraints, assessing the robustness of solutions is vital (Avigad and Branke 2008). The robustness assessment of design alternatives is an evaluation process that provides information about 'the magnitude of their performance changes due to variations of input parameters' (Struck 2012). Such information is valuable in the context of building design exploration and decision-making, as it can minimise the risks that are introduced by the natural variability in the behaviour of any uncertain conditions (the so-called aleatoric uncertainties), and therefore support designers in achieving their aspired performance outcomes (Hopfe *et al.* 2013).

Accounting for parameter uncertainty is vital for making informed design decisions, as – even small – perturbations in input data can affect performance prediction and shift nominal optimal solutions to sub-optimal or even infeasible – and consequently practically meaningless – designs (Ben-Tal *et al.* 2009). Since the search for robust designs may return solutions that are different from those of the deterministic Pareto set (i.e. the nominal optimal solutions, these not incorporating parameter uncertainty) (Avigad and Branke 2008), including uncertainty in BPS and optimization is critical for uncovering the consequences of decisions with more confidence (Gokhale 2009). However, the majority of building performance analysis studies employ deterministic simulations that neglect possible variations in any uncertain conditions, this entailing the risk of sub-optimality for the optimized solutions, and consequently of misguided decisions for the DMs (Van Gelder *et al.* 2014).

Although some building design studies have focused on the integration of uncertainty analysis (UA) into BPS to improve confidence in simulation results (Macdonald and Strachan 2001, de Wit and Augenbroe 2002, Hopfe and Hensen 2011), optimization and UA are still predominantly treated as separate procedures. Coupling these two methods is however crucial in the context of robust decision-making, as optimization can ensure the minimisation of the objective function values, while UA can improve the confidence in the optimality of design solutions by evaluating their performance across a number of possible performance scenarios (Hopfe *et al.* 2012). This section will, firstly, cast light on the definition of robustness and, secondly, present existing robustness indicators (as discussed in chapter 1). It will also reveal how optimization and UA are currently brought together to solve robust design optimization problems.

2.5.1 Definitions of robustness

Robustness assessment has its roots in Taguchi's robust design method, which was developed in the 1950s as a means to achieve high-quality products that 'can tolerate greater variations in the production system' (Taguchi and Clausing 1990). Taguchi's robust design method has been applied to various fields such as electronics (Taguchi 1995), automotive industry (Yildiz 2012), and telecommunications (Wu and Chang 2004) to ensure that the manufactured products will perform 'on target' (Andersson 1997), 'regardless of uncertainties in design, manufacture and operation' (Huang and Du 2007). Robust products should hence be 'insensitive to the effects of sources of variability, even through the sources themselves have not been eliminated' (Fowlkes and Creveling 1995). Prior to searching for robust products, specifying any sources of variation is therefore required. According to Beyer and Sendhoff (2007), these can be classified into the following types: uncertain environmental and operating conditions; production tolerances; and model errors. Parkinson *et al.* (1993) divide uncertainties into controllable and uncontrollable parameters, while Jin and Branke (2005) refer to variations in design and environmental parameters.

The discrepancy in the types of uncertainty that have been accounted for by different studies on the robustness assessment of candidate solutions, reveals the existence of multiple definitions of robustness in the literature (Walsh *et al.* 2013). In particular, Hopfe *et al.* (2012) suggest that robustness should 'tackle small or large fluctuations in input variables', while Goh and Tan (2009) state that it should 'ensure satisfactory performance in face of any small variations in design and/or environment variables'. Costa *et al.* (2011) define robustness as the 'insensitivity to uncontrollable variables', whereas Olewnik *et al.* (2004) claim that it aims to the 'minimisation of the effect of unforeseeable changes in operating conditions'. According to Bettis and Hitt (1995), robustness aims to increase the 'potential for success under varying future scenarios', with Floricel and Miller (2001) similarly marking its goal to guarantee 'insensitivity to anticipated risks'.

Even though robustness assessment has been applied in different areas of engineering such as structural design (Ben-Tal and Nemirovski 1997, Doltsinis and Kang 2004, Starossek and Haberland 2011, Martinez-Frutos *et al.* 2016), it is still not a prevalent method in the context of building design exploration problems (Tian *et al.* 2018). It thus remains ambiguous how to define robustness, but also what types of uncertainty to incorporate in its assessment. Van Gelder *et al.* (2014) describe robustness as the 'ability to stabilise optimal performance for the entire range of input uncertainties'. Huang *et al.* (2009) claim that a robust solution must 'not only optimise the objective function, but also minimise the variation in responses arising from any fluctuations'. Rysanek and Choudhary (2013) similarly state that it must 'be maximally beneficial and more insensitive to a change in scenario, in relation to all other alternatives'.

Hoes (2014) define robustness as 'the ability to handle changes – or disturbances – in the building's environment while maintaining the required performance'. Kotireddy *et al.* (2018) similarly suggest that a robust design solution should 'reduce the impact of the variations that are caused by the uncertainties in external conditions, such as the occupant behaviour and climate change'. As occupancy gains contribute remarkably to the uncertainty in the performance prediction of candidate solutions (MacDonald 2002), Hoes *et al.* (2011), O'Brien (2013), Buso *et al.* (2015) and Karjalainen (2016) focus on the identification of solutions that are robust against variations in occupant behaviour. Other building studies (Chinazzo *et al.* 2015, Nik *et al.* 2015, Ascione *et al.* 2017) assess the robustness of designs against weather variations, these emerging from the difficulty of predicting future weather (de Wilde and Coley 2012).

2.5.2 Robustness indicators

Robustness assessment could be hence briefly described as a method for disclosing the possible variation in performance (Clausing 1994). The different interpretations of the term (as described in section 2.5.1) have, however, resulted in the development of different indicators by relevant studies (Jin and Branke 2005). It is therefore still an open question how to assess robustness in the context of building design exploration problems and, in particular, how to handle the considered (epistemic and/or aleatoric) uncertainties. Following the categorisation that was described in section 2.4.1, there are two main approaches to the robustness assessment of design alternatives, based on the probabilistic – or not – handling of uncertainties. In probabilistic analysis, the probability of each uncertain input value occurring is (assumed to be) known, and the robustness assessment of solutions is thus based on the probability density functions of performance indicators (Van Gelder *et al.* 2014). In contrast, in non-probabilistic analysis, the probability of occurrence of each uncertain value is unknown (or at least not specified with certainty), this hindering the probabilistic treatment of any output distributions (Rysanek and Choudhary 2013). Several (probabilistic as well as non-probabilistic) robustness indicators exist in the literature, the most prevalent of which are presented in section 2.5.2.1, with the objective of demonstrating how robustness is currently assessed (as discussed in chapter 1). Section 2.5.2.2 focuses on robustness assessment in the context of optimization problems that are exposed to uncertainty, this revealing the need for a flexible and comprehensible robustness indicator.

2.5.2.1 Common robustness indicators

Given the different definitions of the notion of robustness, many indicators have been suggested in the literature to numerically evaluate robustness (Jin and Branke 2005). According to Huang and Du (2007), the robustness of a design solution expresses the dispersion of the performance function from its arithmetic mean (μ). The traditional variance (σ^2) (or standard deviation (σ)) and the more recently proposed percentile difference are thus recommended as indicators of robustness. Equations 2.5 and 2.6 show the calculation of the variance and percentile difference (Huang and Du 2007), respectively, of a performance indicator $f(x)$, where x is a design solution – among the alternative designs that belong to the solution set X. Let Y represent all possible values of the performance indicator $f(x)$, as resulted from each possible scenario u (that is, combination of uncertain input values) that belongs to the uncertainty set U. $g_u(u)$ is the joint probability density function of the defined scenarios, while E is the expected value of the squared deviation from the mean of Y (μ_Y):

$$\sigma_Y^2 = E[(Y - \mu_Y)^2] = \int_{-\infty}^{\infty} [f(x) - \mu_Y]^2 g_u(u) du \tag{2.5}$$

$$\Delta y_{a_1}^{a_2} = y^{a_2} - y^{a_1}, \quad a_1 = P(Y \leq y^{a_1}) \text{ and } a_2 = P(Y \leq y^{a_2}) \tag{2.6}$$

where a_1 and a_2 refer to the cumulative distribution function of Y at the left and right tail of the distribution, respectively (shown in figure 2.4). y^{a_1} and y^{a_2} are the values of Y that correspond to a_1 and a_2, respectively and are called percentile values.

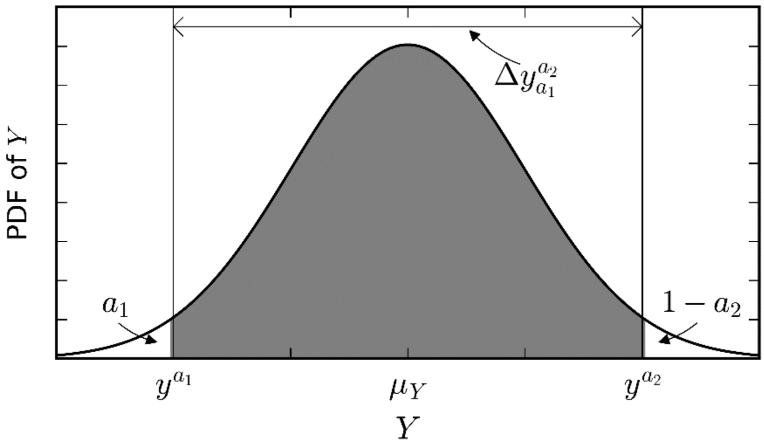

Figure 2.4. Illustration of the percentile difference ($\Delta y_{a_1}^{a_2}$). The grey area signifies the probability of Y having a value between y^{a_1} and y^{a_2}.

These probabilistic formulations of robustness are however infeasible when there is a lack of adequate information on the probability of occurrence of each uncertain input value. Classical decision rules can alternately be utilised to support decision-making under uncertainty (Rysanek and Choudhary 2013). These are scenario-based methods for deciding among – two or more – alternatives when more than one states of nature are considered possible, but their probabilities are not available (Whalen and Churchill 1971). Scenario analysis is hence used when there are uncertainties that are 'largely unquantifiable in probabilistic terms in the context of prediction' (Dessai and Hulme 2004). Robustness will then express the 'potential benefit' under these possible states of nature, which means that increasing the robustness of a solution will improve the likelihood of a satisfactory performance (Bettis and Hitt 1995).

Wald's rule (or minimax[8]) (Wald 1945) is one of the criteria that have traditionally been used in decision situations where 'no full information about the states of nature' had been available (Gärdenfors and Sahlin 1982). It declares that a robust solution is one that has the least worst payoff[9], as it aims to 'minimise the maximum risk' (Wald 1945). This implies that the DMs must identify the worst performance of each design solution across all possible scenarios and then the minimum of those:

$$\begin{gathered} \min \max f(x, U),\, U = \{u_1, \dots, u_n\} \\ \forall\, x \in X,\, X = \{x_1, \dots, x_m\} \end{gathered} \tag{2.7}$$

where n is the total number of performance scenarios in the uncertainty set U.

Hurwicz's rule (Whalen and Churchill 1971) seeks a balance between the minimax and minimin[10] criteria. A coefficient of optimism α ($0 \leq \alpha \leq 1$) is then needed, this expressing the personal view of the DMs about the likelihood of best-case/optimistic conditions and the balance to worst-case/pessimistic conditions – and thus their risk preferences. If the DMs have a risk-taking philosophy, they will set $\alpha = 1$ which will reduce the Hurwicz's criterion to the minimin criterion while, if they are risk-averse, they will set $\alpha = 0$ to reduce it to the minimax criterion (Pažek and Rozman 2009). The DMs must hence firstly calculate a weighted-average return H for each solution and then identify the minimum of those:

[8] This refers to a problem where the performance function needs to be minimised.
[9] In this thesis, the term payoff refers to the performance outcome of a candidate design solution under a given performance scenario.
[10] The goal of the minimin rule is to minimise the minimum payoff. That is, to identify the solution that leads to the best performance under the best-case scenario – which cannot however be guaranteed, thus entailing a high risk in decision-making (Whalen and Churchill 1971).

$$\min H,$$
$$H = a \min f(x, U) + (1 - a) \max f(x, U),\ U = \{u_1, \dots, u_n\} \tag{2.8}$$
$$\forall\ x \in X,\ X = \{x_1, \dots, x_m\}$$

Savage's criterion (or minimax regret) (Savage 1951) is another common robustness indicator, according to which a robust solution is one that has the least worst regret (or opportunity loss) (Rysanek and Choudhary 2013). To implement this criterion, for each performance scenario, the DMs need to identify the best performance across all design solutions and then subtract it from each payoff; that is, calculate the regret of each design solution for this scenario. The next step is to find the maximum regret of each solution across all scenarios, and then the minimum of those:

$$\min \max\, [f(x, u) - \min f(X, u)]$$
$$\forall\ x \in X,\ X = \{x_1, \dots, x_m\} \text{ and } \forall\ u \in U,\ U = \{u_1, \dots, u_n\} \tag{2.9}$$

Range (or max-min) is another common robustness indicator. The range of a design solution represents the difference between its maximum and minimum performance values across all scenarios (Kotireddy *et al.* 2017). The DMs hence need to calculate this difference for each design solution and then identify the minimum of those:

$$\min\, [\max f(x, U) - \min f(x, U)]\ ,\ U = \{u_1, \dots, u_n\}$$
$$\forall\ x \in X,\ X = \{x_1, \dots, x_m\} \tag{2.10}$$

As however argued by Gärdenfors and Sahlin (1982), using a minimax criterion may be 'unnecessarily risk aversive', which is indicated only in the case the DMs are not willing to take any risk in decision situations. Whalen and Churchill (1971) similarly characterise it as a conservative rule, as it aims to minimise the performance function under the worst-case scenario. Given Hurwicz's rule is an adaptation of the minimax criterion, it can be regarded as a pessimistic indicator too (Rysanek and Choudhary 2013). The minimax regret criterion is also considered to be rather conservative as it aims to minimise the worst-case regret (Ehrgott *et al.* 2014), while the max-min rule is likewise deemed to lead to conservative solutions, thus being suitable for decision situations where no performance variation is accepted (Kotireddy *et al.* 2017).

According to Hussain *et al.* (2016), specifying the desired level of conservatism is a fundamental step for evaluating robustness, this being dependent on the probability of scenarios occurring – if this information is however available. It is also subject to the state of mind of the DMs and, in particular, the risks they would be willing to take (Whalen and Churchill 1971). Even though each classical decision rule represents a different state of mind that may express the perspective of the DMs, they do not offer a control of the level of conservatism and therefore of the degree of robustness. That is, they do not provide the DMs with the flexibility in choosing the desired trade-off between performance and robustness (Bertsimas *et al.* 2011). In addition to that, as with many probabilistic indicators as well, they may not be entirely comprehensible to a non-specialist audience (Huang and Du 2007). Finally, it is still not clear how such rules could be extended to problems where multiple performance functions need to be minimised (Rysanek and Choudhary 2013), this being however essential for solving complex real-world problems.

2.5.2.2 Robust design optimization

Robust design optimization (RDO) is a method for handling optimization problems with uncertain input data (Ben-Tal *et al.* 2009). It acts as a decision support tool that accounts for the possibility that the forecasted (also called deterministic or nominal) values of uncertain parameters may never occur as a result of the randomness in their nature (Kouvelis and Yu 2013). A robust design solution is consequently one that not only minimises the objective function values – as deterministic optimization aims to – but is also insensitive to perturbations in uncertain input parameters (Bertsimas *et al.* 2011). As however discussed in 2.5.1, there are many possible notions of robustness that have in turn resulted in the development of different indicators (Jin and Branke 2005). In addition to that, although RDO may have been used over the last few years in engineering fields such as structural design (Doltsinis and Kang 2004, Martinez-Frutos *et al.* 2016), it is still not widely used in building energy studies, this revealing the need for further investigation into the significance and implementation of RDO in building design optimization problems (Nguyen *et al.* 2014).

According to Bertsimas *et al.* (2011), RDO aims to provide the DMs with an optimal solution that is ‘feasible for *any* realisation of the uncertainty in a given set’, this thus ensuring feasibility 'independent of the data'. Given an objective function $f(x,u)$ to be minimised, a constraint $f(x,u) \leq b$ that needs to be met (if applicable), a solution set X and an uncertainty set U, the general formulation of RDO is:

$$\begin{gathered} \min f(x,u) \text{ subject to } f(x,u) \leq b \\ \forall\, u \in U, U = \{u_1, \dots, u_n\} \end{gathered} \tag{2.11}$$

where $x \in X$ is a design solution, u is a combination of values for the uncertain input data (i.e. performance scenario) and n is the total number of considered scenarios.

The uncertainty set U is hence described as 'unknown but bounded', since it contains possible combinations of values for the uncertain input parameters (called scenarios), as specified for the examined problem (Ben-Tal *et al.* 2006). Based on this approach, robust solutions must therefore be 'deterministically immune' to the realisation of all scenarios that belong to the uncertainty set U (Bertsimas *et al.* 2011). This set-based, non-probabilistic treatment of uncertainty originated from criticism on the credibility of probabilistic analysis when limited information is available on the representation of input parameters, particularly at early design stages (Moens and Vandepitte 2005). Nevertheless, a large number of scenarios may be needed to adequately capture input uncertainties, this implying that a rationale should be developed for the selection of scenarios in order to keep the computational cost low (Bertsimas *et al.* 2011).

This concern can be addressed with the application of a worst-case approach, which aims to minimise the objective function under the impact of the specified worst-case scenario(s) (Avigad and Branke 2008). Applying this 'worst-case-oriented' approach to an objective function $f(x,u)$ leads to an adapted (from equation 2.11) formulation of RDO (Ben-Tal *et al.* 2006):

$$\begin{gathered} \min \max f(x,u) \text{ subject to } f(x,u) \leq b \\ \forall\, u \in U, U = \{u_1, \dots, u_n\} \end{gathered} \tag{2.12}$$

This minimax formulation of RDO was introduced in the 1970s (Soyster 1973), but has only been researched more extensively over the last two decades (El Ghaoui and Lebret 1997, Ben-Tal and Nemirovski 1998, Aissi *et al.* 2009, Bertsimas *et al.* 2011, Ehrgott *et al.* 2014). Being based on Wald's decision rule (Wald 1945) (described in section 2.5.2.1), such an approach aims to minimise the objective function against the worst-case realisations of uncertain parameters, which therefore need to be represented by lower and upper bounds that express their expected minimum and maximum values (Thiele *et al.* 2009). In a similar way, being based on Savage's criterion (Savage 1951) (also presented in section 2.5.2.1), a minimax regret formulation was launched in the 1990s as a scenario-based approach to robust design (Kouvelis and Yu 1997) and has thereafter been researched more extensively (Chen and Lin 1998, Averbakh 2000, Kouvelis and Yu 2013). This approach aims to minimise the objective function against the worst-case 'differences between the cost of a scenario when the decided strategy is implemented and the ideal cost that could have been obtained' (Mavromatidis 2017).

Adopting a worst-case approach may, however, lead to overly conservative design solutions (Hussain *et al.* 2016). Ben-Tal *et al.* (2004) introduced the adjustable robust counterpart to deal with this issue, treating decision variables as adjustable variables that are specified as affine functions of the uncertain input data. Variables can hence be tuned to the true values of uncertain data, as soon as these are realised. However, this formulation of RDO is not suitable for handling aleatoric uncertainties that are not eliminated during the design process, while it may be computationally intractable due to the quadratic dependence of variables on uncertainty (Bertsimas *et al.* 2011).

Finding the best combination of variable values to solve the defined RDO problem is more complex in the case of multiple optimization objectives being considered, with the designers therefore most commonly accounting for only two objectives (Nguyen *et al.* 2014). Given the recent interest in concepts such as the minimax and minimax regret RDO, there are still not many studies that focus on extending these concepts from single- to multi-objective problems and overcoming any associated limitations (Ehrgott *et al.* 2014). A weighted-sum method (described in section 2.3.1) may be used to simplify a complex multi-objective problem (Van Gelder 2014), but this may not be entirely comprehensible to a non-specialist audience. In addition to that, converting a complex multi-objective problem into a simplified single-objective problem leads to biased solutions, as the articulation of stakeholder preferences precedes optimization (Branke *et al.* 2008). It is thus important that the selected approach to RDO supports the *a posteriori* articulation of any preferences and the risk aversion level of the DMs

(Rezvan *et al.* 2012), providing them with the opportunity to select their preferred trade-off between performance and robustness (Jin and Sendhoff 2003).

2.6 Summary

Chapter 2 provided an overview of building design exploration and highlighted the beneficial role of robust optimization in this explorative process that aims to address building design problems under uncertain conditions. Even though RIBA suggests a number of key design stages and associated outcomes, no specific steps are specified regarding how to explore the design space in the light of uncertain conditions such as the weather – that is, how to evaluate the performance of candidate design solutions. When coupled with BPS, optimization enables the efficient exploration of the design space, as it facilitates the comparison of several alternative design options with respect to prevalent performance indicators such as energy consumption, cost and/or thermal comfort. Even though some building design studies have focused on the integration of UA into BPS to improve confidence in simulation results, optimization and UA are still most commonly treated as separate procedures. Coupling these two methods is however crucial in the context of robust decision-making, as optimization can ensure the minimisation of objective function values, while UA can improve the confidence in the optimality of design solutions by evaluating their performance across a number of possible performance scenarios.

Prior to developing a new framework for coupling optimization and UA (in chapter 3), investigating the different sources of uncertainty and how these can be quantified was fundamental (as discussed in chapter 1). Chapter 2 therefore described any influential design parameters referring to building form, construction and operation that should be explored early in the building design process to ensure satisfactory performance. Any uncertain conditions that may greatly influence building performance were also described. Regarding their quantification, two main approaches were identified in the literature: probabilistic and non-probabilistic. Probabilistic formulations of robustness are however infeasible in the case of an inadequacy of information on the probability of occurrence of uncertain input values, this being the case for aleatoric uncertainties such as the weather. Scenario analysis is thus suggested when there are uncertainties which are unquantifiable in probabilistic terms, with scenarios representing plausible combinations of uncertain input values. However, given that robustness assessment is still not a commonly applied method in the context of building design exploration, it remains ambiguous how to assess robustness under such scenarios.

Chapter 2 hence also presented existing robustness indicators, with the objective of revealing how robustness is assessed (as discussed in chapter 1). Existing indicators are found to be incapable of providing the DMs with the flexibility in selecting their desired degree of robustness and consequently of incorporating their risk preferences. They may also not always be entirely comprehensible to a non-specialist audience. Finally, it is still unclear how they could be extended to optimization problems where multiple performance functions need to be minimised, this being however essential for addressing complex real-world problems.

Chapter 3

Methodology

This chapter describes the suggested approach for robust optimization in the context of building design exploration, which can lead to the identification of design solutions that perform well under uncertainty, while satisfying the requirements of the building regulations and stakeholder preferences. The theoretical framework of the explorative procedure presented here comprises five principal steps (as shown in figure 3.1): a) uncertainty quantification; b) exhaustive search; c) building performance simulation (BPS); d) robust optimization; and e) solution analysis.

3.1 Robust building design optimization framework

The goal of the building design process is to produce a solution that responds to the requirements of the client and building regulations (section 2.1). Design exploration is an integral part of this process that can result in the identification of a satisfactory solution through the generation and evaluation of alternative design options. Robust optimization supports design exploration by ensuring satisfactory performance under uncertain conditions. This section will describe the five suggested steps for robust design optimization – that will then be applied to two case study buildings: a test cell and a new real-world community centre (in chapters 4 and 5, respectively). 3.1.1 will elucidate the quantification of uncertain design parameters and uncertain conditions. 3.1.2 will describe the generation of design solutions and performance scenarios by applying an exhaustive search to combine all uncertain values. 3.1.3 will describe the prediction of the performance of solutions with the help of BPS. 3.1.4 will present a new robust optimality criterion for evaluating the performance of solutions under all scenarios. 3.1.5 will finally focus on the communication of the evaluation results.

Figure 3.1 shows the five steps that compose the robust optimization framework. The equations that express the new robustness criterion will be described in section 3.1.4.3.

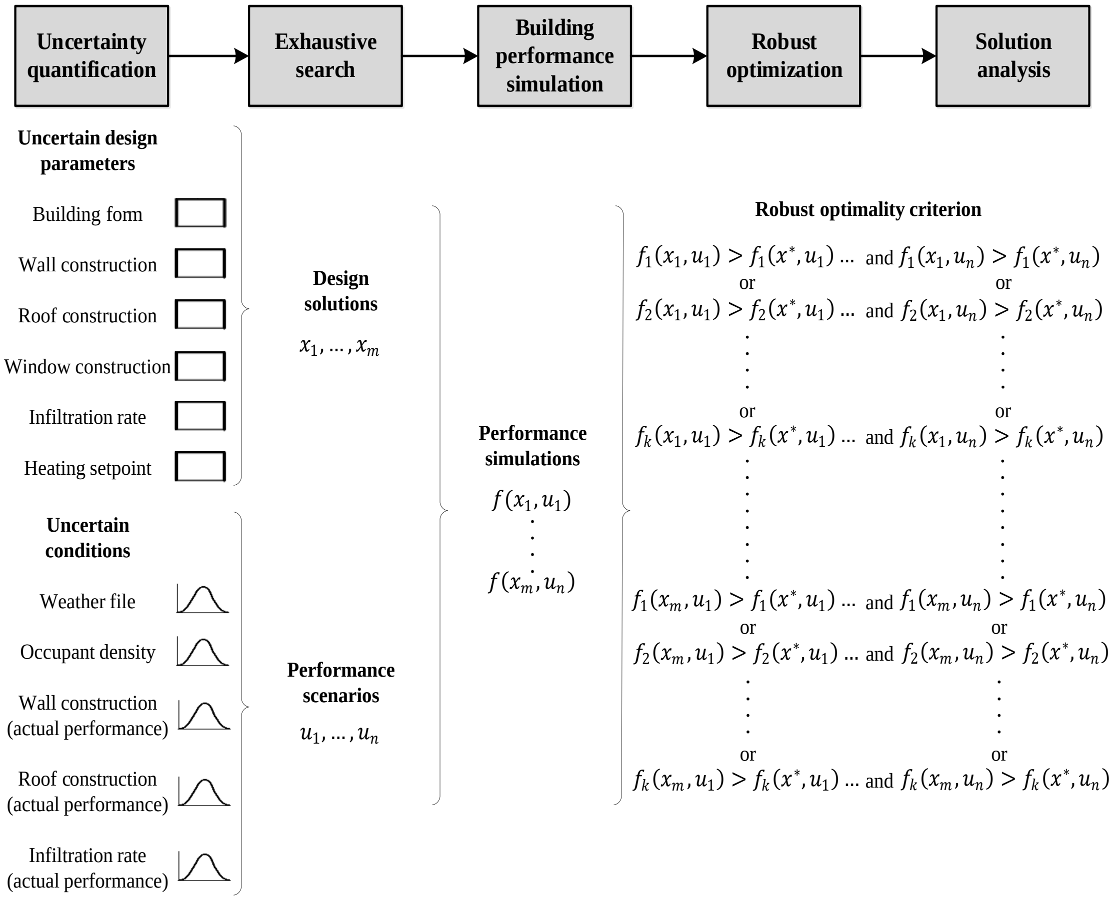

Figure 3.1. The proposed framework for robust building design optimization, which supports the identification of robust solutions (x^*).

3.1.1 Uncertainty quantification

The first step of the design process is the explicit formulation of the design problem (section 2.1.2), this including the definition of both design and performance variables as sources of epistemic and aleatoric uncertainty, respectively. This section describes the quantification of both types of uncertainty as a first step in dealing with a design problem that is exposed to uncertainty (as discussed in chapter 1).

3.1.1.1 Uncertain design parameters

At the early design stages, building form and the remaining design parameters that are related to construction and operation are not finalised yet. As shown in table 2.2 and discussed in section 2.4.1, these are sources of epistemic uncertainty that will be later eliminated, with the increase in the design detail. Focusing on form, design options express the conceptual ideas that are triggered by the project brief and emerged from the brainstorming of the design team. Note that, due to the unique characteristics of each project, design options vary from one case study to another. Chapters 4 and 5 will present the design variables (and their values) that refer to building form in the case of the test cell and the examined real-world community centre, respectively.

Table 3.1. List of design variables (construction and operation) and variable values.

Subcategories	Variables	Variable values	References
Construction	External wall construction (W/m^2K) [11, 12]	1) HW-PH (0.140)	(IBO 2009, International Passive House Association 2018)
		2) LW-PH (0.143)	
		3) HW-PL (0.342)	(Neufert *et al.* 2012, UK Government 2013a)
		4) LW-PL (0.342)	
	Roof construction (W/m^2K)	1) HW-PH (0.146)	(IBO 2009, International Passive House Association 2018)
		2) LW-PH (0.144)	
		3) HW-PL (0.243)	(Neufert *et al.* 2012, UK Government 2013a)
		4) LW-PL (0.239)	
	Window construction (W/m^2K)	1) PH (0.780)	(IBO 2009, International Passive House Association 2018)
		2) PL (2.129)	(Neufert *et al.* 2012, UK Government 2013a)
	Infiltration rate (ac/h)	1) PH (0.050)	(CIBSE 2006, McLeod *et al.* 2014)
		2) PL (0.500)	(CIBSE 2006, ATTMA 2010)
Systems and operation	Heating setpoint (°C)	1) 19	(BRE 2015, International Passive House Association 2018)
		2) 20	
		3) 21	
		4) 22	
		5) 23	

[11] HW/LW denotes the thermal mass of each construction (heavyweight and lightweight construction, respectively). PH/PL signifies the standard each construction complies with (the Passivhaus Standard (International Passive House Association 2018) and the Building Regulations Part L (UK Government 2013a), respectively).
[12] The U-value of each construction option is provided (in W/m^2K).

The remaining design variables that are considered in this thesis can be found in table 3.1, these being influential – as revealed by the literature review in section 2.4.1.1 – design parameters. Five variables that are related to the construction and operation of the building are selected due to their impact on design objectives: wall construction; roof construction; window construction; infiltration rate; and heating setpoint. With respect to the wall and roof constructions, four types are selected for each element: two options complying with the Passivhaus Standard (International Passive House Association 2018) (mentioned in the table as PH); and two options adhering to the Approved Document L2A (new non-domestic buildings) of the Building Regulations Part L (UK Government 2013a) (abbreviated to PL). This enables the comparison of the two building standards with regard to the uncertainty in the predicted performance of design solutions – while taking into consideration the possibility of constructing a Passivhaus building. The U-values of the constructions are informed by the limiting values of the standards (table 3.2).

Table 3.2. Limiting values for different fabric parameters according to the two applied standards.

	Limiting value	
Fabric parameter	Passivhaus Standard (International Passive House Association 2018)	Building Regulations (UK Government 2013a)
Wall	0.15 W/m^2K	0.35 W/m^2K
Roof	0.15 W/m^2K	0.25 W/m^2K
Window	0.80 W/m^2K	2.20 W/m^2K
Infiltration rate	0.60 ac/h at 50 Pa	10 m^3/hm^2 at 50 Pa

The two options that conform to each standard have similar U-values but different levels of thermal mass: heavyweight (HW) (concrete) construction; and lightweight (LW) (timber-frame) construction. This allows the impact of thermal mass on the performance of solutions to be investigated; that is, how the lightweight or of more massive construction building elements can influence the diurnal heating (or cooling) cycle of the building (Hopfe and McLeod 2015). The Passivhaus constructions are specified upon a catalogue of ecologically rated constructions (IBO 2009) and the Passivhaus guide of the Association for Environment Conscious Building (AECB

2007). The Architects' data book by Neufert *et al.* (2012) is consulted for creating the Part L constructions – with their difference lying in the thickness of insulation.

In addition to supporting the calculation of the capital cost of candidate solutions, the Spon's Architects' and Builders' book (AECOM 2015) ensures that all constructions consist of commercially available products. Tables A.1 and A.2 of appendix A show the material layers of all – external wall and roof, respectively – constructions along with the nominal values of their thermophysical properties. These are defined upon the manufacturers' data (where available) and the CIBSE Guide A (CIBSE 2006).

With respect to the window construction as well as the infiltration rate, two types are similarly defined: one option complying with the Passivhaus Standard (International Passive House Association 2018) and another one with the Building Regulations Part L (UK Government 2013a). Window U-values and infiltration rates are informed by the limiting values of the two standards (table 3.2). In the case of infiltration rate, the conversion of these values is necessary as the BPS tool that is employed in this thesis (EnergyPlus (U.S. Department of Energy 2016a)) requires the number of air changes per hour at no differential pressure (ac/h) in order to calculate the design flow rate of each thermal zone. This conversion is performed with the help of the standard on air permeability (published by the Air Tightness Testing and Measurement Association (ATTMA 2010)) and of the CIBSE Guide A (CIBSE 2006) that provides an estimate for the infiltration rates of buildings which are located on normally-exposed sites.

The heating setpoint values express the air temperatures that are recommended by the activity database of the National Calculation Method (NCM) (BRE 2015) for a variety of building types. For Passivhaus buildings, the recommended value is 20 ℃ (in most cases) (International Passive House Association 2018). As no preference weights are here considered, all design variables are assumed to have a uniform distribution (de Wilde and Tian 2009). Each solution (i.e. combination of design variable values) has thus equal chance of being selected.

3.1.1.2 Uncertain conditions

Considering the variability in the predicted performance of candidate solutions due to the uncontrollable behaviour of uncertain conditions, possible performance scenarios are defined – that is, combinations of performance variable values. Five performance variables are selected (table 3.3) due to their influence on optimization objectives – as revealed by the literature review (see section 2.4.1.2): weather file; occupant density; wall construction (actual performance); roof construction (actual performance); and infiltration rate (actual performance). As shown in table 2.2 and discussed in section 2.4.1, these are influential sources of aleatoric uncertainty that cannot be eliminated during the design process due to their random variability. The distribution for variables related to aleatoric uncertainty is assumed to be normal (de Wilde and Tian 2009).

Due to the absence of sufficient information on the probability of each combination of performance variable values occurring, however, performance scenarios cannot be treated probabilistically. A worst-case approach (Parkinson *et al.* 1993) is hence used to handle aleatoric uncertainty in the context of robust optimization. In particular, as the probability distribution function of each scenario cannot be easily determined, a robust design solution is one that is 'least-affected by possible worst-case conditions' (Rysanek and Choudhary 2013). A critical step is hence to define the 'extreme point scenarios' that act as worst-case conditions (Kouvelis and Yu 2013) and express the maximum fluctuation from the nominal values of performance variables that may be encountered (Parkinson *et al.* 1993). In this thesis, each aleatoric uncertainty is hence represented by an 'expected' value and two limiting values that express 'extreme' – but still possible – conditions. Table 3.3 displays the three values that are considered for each variable: its lower bound, nominal value and upper bound, respectively.

Concerning the weather file, these three values refer to: the monitored data of 1979 (CIBSE 1979); the test reference year (TRY) (CIBSE 2016); and the (long) design summer year (DSY 3) (CIBSE 2016) for London[13]. In more detail, 1979 is calculated to be the coldest year of the last forty years (for that location); that is, the year with the maximum heating degree days. Heating degree days are a measure of the heating energy required to maintain internal environmental conditions at comfortable levels (Belcher *et al.* 2005). They show the mean number of degrees by which the external temperature on a given day is less than the base temperature (that is, 15 ℃ (Virk and Eames 2016)), totalled for all days in the considered period (UK Department of the

[13] This is where the examined case study buildings are located.

Environment 1993). The TRY weather file is used to predict the energy usage of a building during its design stages (Eames *et al.* 2016) and ensure compliance with the Building Regulations Part L (UK Government 2013a). It acts as a typical year, as it consists of average months selected from a historical baseline of 1984 to 2013 (Virk and Eames 2016).

Table 3.3. List of performance variables and variable values.

Subcategories	Variables	Variable values	Description/ References
Weather	Weather file	1) 1979	Cold year: maximum heating degree days (CIBSE 1979)
		2) TRY	Typical year (CIBSE 2016)
		3) DSY 3	Hot year: long, less intense warm spell (CIBSE 2016)
Occupancy	Occupant density (persons/m^2)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	(BRE 2015)
Construction (actual performance)	External wall construction (W/m^{2}K)	1) Fast response	Nominal values refer to the design variable values of table 3.1. The lower and upper bounds represent possible variations in the response of the thermal mass. The considered variations in the thermal properties of individual material layers depending on their general category (Clarke *et al.* 1990) are included in tables A.3, A.4 and A.5 of appendix A.
		2) Nominal	
		3) Slow response	
	Roof construction (W/m^{2}K)	1) Fast response	
		2) Nominal	
		3) Slow response	
	Infiltration rate (ac/h)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	See table 3.1
		3) Nominal + 50%	(MacDonald 2002)

The DSYs are used to assess the overheating risk of a building during its explorative process, as they express extreme summer conditions (Eames 2016). The new CIBSE data sets (CIBSE 2016) include three metrics for the evaluation of overheating risk. The DSY 3 is chosen in this thesis, this indicating a year with a more intense extreme and a longer duration than the moderate summer year – but a less intense extreme than the high intensity year (Virk and Eames 2016). The selected year for the DSY 3 file of London is 1976 (CIBSE 2016) which is also calculated to be the warmest year of the last forty years; that is, the year with the maximum cooling degree days. In this respect, the ‘cold’ and ‘warm’ years are selected on the same basis of degree days.

With respect to the occupant density of the different building zones, nominal values are informed by the NCM activity database (BRE 2015). The lower bound represents a 50% reduction in occupancy sensible gains (and associated internal heat gains from electrical equipment); i.e. minus three standard deviations as proposed by MacDonald (2002). As mentioned in section 2.4.2, if a normally distributed variable is limited to plus and minus three standard deviations from the mean ($\mu \pm 3\sigma$), the probability that a variable value lies in this range is 99.7% – which indicates that the associated error is marginal (Haldar and Mahadevan 2000). An upper bound is not assumed for this variable, as a severe increase in occupancy is not considered to be a possible scenario for the examined case study buildings – especially for their office zones, which are designed for a specific number of users.

The selection of nominal values for the wall and roof constructions has already been discussed (these are included in table 3.1). However, even if the design specifications of all their material layers are known (i.e. provided by their manufacturers), there is still a natural variability in the actual performance of the constructions (de Wilde and Tian 2009). This inherent uncertainty can be due to the fluctuation of their moisture content, which can result in the variation of their nominal thermophysical properties (Clarke *et al.* 1990). MacDonald (2002) has quantified the effect of this uncertainty on the three main material categories that are identified by Clarke *et al.* (1990): non-hygroscopic (e.g. wool insulation); inorganic-porous (e.g. reinforced concrete); and organic-hygroscopic (e.g. chipboard) materials. The considered variations (in %) for each material category and thermal property can be found in table 3.4. In particular, for moisture contents of 1%, 4% and 7% for non-hygroscopic, inorganic-porous and organic-hygroscopic materials respectively, an uncertainty of ± 5%, 15% or 25% – this being subject to the material category – is added to the nominal values of thermal conductivity (MacDonald 2002). ± 13%, 4% and 11% are the equivalent percentages for density, while ± 4%, 19% and 8% are the assumed variations in the case of specific heat capacity (MacDonald 2002).

Table 3.4. List of the considered variations in the thermal properties of materials depending on the general category they belong to.

Thermal properties	Variations	Description/ References
Thermal conductivity (W/mK)	Nominal ± 5%, 15% or 25%	Nominal values are taken from the manufacturers' data and the CIBSE Guide A (CIBSE 2006). Three percentages are provided for each thermophysical property (MacDonald 2002), these referring to the impact of moisture content on the following material categories (Clarke *et al.* 1990): non-hygroscopic; inorganic-porous; and organic-hygroscopic. The considered moisture contents are 1%, 4% and 7%, respectively (MacDonald 2002).
Density (kg/m^3)	Nominal ± 13%, 4% or 11%	
Specific heat capacity (J/kgK)	Nominal ± 4%, 19% or 8%	

Tables A.3, A.4 and A.5 (appendix A) describe how these percentages are combined in the case of each material category, in order to allow for the quantification of the variation in the performance of each material layer of a multi-layer – wall or roof – construction, and subsequently of the overall variation in the actual performance of the construction. This overall variation refers to the response of the thermal mass of the construction under the influence of the fluctuation of an uncertain parameter (i.e. the moisture content in this thesis) that is defined in the literature as the *thermal time constant* of the construction (Tsilingiris 2004). The time constant is thus used in this thesis to account for the multiple material layers of each – wall or roof – construction and combine the multiple thermal properties of each of these layers (nominal values are shown in tables A.1 and A.2 of appendix A). It also supports the quantification of the two extreme values of the actual performance of each construction (based on the variations presented in tables A.3, A.4 and A.5 of appendix A), with the lower bound representing a fast response of the thermal mass (or short time constant) and the upper bound signifying a slow response (or long time constant).

In particular, the short time constant of each (wall or roof) construction derives from the combination of the maximum value of thermal conductivity with the minimum values of density and specific heat capacity (for each material layer). The long time constant is similarly deduced from the combination of the minimum value of thermal conductivity with the maximum values of density and specific heat capacity (for each material layer). These propositions are based on equations 3.1 and 3.2 (Hassid 1985) that calculate the external (τ_o) and internal (τ_i) thermal time constants respectively of a multi-layer construction, consisting of k material layers (counted from outside to inside) and being represented by two resistors R_o, R_i and a capacitor C (figure 3.2):

$$\tau_o = R_o C = \sum_{i=1}^{k} l_i \rho_i c_{pi} \left[\frac{1}{h_o} + \sum_{j=1}^{i-1} \frac{l_j}{\lambda_j} + \frac{l_i}{2\lambda_i} \right] \tag{3.1}$$

$$\tau_i = R_i C = \sum_{i=1}^{k} l_i \rho_i c_{pi} \left[\frac{l_i}{2\lambda_i} + \sum_{j=i+1}^{k} \frac{l_j}{\lambda_j} + \frac{1}{h_i} \right] \tag{3.2}$$

where l_i is the thickness of each layer and λ_i, ρ_i and c_{pi} are its thermal conductivity, density and specific heat capacity, respectively. h_o and h_i are the external and internal surface conductance, respectively.

Equations 3.1 and 3.2 show that, for a given construction, the shortest time constant occurs when thermal conductivity is on its highest value, while density and specific heat capacity are on their lowest values. In a similar way, the longest time constant occurs when thermal conductivity takes its lowest value, while density and specific heat capacity take their highest values. A caveat associated with these propositions is the difficulty in calculating the probability that all these values occur simultaneously for each material layer. However, this is not necessary in this thesis, as the suggested framework adopts a worst-case approach to robust optimization that does not rely on the probability distribution of the uncertain quantities being known, but rather on the limits of such a distribution being known.

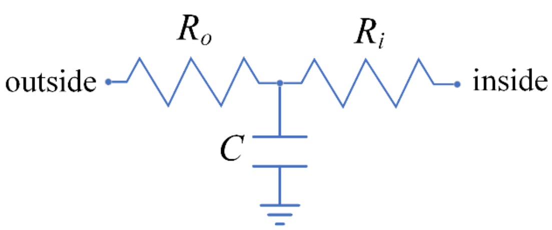

Figure 3.2. Representation of a multi-layer construction (adapted from Hassid 1985).

Concerning the infiltration rate of the building, the two extreme values indicate a ± 50%[14] deviation (MacDonald 2002) from the nominal values that are shown in table

[14] Similarly to the occupant density, this represents plus and minus three standard deviations (± 3σ).

3.1. No fluctuations from the nominal values are considered in the case of the window constructions, as manufactured windows are not vulnerable to this uncertainty type (Van Gelder 2014). Finally, even though the actual heating setpoint values may vary from the nominal values as a result of the precision error of (single point) temperature sensors (Kelso 2003), no worst-case conditions are added to the list of performance variable values that are displayed in table 3.3. This is due to the fact that, firstly, the design and operation of the HVAC system are out of the scope of this thesis; and, secondly, given that this type of uncertainty can lead to a maximum error of ± 1 ℃[15] (Buswell 2001, Kelso 2003), extreme values are overlapped by the nominal values of table 3.1. In particular, the defined values have a step of 1 ℃, while they include 19 and 23 ℃ as edges, these being the borderline values for achieving thermal comfort, as recommended by the NCM (BRE 2015) for different types of thermal zones.

3.1.2 Exhaustive search

After having specified all the design and performance variables – these representing influential sources of uncertainty at the examined design stage – and their values, an exhaustive search method is used to define all possible design solutions $(x_1, \dots, x_m)$ and performance scenarios $(u_1, \dots, u_n)$ (figure 3.1). As discussed in 2.3.2, given that all candidate design solutions are known, their Pareto optimality (within the defined problem) will be certain, since there is no doubt about the convergence behaviour of the search method – as might be the case for an optimization algorithm, which could possibly fail to find the global optimum (Wetter and Wright 2004). As an exhaustive search method supports the evaluation of all design solutions prior to the assessment of their optimality, its computational performance is not affected by the number of optimization objectives and constraints, thus enabling the identification of solutions that are Pareto optimum with respect to multiple criteria (four in this thesis: heating energy demand; winter thermal discomfort; summer thermal discomfort; and cost).

Having all design solutions and their performance under all scenarios available prior to assessing optimality also allows for more questions to be answered regarding the

[15] This again represents plus and minus three standard deviations (± 3σ).

examined problem. This enables a better understanding of the relationship between solutions and objectives, and therefore a greater support for robust building design optimization. Not having to run an optimization algorithm[16] whenever modifying the problem is important in the context of building design exploration, where the number of variables, objectives and constraints often changes along the way due to 'updated information' (such as a shift of stakeholder preferences) (Kochenderfer 2015).

A significant limitation of an exhaustive search is however that computational load increases exponentially with the number of (design and performance) variables. Even though a valuable aid is provided by the concurrent simulation of (20) combinations of design and performance variable values (20 threads are used in this thesis), restricting the number of variables and their values is crucial for the feasibility of such a search method. This provides an additional argument for limiting the design space based on the requirements of the regulations and any stakeholder preferences, and restricting the number of uncertain conditions following a worst-case approach that necessitates the specification of only three values for each uncertain quantity (that is, a nominal value and two outlying values), as described in section 3.1.1.

3.1.3 Building performance simulation

The exploration of the design space is performed in this thesis with the help of BPS and optimization methods. Prior to assessing solution optimality, the performance of candidate solutions is predicted (under all performance scenarios), using EnergyPlus (U.S. Department of Energy 2016a) as an engine. Despite its calculation capabilities, EnergyPlus does not support the expeditious creation of building geometry, as it is a console-based program that operates by reading input and writing output as text files, thus necessitating the application of a third-party graphical user interface. SketchUp (Trimble Navigation 2016) is used in this thesis, as it is a user-friendly 3D modelling tool, while its OpenStudio plug-in (U.S. Department of Energy 2015) guarantees the interoperability with EnergyPlus. After creating the building geometry in SketchUp with the assistance of its OpenStudio plug-in, the model is exported as an input data file (IDF) and imported into EnergyPlus. This is where any supplementary input data

[16] This refers to the case where the new problem is a sub-set of the problem already evaluated.

is specified, prior to running all simulations. The values of the considered design and performance variables were described in section 3.1.1. Section 3.1.3.1 will present any fixed parameter values.

Since an exhaustive search method is used to evaluate all possible design solutions $(x_1, \ldots, x_m)$ and performance scenarios $(u_1, \ldots, u_n)$, the total number of simulations that are run in EnergyPlus are calculated by multiplying the total number of solutions (m) by the total number of scenarios (n). In this thesis, n equals 162, as resulted from the exhaustive combination of the performance variable values in table 3.3, while m varies from one case study to another, as it is affected by the special characteristics of each project. Concurrent processing is used to reduce the computational time of BPS, with 20 simulations being executed in parallel (by the 20 threads of the computer) for better performance, using a bespoke (Java) script. Simulation results are exported to a comma-separated file (CSV), which contains the predicted performance values for heating energy demand, winter thermal discomfort and summer thermal discomfort. By using a programming language (Python) and the Spon's Architects' and Builders' price book (AECOM 2015) for reference, the capital cost of each design solution is also calculated and added to the CSV file. The file is then post-processed (in Python) to apply the new robust optimality criterion, as described in 3.1.4.3.

3.1.3.1 Model configuration

Each simulation that is run in EnergyPlus refers to an annual run period which starts on the 1st of January and ends on the 31st of December, as defined in the weather file. 6 timesteps per hour are used for heat transfer and load calculations, as suggested by EnergyPlus (U.S. Department of Energy 2016b). After creating the building geometry in SketchUp (using its OpenStudio plug-in), the IDF that is imported into EnergyPlus contains all the required geometric information for each thermal zone. With regard to their construction, the external wall, roof and window constructions and infiltration rates were described in 3.1.1, as these are part of the optimization process. Details on any constructions that are fixed across all simulations (internal wall, slab foundation, internal floor and internal door) are found in table A.6 of appendix A.

With regard to operation, winter heating and air-conditioning are supplied to thermal zones by an Ideal Loads Air System – as this thesis focuses on comparing alternative designs and not on proposing a HVAC system. This component can be thought as 'a unit that mixes air at the zone exhaust condition with the specified amount of outdoor air and then adds heat at 100% efficiency' (U.S. Department of Energy 2016b). Note that, there is (sensible) heat recovery when the zone exhaust air temperature is more favourable than the outdoor air temperature (U.S. Department of Energy 2016b).

Table 3.5. List of fixed parameter values in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for office spaces.

Object	Field	Value
People	People per Zone Floor Area (persons/m^2)	0.111
	Sensible Heat Fraction	0.5935
Lights	Watts per Zone Floor Area (W/m^2)	9
ElectricEquipment	Watts per Zone Floor Area (W/m^2)	11.77
	Fraction Latent	0.75
DesignSpecification: OutdoorAir	Outdoor Air Flow per Person (m^3/s person)	0.01

Table 3.6. List of Schedule:Compact objects in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for office spaces.

Activity Level	People	Lights	Electric Equipment
Through: 12/31 For: AllDays Until: 24:00 123	Through: 12/31 For: Weekdays Until: 07:00 0 Until: 08:00 0.2 Until: 09:00 0.6 Until: 12:00 1 Until: 14:00 0.8 Until: 17:00 1 Until: 18:00 0.6 Until: 19:00 0.2 Until: 24:00 0 For: AllOtherDays Until: 24:00 0	Through: 12/31 For: Weekdays Until: 07:00 0 Until: 19:00 1 Until: 24:00 0 For: AllOtherDays Until: 24:00 0	Through: 12/31 For: Weekdays Until: 07:00 0.0539 Until: 19:00 1 Until: 24:00 0.0539 For: AllOtherDays Until: 24:00 0.0539

Heating setpoints were presented in section 3.1.1, as they are part of the optimization process. Outdoor air flows are informed by the National Calculation Method (NCM) (BRE 2015), with their values being dependent on the type of each zone. In summer, zones are naturally ventilated and therefore no cooling or air-conditioning system is used. The Wind and Stack Open Area object is used in EnergyPlus (U.S. Department of Energy 2016b) to model the natural ventilation air flow – only when the building is occupied due to safety reasons.

Table 3.5 displays the considered parameter values that are related to People, Lights and Electric Equipment, and table 3.6 demonstrates the schedules of these objects in EnergyPlus, as proposed by the NCM. Given that the test cell is a single-zone office building and the real-world building has several office zones (section 3.2), tables refer to office spaces. Chapters 4 and 5 will provide more details for each of the buildings.

3.1.4 Robust optimization

In this thesis, the exhaustive search is used to generate all possible design solutions and performance scenarios, with the identification of the optima being later achieved through the Pareto ranking of solutions. Optimization hence acts as a post-processing step (figure 3.1), while robust design solutions are then identified with the help of the new robust optimality criterion that will be introduced in section 3.1.4.3. Prior to the implementation of robust optimization, sections 3.1.4.1 and 3.1.4.2 will describe the definition of objective and constraint (if applicable) functions, respectively.

3.1.4.1 Objective functions

As indicated by Prowler (2008), in order to achieve a successful design solution, it is important to specify the project objectives early on in the design process and maintain them in balance from the conceptual to the detailed design stages. In case optimization is applied as a method to explore the design space (as suggested in this thesis), these objectives also act as the goals of the optimization process, which are related to the maximisation or minimisation of a function (such as comfort or cost, respectively). Based on the literature (Attia *et al.* 2013, Chardon *et al.* 2016, Huang and Niu 2016, Østergård *et al.* 2016, Touloupaki and Theodosiou 2017, Kheiri 2018, Longo *et al.* 2019), the most common objectives are: a) energy use; b) cost; and c) thermal comfort.

Hence, in this thesis, the performance of candidate solutions is assessed with respect to the following objectives that all need to be minimised: a) heating energy demand; b) winter thermal discomfort; c) summer thermal discomfort; and d) investment cost. As highlighted in section 2.3.1, considering multiple objectives can moderate the bias that characterises the conventional one- and two-objective problem formulations by providing the DMs with additional trade-offs that can increase their understanding of the consequences of decisions (Kollat *et al.* 2011). In the future, additional objectives could be included such as carbon emissions, visual comfort and indoor air quality.

Table 3.7 displays the four optimization objectives that are considered in this thesis – and later applied to the analysed buildings (in chapters 4 and 5). In addition to that, it presents the metrics that are used to quantify the performance of candidate solutions with respect to these four objectives. The predicted values for (annual) heating energy demand, winter thermal discomfort and summer thermal discomfort are the results of EnergyPlus (U.S. Department of Energy 2016a).

Table 3.7. The four design objectives that are considered in this thesis and the applied metrics.

Design objective	Metric	Reference
Heating energy demand	kWh/m^2.yr	EnergyPlus (U.S. Department of Energy 2016a)
Winter thermal discomfort	% of total occupied hours that PMV < -0.5	
Summer thermal discomfort	% of total occupied hours that acceptability < 80%	
Capital cost	£/m^2	Spon's price book (AECOM 2015)

Heating energy demand is calculated in kWh/m^2.yr to indicate the normalised per conditioned floor area space heating energy demand for the occupied winter period (note that, there is no additional heating outside the occupied hours). Winter thermal discomfort refers to the percentage of total occupied hours within the winter period that the PMV (i.e. the Predicted Mean Vote according to the Fanger's comfort model (Fanger 1970)) is less than -0.5. Summer thermal discomfort refers to the percentage of total occupied hours within the summer period that acceptability (according to the adaptive model (ASHRAE 2013)) is less than 80%. These limits were specified upon the acceptable thermal conditions that are recommended by the ASHRAE Standard 55-2013 (ASHRAE 2013) for spaces that are mechanically and naturally conditioned, respectively. Optimization thus aims to minimise the total number of occupied hours (within both the winter and summer periods) that environmental conditions are outside the defined comfort zone – i.e. to minimise exceedance hours.

Note that, in order to predict the values of these objective functions and export them in a CSV file (that will then be used to implement optimization), the following output variables need to be included in the EnergyPlus (U.S. Department of Energy 2016a) model: Zone Ideal Loads Supply Air Total Heating Energy; Zone Thermal Comfort Fanger Model PMV; and Zone Thermal Comfort ASHRAE 55 Adaptive Model 80% Acceptability Status, respectively. Alternative variables are available in EnergyPlus to predict performance values, this revealing the uncertainty in the formulation of the optimization problem, which is however out of the scope of this thesis.

Finally, a bespoke script is implemented in Python to calculate the capital cost of all solutions, this expressing the sum of construction materials and labour hours based on the Spon's Architects' and Builders' price book (AECOM 2015). Note that, this sum refers to the elements of the building envelope that are included in optimization (table 3.1), and not on any other elements that are related to construction (e.g. internal walls) or operation (e.g. the HVAC system). The calculated values are normalised to express the capital cost of solutions per treated floor area (in £/m^2) and added to the CSV file that is exported from EnergyPlus (U.S. Department of Energy 2016a), this containing the predicted values for the remaining three objectives.

3.1.4.2 Constraint functions

The constraints of the design problem represent the criteria that a design option needs to meet in order to be considered feasible. In this thesis, the building regulations and guides and any stakeholder preferences are taken into account for the formulation of the design problem and in particular, for the specification of any constraint functions. To avoid the risk of 'cognitive hysteresis' (Gettys and Fisher 1979), in this thesis, the application of constraints to the objective functions is posterior to the implementation of optimization; i.e. it is part of solution analysis. This disburdens the exploration of the design space of the bias that characterises the highly constrained problems, where the resulted solution set is limited by the initial conceptions of the DMs (Reed *et al.* 2013). These conceptions may however change along the way, with even small shifts being able to modify the resulted solution set (Robinson *et al.* 2016) and thus exclude well-performing solutions from exploration. Not applying a constrained optimization method also bolsters the direction of the search towards the truly optimum (Farmani and Wright 2003). However, note that, the framework that is presented in this thesis can also support the *a priori* application of constraints to the objective functions – in case the DMs are confident that the defined constraints will not change later on.

The intention of the suggested approach for robust optimization is hence to provide the DMs not with a single robust design solution, but with a set of robust alternatives to select from. During the analysis of the solution set (as described in section 3.1.5), constraints are imposed to the objective function values based on the requirements of standards and guides and any preferences of the stakeholders. As an example, if the client decides to construct a building that is compliant with the Passivhaus Standard (International Passive House Association 2018), its predicted heating energy demand must be less than or equal to 15 kWh/m^2.yr. Table 3.8 shows the assumed constraints on predicted thermal comfort, as recommended by the ASHRAE Standard 55-2013 (ASHRAE 2013). In the PMV method (employed when the building is mechanically ventilated), comfort zone is defined as 'conditions falling within and including PMV levels from -0.5 to +0.5' (ASHRAE 2013). In the adaptive method (applied when the building is naturally ventilated), an environment is considered as acceptable if it does not exceed the 80% acceptability limits – i.e. when the indoor operative temperature is no greater than 3.5 °C from the comfort temperature, which is based on the daily average outdoor dry-bulb temperatures of the previous 30 days.

Table 3.8. Constraints on the predicted thermal comfort of buildings based on their ventilation type and applied comfort model.

Ventilation type	Applied method	Constraint	Reference
Mechanical	Deterministic thermal comfort model	$-0.5 \leq \text{PMV} \leq +0.5$	ASHRAE Standard 55-2013 (ASHRAE 2013)
Natural	Adaptive thermal comfort model	Operative temperature - Comfort temperature ≤ 3.5 °C (80% acceptability)	

However, the DMs may consider a certain range of exceedance hours as acceptable. This possibility is also supported by guides claiming, for example, that 300 ‘unmet’ hours may be tolerated (ASHRAE 2007), these representing (approximately) the 4% of total simulation time (U.S. Department of Energy 2016b). The DMs may also limit the extent of functional change – due to the variations in input data – to a user-defined value (Deb and Gupta 2006). For example, they may decide that no more than 10% of total occupied hours within the winter (and/or summer) period must be outside the comfort zone (under all performance scenarios). A change in the original budget may similarly limit the feasible region. For example, the client may use 350 £/m^2 as the maximum limit to the construction cost of the building envelope. Note that, as these constraints are determined by the characteristics of each project, they are case-sensitive and thus constitute possible but not compulsory decisions. Given that the focus of this thesis is primarily on the design exploration process and not on the final selection of a design alternative based on actual stakeholder preferences, such constraints are here regarded as hypothetical ‘what-if’ scenarios that aim to demonstrate the ability of the new robust optimality criterion to support the *a posteriori* articulation of preferences as part of solution analysis.

The DMs are also provided with the opportunity to add a constraint on the level of robustness of candidate solutions based on their risk perception and preferences. The application of constraints is further discussed in section 3.1.5, which deals with the visualisation of the performance outcomes of design solutions and the investigation of several what-if scenarios. After the completion of solution analysis, the DMs are then responsible for selecting the most preferred solution. This procedure is referred in the literature as *a posteriori* relationship between search and decision (Miettinen 2001).

3.1.4.3 New robust optimality criterion

By coupling optimization and uncertainty analysis, robust optimization can support the identification of solutions that perform well under uncertainty. In particular, its goal is not only to minimise the objective function value(s), but also to deal with the deviations of any uncertain input data from their nominal values (Hopfe *et al.* 2012). Robust optimization is hence a method for addressing optimization problems that are exposed to uncertainty. As already mentioned in 2.5.1, it has been applied across a wide spectrum of domains such as finance or statistics, as well as in various areas of engineering such as structural design. However, it is still not popular in the area of building design exploration, where the majority of studies make use of deterministic simulations that disregard any possible variations in the operation of the building or its environmental conditions, this entailing the danger of sub-optimality for candidate design solutions (Van Gelder *et al.* 2014). There is also not a single, widely-applied definition of robustness, this resulting in various (mathematical) interpretations of the term and thus in several robustness indicators being available in the literature.

According to Bertsimas *et al.* (2011), robust optimization aims to provide the DMs with optimum solutions that remain ‘feasible for *any* realisation of the uncertainty in a given set’, this ensuring feasibility ‘independent of the data’. Adjusting this general interpretation of robust optimization to building design exploration problems, a new robust optimality criterion is presented that aims to ensure optimality independent of the sources of aleatoric uncertainty such as the weather and occupancy. According to this new criterion, *a robust solution is one that remains Pareto optimal regardless of the uncertainty in the predicted building performance* that is due to the variability in the behaviour of any uncertain conditions. Combining equation 2.3 (that refers to Pareto optimality) and equation 2.11 (that refers to robust optimization), equation 3.3 states that a solution x^* is robust, if it is Pareto optimal under all conditions. That is, if there exists no solution x which decreases[17] a criterion $f_i(x,u)$ without causing a simultaneous increase in at least one (out of k) criterion, under any scenario u:

$$\begin{gathered} f_i(x,u) > f_i(x^*,u) \text{ for at least one } i \in I,\, I = \{1,\dots,k\} \\ \forall\, x \in X,\, X = \{x_1,\dots,x_m\} \text{ and } \forall\, u \in U,\, U = \{u_1,\dots,u_n\} \end{gathered} \tag{3.3}$$

where m is the total number of candidate design solutions in the solution set X, and n is the total number of performance scenarios in the uncertainty set U.

In particular, the steps for implementing the robust optimality criterion are:

1) For each scenario u in the uncertainty set U (162 scenarios in total, resulting from the exhaustive combination of the performance variable values in table 3.3), find the Pareto set of design solutions.

[17] That applies to a minimisation problem, as required for this thesis.

2) For each design option x in the solution set X, count the number of scenarios for which the solution is Pareto optimal. If this is equal to the total number of scenarios (162 in this thesis), the robustness of the solution is maximum (for this problem).

Through the application of this new approach to robust design optimization, the DMs are able to identify solutions that remain Pareto optimal when exposed to aleatoric uncertainty; that is, solutions which are 'tolerant of variation' (Parkinson *et al.* 1993). This variation is here quantified by means of extreme values that provide lower and upper limits on the deviation of performance variables about their nominal values (as described in section 3.1.1.2). After specifying these three values (i.e. lower bound; nominal value; and upper bound) for each performance variable, an exhaustive search method is applied to define the (162) performance scenarios. In order to characterise a design solution as robust, this should be immune to the realisation of *all* these *a priori* scenarios; that is, it should remain Pareto optimal when performance scenarios vary within the defined uncertainty set U. Given that the entire uncertainty set U is here considered, such a solution could be characterised as *globally robust* (Doumpos *et al.* 2016).

Finding globally robust solutions that are immune to all the realisations of uncertain input data is a reasonable approach when uncertainty is not stochastic, or when the available data on the underlying distribution is not adequate (Bertsimas *et al.* 2011). However, as it is very unlikely that all fluctuations occur simultaneously in the worst possible combination (extreme scenario), a small number of 'rejects' (e.g. 1%) could be allowed, the magnitude of which needs to be decided by the DMs (Parkinson *et al.* 1993) and applied in the form of constraints (as discussed in 3.1.4.2). Given the low probability of a worst-case combination, a more flexible notion of robustness could thus be applied during solution analysis (particularly at the early stages of the design process), this accounting for the risk perception and preferences of the DMs.

3.1.5 Solution analysis

Solution analysis is the last step of the proposed robust building design optimization framework (figure 3.1), this referring to the visualisation of the performance outputs of candidate design solutions and the exploration of plausible what-if scenarios. The communication of performance results is vital for understanding the behaviour of the building and making informed design decisions, especially in the case of large design spaces (Kotireddy *et al.* 2018). Section 3.1.5.1 will describe how the visualisation of performance results can assist the DMs in increasing their understanding of how the building may behave in the real world. Section 3.1.5.2 will focus on the investigation of what-if scenarios that can assist the DMs in making informed decisions.

3.1.5.1 Visualisation of performance results

Visualising a multi-dimensional Pareto front is challenging (section 2.3.1). This is due to the difficulty in, firstly, calculating a multi-dimensional – that is, larger than three-dimensional – Pareto optimal surface and, secondly, disseminating it in a user-friendly manner (Deb and Saxena 2005). Parallel coordinates plots are used in this thesis to visualise the (four) optimization objectives in a two-dimensional graph that provides a rigorous way of displaying the relationship between design solutions and objectives (Fleming *et al.* 2005). Scatter plots are also used to assist the DMs in gaining a better understanding of the relationship between design solutions and objectives and hence becoming aware of the consequences of design choices, by exploring the trade-offs between the (four) optimization objectives (Kollat *et al.* 2011).

The analysis of the performance of Pareto optimal solutions can support the DMs in obtaining a deeper understanding of the problem and, in particular, identifying any ‘commonality principles’ among all or many of these solutions (Deb and Srinivasan 2006). Such principles will indicate properties that can ensure Pareto optimality (Deb *et al.* 2014). Knowledge is also obtained from the analysis of the set of sub-optimal solutions, which can reveal the characteristics that make this set differ from the rest of solutions, but also the constraints that trigger sub-optimality. Solution analysis can finally yield knowledge specific to the region of interest of the DMs, relating regions in the objective space with regions in the decision space in order to inform decision-making (Bandaru *et al.* 2017).

Communicating the sources of uncertainty and the related magnitude of performance to the DMs is, however, necessary for making robust decisions (Paté-Cornell 1996). Being aware of the possible states and outcomes of each candidate solution is crucial when investigating the risk of potential decisions (Gärdenfors and Sahlin 1982). For a problem that is exposed to uncertainty, risk refers to ‘the probability of failure to satisfy some performance criterion’ (Haldar and Mahadevan 2000). In the context of building design problems though, ‘probability of failure’ cannot be easily quantified due to the difficulty of explicitly quantifying the probability of individual scenarios occurring (Rysanek and Choudhary 2013). Risk hence expresses ‘the consequence of failure’, this signifying unsatisfactory performance (Haldar and Mahadevan 2000).

In this thesis, the performance of a design solution is characterised as unsatisfactory when the solution is not globally robust – that is, when it is not Pareto optimal under all (162) performance scenarios. Nevertheless, this worst-case approach may result in conservative decisions that are determined by rather unlikely events (Doumpos *et al.* 2016). The new robust optimality criterion that is suggested in this thesis provides the DMs with the flexibility to specify their desired level of robustness (which is visually communicated with the help of parallel coordinates and scatter plots), based on how large risks they wish to take. The more risk-averse the DMs are, the higher the chosen level of robustness must be (Gärdenfors and Sahlin 1982); i.e. the higher the number of performance scenarios for which the design solution is Pareto optimal should be.

3.1.5.2 Investigation of what-if scenarios

What-if analysis is described as ‘a data-intensive simulation whose goal is to inspect the behaviour of a complex system (such as a building) under some given hypotheses called scenarios’ (Golfarelli *et al.* 2006). Such scenarios express potential approaches to addressing the formulated building design problem (Sears and Jacko 2009). Their investigation can therefore indicate the steps that are required for optimizing building performance (Lerum 2008), also driving design decisions towards the direction that satisfies the needs of the DMs (Sears and Jacko 2009). By demonstrating the positive and negative consequences of preferred design choices, what-if scenarios can support robust optimization and decision-making (Howell and Batcheler 2005). As discussed in section 3.1.4.2, stakeholder preferences inform the definition of what-if scenarios, which are then expressed as (*a posteriori*) constraints to the defined problem.

Parallel coordinates are used to illustrate the articulation of stakeholder preferences, as they provide the possibility to zoom in on a region of interest and isolate solutions with satisfactory characteristics (Fleming *et al.* 2005). By adding constraints to the outputs (design objectives) or inputs (design variables), the DMs can explore the sub-regions of the search space that satisfy their user-defined filter criteria (Østergård *et al.* 2017). Constraints are therefore here implied by the (hypothetical) preferences of stakeholders (as discussed in section 3.1.4.2), but also the requirements of standards and guides. As the applied exhaustive search method enables the re-focusing of the problem as a post-processing step, there is the possibility of effortlessly considering multiple sets of objective and constraint functions out of the initial simulated dataset (Rysanek and Choudhary 2013). This can lead to the discovery of solution 'attributes' which can further inform decision-making (Ware 2012).

Given the fact that the search for robust design alternatives may return solutions that are different from those of the deterministic Pareto set (that is, the nominal optimum solutions) (Avigad and Branke 2008), accounting for aleatoric uncertainty is vital for predicting the impact of decisions with more confidence (Gokhale 2009). Visualising uncertainty is therefore important, although not always easy to achieve (Ware 2012). Box plots are used to visualise the variations in the predicted objective values (for the solutions that meet stakeholder preferences) due to the effect of aleatoric uncertainty (de Wilde and Tian 2009), this being expressed by the 162 scenarios that were defined in section 3.1.1.2. Box plots provide a simple way of visualising the distribution of possible values for each objective function (Min *et al.* 2005). However, note that, this distribution expresses the nominal and extreme values that were introduced in section 3.1.1.2; its shape may thus change if additional values are considered.

3.2 Experiments and case study buildings

The proposed framework for robust building design optimization (figure 3.1) will be applied to two case study buildings in chapters 4 and 5. In more detail, chapter 4 will describe the experimental 'proof of concept' for the robust optimization approach, with the objective of exploring the behaviour of the new robust optimality criterion (as discussed in chapter 1). The solution set that will be derived from the application of the criterion (introduced in section 3.1.4.3) will be analysed as well as compared with the solution sets that will be obtained from the application of existing robustness indicators (presented in section 2.5.2.1). Note that, such a comparison aims to cast light on the behaviour of the new criterion – and not to identify the best-performing indicator, as this is dependent on the (risk) preferences of the DMs. The experiment will be performed using the 'test cell' that is illustrated in figure 3.3. This is a single-zone office space with a widely used geometry (Judkoff and Neymark 1995). Thanks to its simple geometry, the robust optimization problem can be easily formulated, thus drawing attention to the behaviour of the new robust optimality criterion.

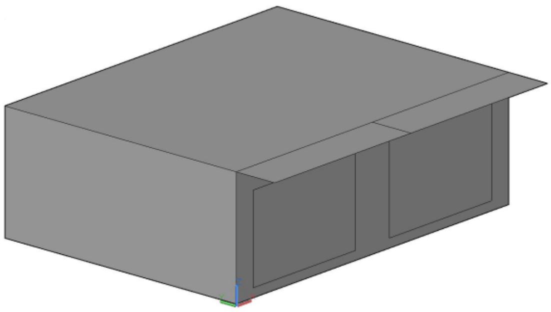

Figure 3.3. Test cell – The building form.

Chapter 5 will describe an example application of the robust optimization approach, with the objective of demonstrating its potential to support design exploration and decision-making under uncertain conditions within a real-world context (as discussed in chapter 1). This experiment will be performed using a community centre as an example building. This is planned to be constructed in London, incorporating a shop, café, visitor space and third-party offices. As it comprises a variety of building uses (and therefore of thermal zones and requirements), it is suitable for demonstrating the potential of the proposed approach in the case of complex real-life problems. Three alternative building forms will be considered (as conceived by the design team), thus also accounting for the complexity of building geometry, as illustrated in figures 3.4, 3.5 and 3.6.

Figure 3.4. Real-world building – Form A (source: Eco Design Partnership ©).

Figure 3.5. Real-world building – Form B (source: Eco Design Partnership ©).

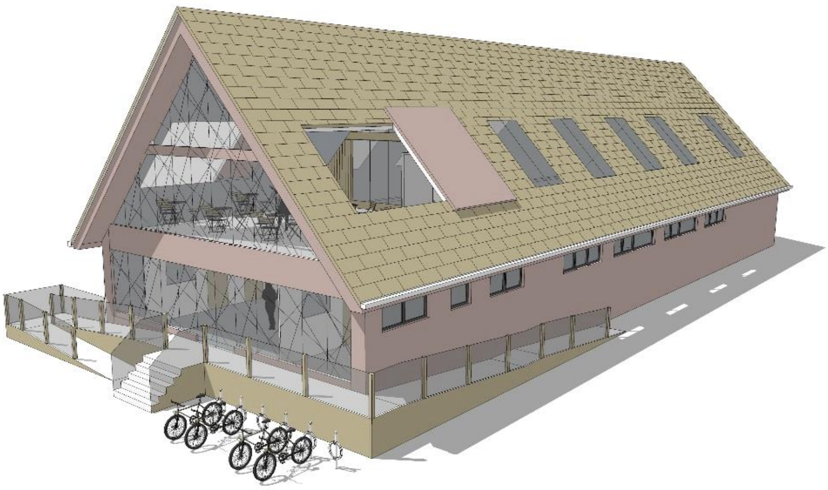

Figure 3.6. Real-world building – Form C (source: Eco Design Partnership ©).

3.3 Summary

Chapter 3 described the new robust building design optimization framework, which aims to handle building design problems that are exposed to uncertain conditions, thus supporting building design exploration under uncertainty (as discussed in chapter 1). Building design exploration is a complex multi-step process that aims to identify the best-performing design solution (chapter 2). This process was here translated into a multi-objective robust optimization problem, the definition of which is informed by the requirements of the regulations and any possible preferences of the stakeholders. The DMs are called to solve this optimization problem that is exposed to a defined uncertainty set, which contains possible performance scenarios associated with the behaviour of any defined uncertain conditions.

To solve this problem, all decisions need to be taken prior to the realisation of any performance scenario, as the naturally unpredictable sources of aleatoric uncertainty cannot be eliminated during the design process. By using the new robust optimality criterion that was introduced in this chapter, the DMs can identify a set of Pareto optimal solutions whose optimality is unaffected by the entire uncertainty set, these being here characterised as *globally robust* solutions. In terms of mathematics, such a robust optimization problem is solved by generating the Pareto front for each of the defined performance scenarios and then spotting the solutions that appear in all these Pareto fronts. Note that, the robust optimality criterion provides the DMs with the flexibility to specify their desired level of robustness, and therefore select a solution that appears in a user-defined number of Pareto fronts.

However, in terms of decision-making, the problem is considered to be solved only when a single, final solution is obtained. As multiple objectives need to be minimised (heating energy demand; winter thermal discomfort; summer thermal discomfort; and capital cost), the implementation of robust optimization will result in more than one design alternatives. This is due to the fact that, if the dimensionality of the objective space increases, the dimensionality of the resulted Pareto frontier also increases. The DMs are thus provided with the opportunity to make the final decision. In particular, during solution analysis, the performance results of candidate solutions are presented to the DMs who can then choose the most preferred option, this being referred in the literature as *a posteriori* decision-making. This method can be further investigated in the future, as the focus of this thesis is primarily on the design exploration process – that is, the generation and evaluation of alternative designs – and not on the selection of the (single) design that will be refined later on in the design process.

Finally, note that, the robust building design optimization framework does not currently include sensitivity analysis. This means that the selected design parameters represent sources of epistemic uncertainty that are influential based on the conducted literature review, not on the mapping from analysis inputs to analysis outputs for the given case study buildings. In the future, sensitivity analysis could be incorporated in the robust building design optimization framework to enable a customised list of the parameters that greatly influence performance prediction and should therefore attract the attention of stakeholders during the design exploration process.

Chapter 4

Test cell – Proof of concept

Chapter 4 describes the application of the suggested framework for robust building design optimization to a test cell. The behaviour of the new robust optimality criterion is elucidated by analysing the solution set that is derived from the application of the new criterion and comparing it with the solution sets that result from the application of existing robustness indicators.

4.1 Description of the building

The 'test cell' that is used to validate the suggested framework is illustrated in figure 4.1. This is a single-zone office building in London with a simple geometry that enables the smooth application of the framework, thus drawing attention to the behaviour of the new robustness indicator. The geometry of the building was derived from a Building Energy Simulation Test (BESTEST) that was developed by the International Energy Agency (IEA) for testing whole-building energy simulation software tools (Judkoff and Neymark 1995). The dimensions of the building are 8 m x 6 m x 2.7 m. The building has no doors and two south-facing windows (each of them with a maximum area of 6 m^2) that are shaded by an overhang (with a maximum width of 1 m).

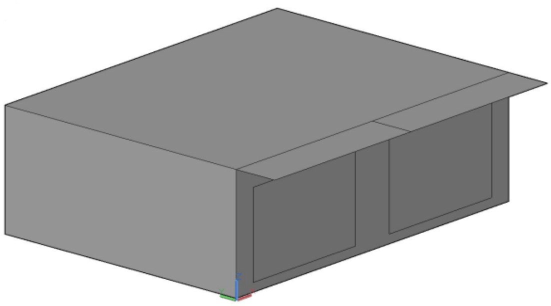

Figure 4.1. Test cell – The building form.

4.2 Application of the robust optimization framework

This section will focus on the application of the proposed robust design optimization framework (introduced in chapter 3) to the described test cell. The implementation of the five recommended steps to solving a robust optimization problem (summarised in figure 3.1) will be discussed in sections 4.2.1 to 4.2.5.

4.2.1 Uncertainty quantification

According to the suggested framework, the first step to solving a robust optimization problem is to specify the design and performance variables that represent its sources of epistemic and aleatoric uncertainty, respectively. Table 4.1 summarises the design variables and variable values that are considered in the case of the test cell. Regarding its building *form*, two variables are defined (due to their effect on design objectives, as revealed by the literature review in chapter 2): window-to-wall ratio (WWR) and overhang depth. Two WWRs of 55.6 % and 27.8 % are selected. The larger area is the default BESTEST case (Judkoff and Neymark 1995), with the smaller area being half the default case. Note that, the smaller area is achieved by halving the height of both windows (the width of both windows is fixed, and their upper edges also remain fixed). Two overhang depths of 1.0 m and 0.3 m are selected, these being informed by the default BESTEST case and the Spon's book (AECOM 2015), respectively.

Regarding the *construction* of the test cell, the defined variables and variable values are identical to those described in section 3.1.1.1, with the values being drawn from the two standards: the Passivhaus Standard (International Passive House Association 2018) and the Building Regulations Part L (UK Government 2013a). Four variables are considered: external wall construction; roof construction; window construction; and infiltration rate. Concerning the wall and roof constructions, two options comply with the Passivhaus Standard and two options satisfy the Building Regulations. The two options that conform to each standard have similar U-values, but different levels of thermal mass (heavyweight and lightweight constructions). Two types of window construction and infiltration rate, are similarly defined: one meeting the requirements of the Passivhaus Standard and another one of the Building Regulations Part L.

Regarding the *operation* of the test cell, five heating setpoint values are considered, these expressing the air temperatures that are suggested by the activity database of the National Calculation Method (NCM) (BRE 2015). Design variables are assumed to have a uniform distribution.

Table 4.1. List of design variables and variable values.

Subcategories	Variables	Variable values	References
Form	WWR (%)	1) 55.6 2) 27.8	(Judkoff and Neymark 1995)
	Overhang depth (m)	1) 1.0	(Judkoff and Neymark 1995)
		2) 0.3	(AECOM 2015)
Construction	External wall construction (W/m^2K) [18, 19]	1) HW-PH (0.140) 2) LW-PH (0.143)	(IBO 2009, International Passive House Association 2018)
		3) HW-PL (0.342) 4) LW-PL (0.342)	(Neufert *et al.* 2012, UK Government 2013a)
	Roof construction (W/m^2K)	1) HW-PH (0.146) 2) LW-PH (0.144)	(IBO 2009, International Passive House Association 2018)
		3) HW-PL (0.243) 4) LW-PL (0.239)	(Neufert *et al.* 2012, UK Government 2013a)
	Window construction (W/m^2K)	1) PH (0.780)	(IBO 2009, International Passive House Association 2018)
		2) PL (2.129)	(Neufert *et al.* 2012, UK Government 2013a)
	Infiltration rate (ac/h)	1) PH (0.050)	(CIBSE 2006, McLeod *et al.* 2014)
		2) PL (0.500)	(CIBSE 2006, ATTMA 2010)
Systems and operation	Heating setpoint (°C)	1) 19 2) 20 3) 21 4) 22 5) 23	(BRE 2015, International Passive House Association 2018)

[18] HW/LW denotes the thermal mass of each construction (heavyweight and lightweight construction, respectively). PH/PL signifies the standard each construction complies with (the Passivhaus Standard and the Building Regulations Part L, respectively).
[19] The U-value of each construction option is provided (in W/m^2K).

Table 4.2 summarises all performance variables and variable values (as described in section 3.1.1.2). Regarding the *weather*, three weather files are defined: the monitored data of 1979 (CIBSE 1979); the test reference year (TRY) (CIBSE 2016); and the design summer year (DSY 3) for London (CIBSE 2016). Concerning the *occupancy* of the cell, two occupant densities (and internal heat gains) are specified: a nominal value that is informed by the NCM activity database (BRE 2015) and a lower bound that refers to a 50% reduction in sensible gains (MacDonald 2002). Regarding the *actual performance* of wall and roof constructions, nominal values express the values of table 4.1. Lower and upper bounds represent faster and slower responses of the thermal mass, respectively (Clarke *et al.* 1990, MacDonald 2002). Three infiltration rates are similarly defined: a nominal value (table 4.1) and two extreme values that indicate a ± 50% variation (MacDonald 2002); that is, plus and minus three standard deviations ($\mu \pm 3\sigma$). All performance variables have a normal distribution.

Table 4.2. List of performance variables and variable values.

Subcategories	Variables	Variable values	Description/ References
Weather	Weather file	1) 1979	Cold year: maximum heating degree days (CIBSE 1979)
		2) TRY	Typical year (CIBSE 2016)
		3) DSY 3	Hot year: long, less intense warm spell (CIBSE 2016)
Occupancy	Occupant density (persons/m^2)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	(BRE 2015)
Construction (actual performance)	External wall construction (W/m^{2}K)	1) Fast response	Nominal values refer to the design variable values of table 4.1. The lower and upper bounds represent possible variations in the response of the thermal mass. The considered variations in the thermal properties of individual material layers depending on their general category (Clarke *et al.* 1990) are included in tables A.3, A.4 and A.5 of appendix A.
		2) Nominal	
		3) Slow response	
	Roof construction (W/m^{2}K)	1) Fast response	
		2) Nominal	
		3) Slow response	
	Infiltration rate (ac/h)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	See table 4.1
		3) Nominal + 50%	(MacDonald 2002)

4.2.2 Exhaustive search

Based on the proposed framework, after having specified all design and performance variables, the next step to solving a robust optimization problem is to form all design solutions $(x_1, \dots, x_m)$ and performance scenarios $(u_1, \dots, u_n)$. Since this thesis makes use of an exhaustive search method, the total number of solutions (m) and the total number of scenarios (n) result from the exhaustive combination of the defined design variable values and performance variable values, respectively. In the case of the test cell, m equals 1,280 (2 WWRs x 2 overhang depths x 4 external wall constructions x 4 roof constructions x 2 glazing types x 2 infiltration rates x 5 heating setpoints) and n equals 162 (3 weather files x 2 occupant densities x 3 external wall constructions (actual performance) x 3 roof constructions (actual performance) x 3 infiltration rates (actual performance)). This results in 207,360 combinations (1,280 design solutions x 162 performance scenarios) and associated building performance simulations (BPS).

4.2.3 Building performance simulation

The next step is to explore the design space, which is performed with the assistance of BPS and optimization methods. Prior to assessing the optimality of solutions, their performance is predicted (under all performance scenarios), using EnergyPlus (U.S. Department of Energy 2016a) as an engine. The modelling process was described in section 3.1.3. In summary, the geometry of the test cell is firstly built (figure 4.2) in SketchUp (Trimble Navigation 2016) using its OpenStudio plug-in (U.S. Department of Energy 2015). The model is then exported as an input data file (IDF) and imported into EnergyPlus, where any input data that refers to its construction and operation is defined (data is summarised in the tables in chapter 3 and appendix A). The test cell operates on weekdays between 8:00 and 18:00, with winter heating and ventilation being supplied by the Ideal Loads Air System of EnergyPlus (U.S. Department of Energy 2016b), which also enables sensible heat recovery when the zone exhaust air temperature is more favourable than the outdoor air temperature. The outdoor air flow is 0.01 m^3/s per person (BRE 2015). In summer, the test cell is naturally ventilated (during working hours) and hence no cooling or mechanical ventilation system is used. Lighting loads are set at 9 W/m^2 and electrical equipment loads at 11.77 W/m^2, with their schedules also being informed by the NCM activity database (BRE 2015).

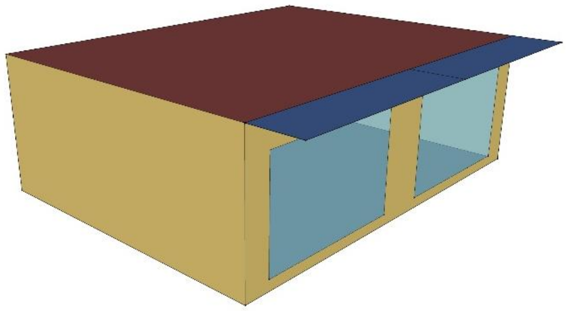

Figure 4.2. Test cell – The SketchUp model.

Since each run takes 12 seconds, 691 hours are needed to complete the experiment. However, thanks to a bespoke (Java) script that supports concurrent processing, 20 simulations are run in parallel, with the total computational time thus being 35 hours. Simulation results are exported to a comma-separated file (CSV) which contains the predicted values for heating energy demand, winter thermal discomfort and summer thermal discomfort. Values have been cross-checked to validate the model, with table B.1 (appendix B) showing the results for a solution that complies with the Passivhaus Standard and a solution that just complies with the Building Regulations (under a given scenario). Thanks to a bespoke (Python) script and the Spon's price book (AECOM 2015), the capital cost of each solution is also calculated and added to the CSV file.

4.2.4 Robust optimization

After predicting the performance of solutions under all scenarios, the next step is to identify the optima through the Pareto ranking of solutions. Optimization is thus a post-processing step, with the identification of robust solutions being then performed using the new robust optimality criterion. According to this criterion, *a robust solution is one that remains Pareto optimal regardless of the uncertainty in the predicted building performance* that is due to the variability in the behaviour of the uncertain conditions. As revealed by equation 4.1, a solution x^* is robust, if it is Pareto optimal under all 162 scenarios. That is, if there exists no solution x which decreases a criterion $f_i(x, u)$ without causing an increase in at least one other criterion, under any scenario u:

$$\begin{gathered} f_i(x,u) > f_i(x^*,u) \text{ for at least one } i \in I,\, I = \{1, \dots, 4\} \\ \forall\, x \in X,\, X = \{x_1, \dots, x_{1280}\} \text{ and } \forall\, u \in U,\, U = \{u_1, \dots, u_{162}\} \end{gathered} \tag{4.1}$$

In particular, the steps for post-processing (in Python) the CSV file that contains all predicted performance values to apply the robust optimality criterion to the cell are:

1) For each scenario u in the uncertainty set U (162 accumulatively), the Pareto set of design solutions is identified.
2) For each solution x in the solution set X (1,280 accumulatively), the number of scenarios for which the solution is Pareto optimal, is counted. If it equals 162, the robustness of the solution is maximum, as it *remains Pareto optimal regardless of the behaviour of the uncertain conditions*.

As indicated by equation 4.1, four optimization objectives are considered: a) heating energy demand; b) winter thermal discomfort; c) summer thermal discomfort; and d) capital cost. Table 4.3 displays the metrics that are used to quantify the performance of each design solution with respect to these four objectives. Heating energy demand is calculated in kWh/m^2.yr to reveal the normalised per conditioned floor area space heating energy demand within the occupied winter period. Winter thermal discomfort refers to the percentage of total occupied hours within the winter period that PMV (Fanger 1970)) is less than -0.5. Summer thermal discomfort refers to the percentage of total occupied hours within the summer period that acceptability (according to the adaptive model (ASHRAE 2013)) is less than 80%. These limits were specified upon the acceptable thermal conditions that are suggested by the ASHRAE Standard 55-2013 (ASHRAE 2013). Optimization thus aims to minimise the number of occupied hours that thermal conditions are outside the comfort zone – i.e. minimise exceedance hours. Capital cost (of the building envelope only) expresses the sum of construction materials and labour hours (AECOM 2015) per treated floor area (in £/m^2).

Table 4.3. The four design objectives and the applied metrics.

Design objective	Metric	Reference
Heating energy demand	kWh/m^2.yr	EnergyPlus (U.S. Department of Energy 2016a)
Winter thermal discomfort	% of total occupied hours that PMV < -0.5	
Summer thermal discomfort	% of total occupied hours that acceptability < 80%	
Capital cost	£/m^2	Spon's price book (AECOM 2015)

4.2.5 Solution analysis

Solution analysis is the last step of the proposed robust building design optimization framework which aims to assist the DMs in understanding how the designed building may behave and ultimately making informed design decisions. This can be achieved by visualising the performance results of candidate design solutions and investigating possible what-if scenarios which are informed by the requirements of regulations and the preferences of different stakeholders. Figures 4.3 to 4.6 illustrate the distribution of the predicted values for each design objective (in the case of the described test cell and problem formulation). Each distribution reflects the 207,360 simulations which resulted from the exhaustive combination of the specified 1,280 design solutions and 162 performance scenarios. As both design and performance uncertainties are taken into account, such distributions can reveal how the test cell may behave in real life.

The minimum heating energy demand is 0 kWh/m^2.yr (figure 4.3). Not surprisingly, this value refers to a solution that is compliant with the Passivhaus Standard – and thus the U-values of its wall, roof and window constructions as well as its infiltration rate are low, compared with a solution that only satisfies the Building Regulations. Both wall and roof constructions are heavyweight. The WWR is on its highest value, and the overhang depth on its lowest value. The heating setpoint is expectedly set to 19 °C (the lowest considered value). With regard to the behaviour of the uncertain conditions, the minimum heating energy demand refers to a hot weather year, a high value of occupant density (and internal gains), a slow response of the thermal mass (for wall and roof constructions) and a lower than expected (i.e. the nominal) infiltration rate.

The maximum predicted heating energy demand is 78 kWh/m^2.yr. This is associated with heavyweight wall and roof constructions that are compliant with the Building Regulations, but not with the Passivhaus Standard. The window constructions and infiltration rate similarly only meet the requirements of the Building Regulations. The WWR is on its lowest value, while the overhang depth and heating setpoint on their highest values. The maximum predicted heating energy demand is associated with a cold weather year, a low value of occupant density and internal gains, a fast response of the thermal mass (for both wall and roof constructions) and a higher than expected infiltration rate.

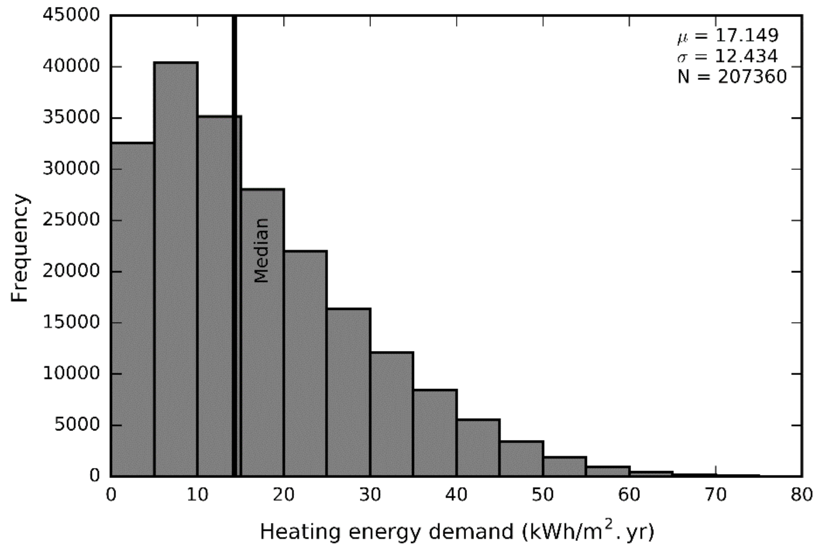

Figure 4.3. The histogram of predicted values for heating energy demand.

Concerning winter thermal discomfort, the minimum predicted value is 0% (figure 4.4). 644 out of the 207,360 combinations of design and performance variable values lead to this percentage, with almost all of them including Passivhaus wall, roof and window constructions and infiltration rate as well as a heating setpoint of 23 °C and the highest value of occupant density and internal heat gains. The maximum predicted value is 99%. This refers to a solution that complies with the Building Regulations and has a heating setpoint of 19 °C. 99% is observed under multiple scenarios, all including the cold weather year and lowest value of occupant density and internal heat gains.

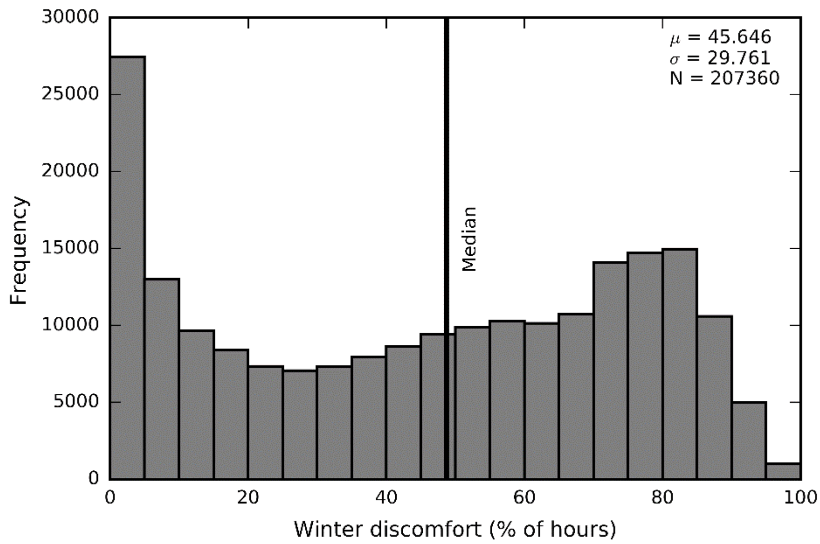

Figure 4.4. The histogram of predicted values for winter thermal discomfort.

The minimum summer thermal discomfort is 0% (figure 4.5). 5,579 out of the 207,360 combinations of design and performance variable values lead to this percentage, with all of them including the lowest WWR and the cold weather year and, most of them, the highest value of overhang depth as well as the lowest value of occupant density and internal heat gains. The maximum percentage of discomfort hours is 40%. This refers to a solution that is compliant with the Passivhaus Standard – and therefore has an airtight construction. As expected, 40% is observed when the hot weather year and highest value of occupant density and internal heat gains occur.

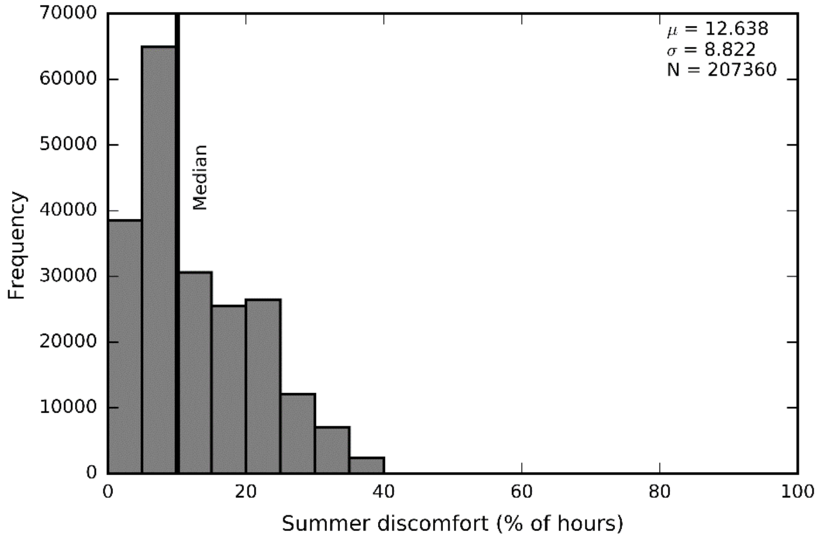

Figure 4.5. The histogram of predicted values for summer thermal discomfort.

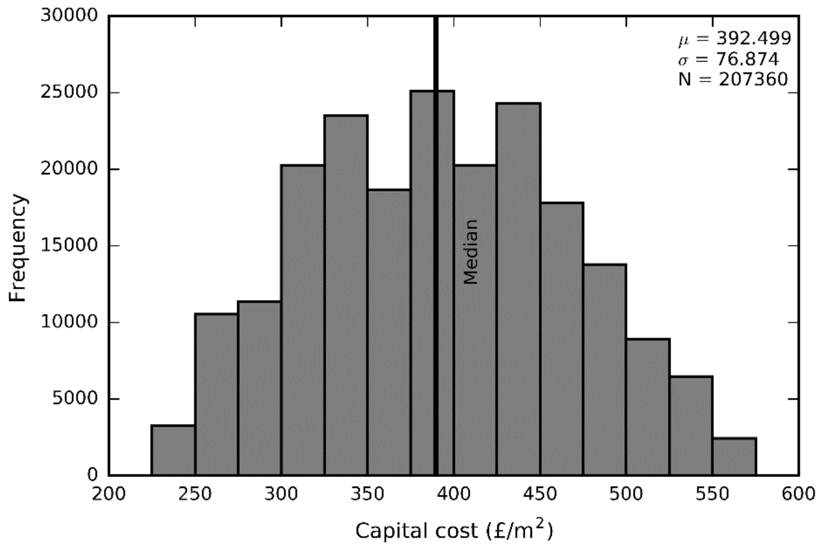

Figure 4.6. The histogram of predicted values for capital cost.

Finally, the minimum capital cost is 230 £/m^2 (figure 4.6). This refers to a design solution that complies with the Building Regulations Part L – and hence, compared with a Passivhaus solution, its wall and roof constructions have a less thick insulation and no airtightness membrane as well as its windows are double glazed, instead of triple glazed. The maximum cost value is 590 £/m^2. This refers to lightweight (timber frame) wall and roof constructions that satisfy the requirements of the Passivhaus Standard, and the highest WWR (as the cost of the window construction is three times higher than the cost of the wall construction). Note that, this maximum cost value is observed under all (162) performance scenarios, as capital cost is not affected by the variability in the behaviour of the uncertain conditions. However, by comparing the distributions that are displayed in figures 4.3 to 4.6 with these in 4.7 (demonstrating deterministic values only), it is evident that aleatoric uncertainties can influence the performance of the test cell in terms of its heating energy demand, winter discomfort and summer discomfort, hence revealing the value of including such uncertainties in design exploration (in the case of winter thermal discomfort, this may be less apparent, as occupant comfort is remarkably affected by the selection of heating setpoint).

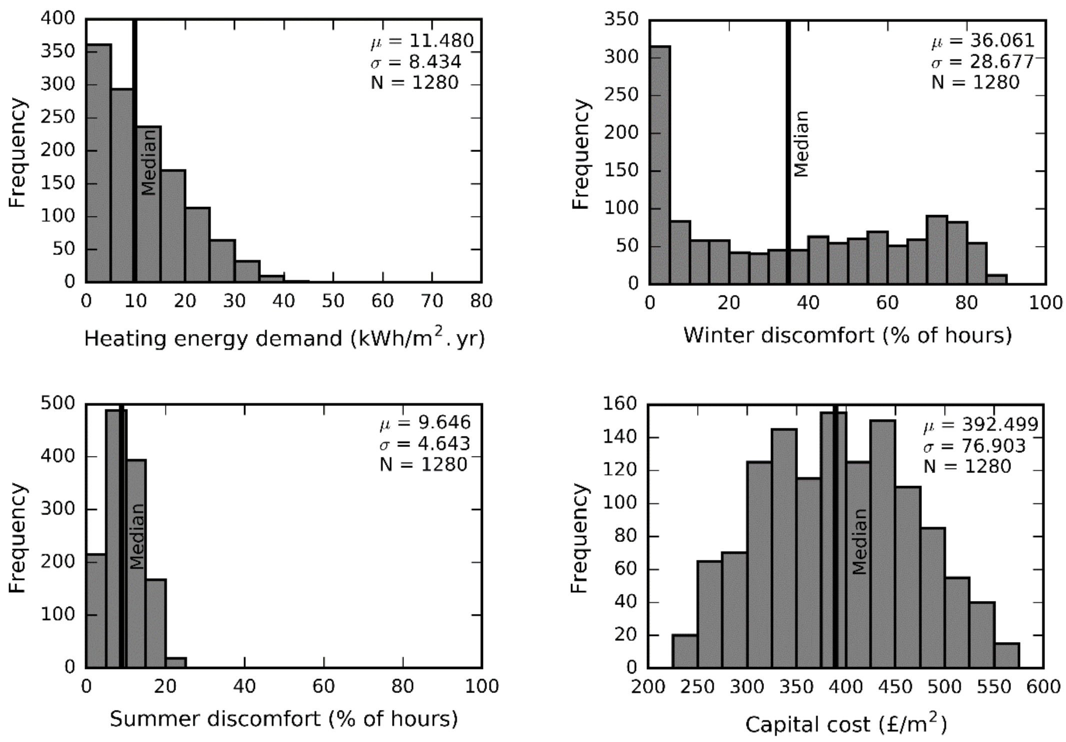

Figure 4.7. The histograms of predicted deterministic values for all four design objectives.

By considering aleatoric uncertainties during design exploration, the DMs can hence become aware of the risk of unsatisfactory performance. This risk is revealed by the comparison between the number of nominal optimum solutions (as resulted from the deterministic Pareto ranking) and the number of robust solutions (as derived from the application of the robust optimality criterion). In particular, as shown in table 4.4, out of the 1,280 candidate design solutions, 217 solutions are found to be Pareto optimum under the nominal value of the uncertain conditions. However, only 68 of them are optimum under all (162) performance scenarios. In addition to these globally robust solutions, 254 solutions are Pareto optimal under one or more scenarios – that is, 322 solutions (including the 217 solutions) are optimal under at least one scenario.

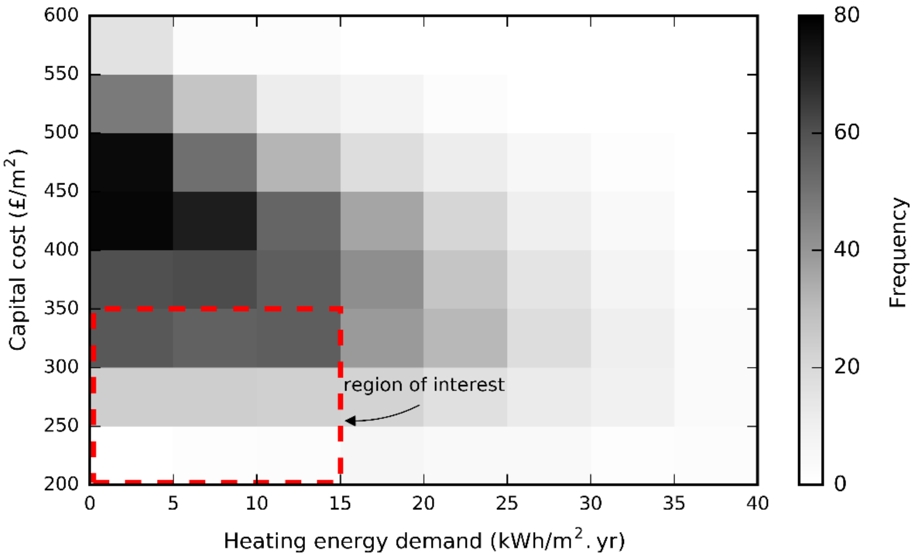

Figure 4.8. Restricted (hypothetical) region of interest in the deterministic objective space. The shading signifies the number of design solutions in each region of the figure.

Table 4.4. Number of solutions (for the described problem formulation).

Type of solutions	Number of solutions	
	Design space	Region of interest
Feasible (under all scenarios)	1,280	51
Nominal optimum	217	22
Optimum under at least one scenario	322	36
Optimum under all scenarios (globally robust)	68	19

The risk of sub-optimality – or even infeasibility – of candidate design solutions due to aleatoric uncertainties can be elucidated by restricting the (hypothetical) region of interest in the objective space. For instance, the DMs may consider 15 kWh/m^2.yr and 350 £/m^2 as the maximum allowable values for heating energy demand and capital cost, respectively (figure 4.8). Out of the 243 feasible design solutions in the deterministic objective space (i.e. in the case of no aleatoric uncertainties), only 51 solutions remain feasible under all scenarios. 22 of them are optimum under nominal conditions, with 19 of them remaining optimum under all scenarios. 36 solutions are optimal under at least one scenario (including the 19 solutions that are 100% robust).

The scatter plot in figure 4.9 can assist the DMs in gaining a better understanding of the relationship between these 19 globally robust solutions (denoted with a rhombus) and the design objectives. 8 of these 19 solutions (no. 10, 11, 12, 13, 15, 16, 17 and 18)[20] fully comply with the Passivhaus Standard, all including concrete wall and roof constructions. They also include the lowest value of overhang depth. Solutions no. 10, 11, 12 and 13 comprise the highest WWR, thus resulting in a higher percentage of summer discomfort hours, compared with solutions no. 15, 16, 17 and 18, which have the lowest WWR. Each group of four solutions refers to the same constructions but different heating setpoint (19, 20, 21 and 22 °C, respectively), therefore leading to identical summer discomfort hours and costs, but different heating energy demands and winter discomfort hours. The remaining globally robust solutions include a roof and/or window construction which does not comply with the Passivhaus Standard.

Since the robust optimality criterion provides the DMs with the flexibility to specify their desired level of robustness, figure 4.9 also displays (using a circle) the 2 design solutions which are 95% robust – i.e. remain optimal under at least 154 performance scenarios. Solution no. 14 is identical to solutions no. 10, 11, 12 and 13 in terms of its form and construction, but has a higher heating setpoint (23 °C). Solution no. 332 differs from solution no. 12 only in terms of its window construction, as this is not compliant with the Passivhaus Standard. If the DMs have a risk-taking attitude, they can decrease the number of scenarios for which the building remains Pareto optimal.

[20] The number refers to the solution “index” and as such, its magnitude does not imply a rank/ order of optimality – in fact, these solutions are all equal in terms of their level of robustness.

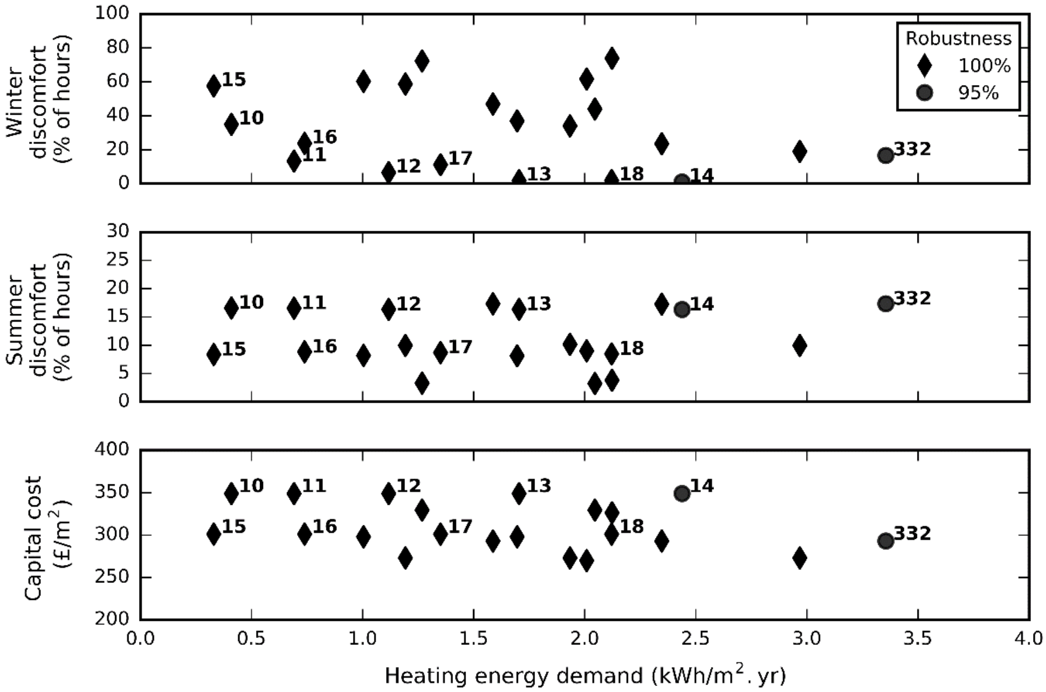

Figure 4.9. The trade-offs between the four optimization objectives under the nominal conditions.

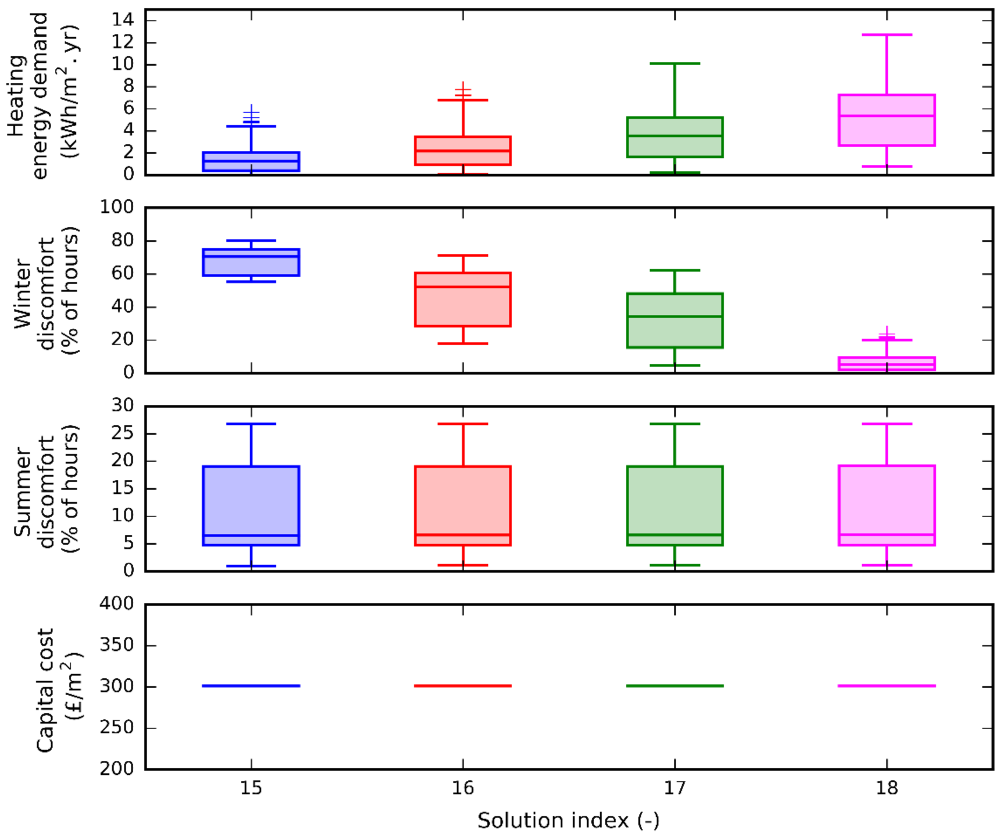

Figure 4.10. The box plots of compatible (for a hypothetical what-if scenario) solutions.

Note that, the objective values that are illustrated in figure 4.9 represent the predicted performance of the test cell under the nominal uncertain conditions. Such values are displayed in table 4.5 for the 19 solutions that remain optimum under all scenarios, in the described region of interest (illustrated in figure 4.8). The combinations of design variable values that led to these performance values (and were described above), are displayed in table 4.6.

Table 4.5. The predicted objective values under the nominal conditions for the 19 solutions that remain optimum under all (162) scenarios, in the described region of interest (figure 4.8). Note that, the solution index does not imply a rank/ order of optimality – in fact, these solutions are all equal in terms of their level of robustness.

Solution index	Design objective			
	Heating energy demand ($kWh/m^2.yr$)	Winter discomfort (% of hours)	Summer discomfort (% of hours)	Capital cost (£/m^2)
10	0.409	35.043	16.595	348.959
11	0.691	13.439	16.547	348.959
12	1.117	6.575	16.331	348.959
13	1.704	1.879	16.355	348.959
15	0.330	57.659	8.357	301.072
16	0.739	23.772	8.836	301.072
17	1.350	11.272	8.716	301.072
18	2.121	1.951	8.477	301.072
175	1.004	60.332	8.190	297.902
176	1.695	37.066	8.118	297.902
325	1.268	72.327	3.305	329.460
326	2.046	44.075	3.257	329.460
330	1.587	47.038	17.313	292.959
331	2.347	23.555	17.265	292.959
335	1.192	58.743	9.962	273.072
336	1.933	34.104	10.177	273.072
337	2.968	19.075	9.962	273.072
485	2.122	73.916	3.807	326.290
495	2.008	61.705	9.028	269.902

Table 4.6. The combinations of design variable values for the 19 solutions that remain optimum under all (162) scenarios, in the described region of interest (figure 4.8). Note that, the solution index does not imply a rank/ order of optimality – in fact, these solutions are all equal in terms of their level of robustness. HW denotes the thermal mass of the construction (that is, heavyweight construction). PH/PL signifies the standard each construction complies with (the Passivhaus Standard and the Building Regulations Part L, respectively).

Solution index	Form		Construction				Operation
	WWR (%)	Overhang depth (m)	Wall construction (–)	Roof construction (–)	Window construction (–)	Infiltration rate (–)	Heating setpoint (°C)
10	55.6	0.3	HW-PH	HW-PH	PH	PH	19
11	55.6	0.3	HW-PH	HW-PH	PH	PH	20
12	55.6	0.3	HW-PH	HW-PH	PH	PH	21
13	55.6	0.3	HW-PH	HW-PH	PH	PH	22
15	27.8	0.3	HW-PH	HW-PH	PH	PH	19
16	27.8	0.3	HW-PH	HW-PH	PH	PH	20
17	27.8	0.3	HW-PH	HW-PH	PH	PH	21
18	27.8	0.3	HW-PH	HW-PH	PH	PH	22
175	27.8	0.3	HW-PH	HW-PL	PH	PH	19
176	27.8	0.3	HW-PH	HW-PL	PH	PH	20
325	27.8	1.0	HW-PH	HW-PH	PL	PH	19
326	27.8	1.0	HW-PH	HW-PH	PL	PH	20
330	55.6	0.3	HW-PH	HW-PH	PL	PH	19
331	55.6	0.3	HW-PH	HW-PH	PL	PH	20
335	27.8	0.3	HW-PH	HW-PH	PL	PH	19
336	27.8	0.3	HW-PH	HW-PH	PL	PH	20
337	27.8	0.3	HW-PH	HW-PH	PL	PH	21
485	27.8	1.0	HW-PH	HW-PL	PL	PH	19
495	27.8	0.3	HW-PH	HW-PL	PL	PH	19

Figure 4.10 can then notify the DMs of the possible variations in these deterministic objective values (due to the effect of uncertainty), and inform them of the possible consequences of their design decisions. In particular, the box plots in figure 4.10 illustrate the distributions of possible objective values for design solutions no. 15, 16, 17 and 18. Given a (hypothetical) what-if scenario in which the DMs wish to construct a building which complies with the Passivhaus Standard but also minimises investment

cost, these are the only 4 globally robust design options. Since they refer to the same construction but different heating setpoint (19, 20, 21 and 22 °C, respectively), they result in (almost) identical summer discomfort hours, with their lowest percentage (1%) being observed in the case of the slow response of thermal mass (for both wall and roof constructions), the higher than expected infiltration rate, the cold weather year as well as the lowest value of occupant density (and internal heat gains). The highest summer discomfort is 27% and is observed in the case of the fast response of thermal mass, the lower than expected infiltration rate, the hot weather year and highest value of occupant density (and internal heat gains). As indicated by figure 4.10, such design solutions also result in an identical capital cost that is equal to 301 £/m^2 under all scenarios (as capital cost is not affected by the natural variability in the behaviour of the uncertain conditions). As expected, the lower the setpoint, the lower the heating energy demand but also the higher the winter thermal discomfort.

These solution characteristics are also reflected in figure 4.11 that displays the radar plots of solutions no. 15, 16, 17 and 18. These plots provide the DMs with useful information on the predicted performance of each design option under each scenario. Focusing on the scenarios that lead to the highest values of heating energy demand and winter discomfort, the displayed radar plots reveal the predicted objective values under the 54 performance scenarios which include the cold weather year. Out of these 54 scenarios, scenarios no. 27 to 53 include the lower than expected occupant density, which is accompanied by a large decrease in internal gains and thus a great increase in annual heating energy demand. For all 4 design options, the highest heating energy demand is observed under scenario no. 45 – i.e. a fast response of the thermal mass (for both wall and roof constructions) and a higher than expected infiltration rate.

Observing the solution characteristics that drive satisfactory performance can support the DMs in making informed decisions. For instance, for the examined building and problem formulation, all globally robust solutions (as derived from the application of the robust optimality criterion) include an external wall construction and an infiltration rate that meet the requirements of the Passivhaus Standard. They also include concrete wall and roof constructions. The majority of them include the lowest value of overhang depth. 19 °C and 20 °C are the two most commonly encountered values for the heating setpoint. With the objective of demonstrating the potential of the new robust optimality criterion within a real-world context, chapter 5 will further discuss the identification of solution characteristics that can ensure Pareto optimality, with parallel coordinates plots providing a rigorous way of demonstrating the relationship between the resulted robust solutions and the defined objectives (as described in section 3.1.5.1).

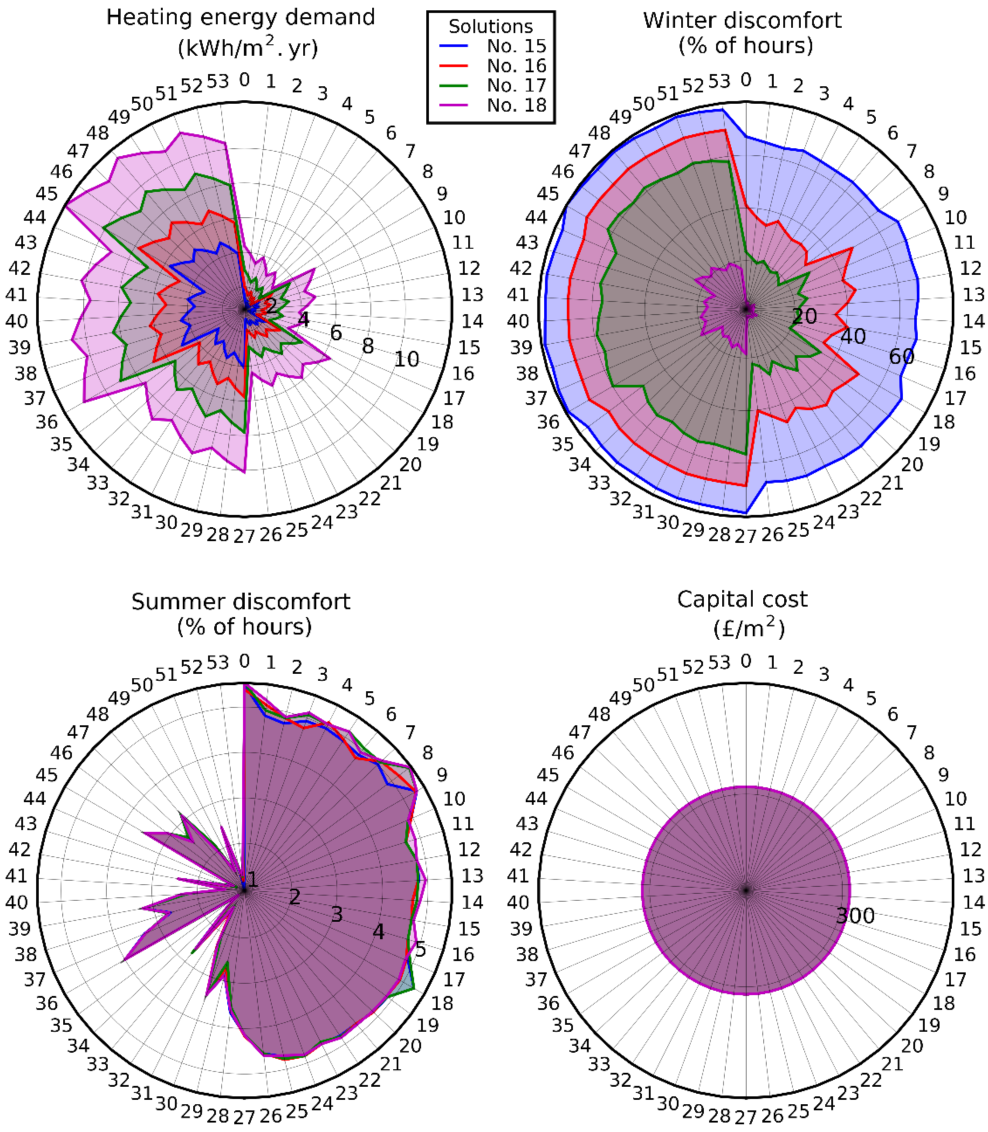

Figure 4.11. The radar plots of compatible (for a hypothetical what-if scenario) solutions.

4.3 Comparison with common robustness indicators

Since this chapter aims to explore the behaviour of the robust optimality criterion (as discussed in chapter 1), after having applied it to the test cell problem and analysed the derived solution set (in section 4.2), the resulted robust design solutions are compared with the solutions that are obtained from the application of existing robustness rules (presented in section 2.5.2.1). This comparison does not, however, aim to reveal the best-performing rule, as the suitability of a robustness indicator for a design problem depends on the (risk) preferences of the DMs and is thus case-sensitive – and out of the scope of this thesis.

As discussed in section 2.5, the different interpretations of the term 'robustness' has led to the development of various indicators by relevant studies. These are commonly classified into probabilistic and non-probabilistic methods (based on the probabilistic or not handling of inherent uncertainties). Given that, for building design exploration problems, the probability of occurrence of uncertain values is not known (or at least not defined with certainty), this thesis focuses on the non-probabilistic assessment of robustness. Wald's rule (or minimax) (Wald 1945); Savage's rule (or minimax regret) (Savage 1951); and range (or max-min) are common non-probabilistic indicators that are used in situations where uncertainties cannot be quantified in probabilistic terms. According to the minimax rule (equation 4.2), a robust solution is one that results in the least worst performance outcome across all scenarios. According to the minimax regret rule (equation 4.3), a robust solution is one that leads to the least worst regret[21] (or opportunity loss). According to the max-min rule (equation 4.4), a robust solution is one that results in the smallest difference between the worst and best performance outcomes across all scenarios:

$$\begin{gathered} \min \max f(x, U),\ U = \{u_1, \dots, u_n\} \\ \forall\, x \in X,\ X = \{x_1, \dots, x_m\} \end{gathered} \tag{4.2}$$

$$\begin{gathered} \min \max\, [f(x, u) - \min f(X, u)] \\ \forall\, x \in X,\ X = \{x_1, \dots, x_m\} \text{ and } \forall\, u \in U,\ U = \{u_1, \dots, u_n\} \end{gathered} \tag{4.3}$$

$$\begin{gathered} \min\, [\max f(x, U) - \min f(x, U)]\ ,\ U = \{u_1, \dots, u_n\} \\ \forall\, x \in X,\ X = \{x_1, \dots, x_m\} \end{gathered} \tag{4.4}$$

[21] For a given scenario, regret refers to the difference between the performance outcome of a solution and the best performance outcome across all solutions.

Table 4.7 summarises the number of solutions that are obtained from the application of these three robustness indicators (in the case of both the defined design space and described region of interest). Out of the 1,280 total design solutions, 242, 256 and 45 solutions are found to be robust according to the minimax, minimax regret and max-min rule, respectively. Minimax and minimax regret result in almost identical robust solution sets as they have 231 solutions in common, with 26 of them also appearing in the solution set that is derived from the application of the max-min rule. It is worth noting that all these 26 solutions are Pareto optimum under at least one performance scenario, with 6 of them remaining optimal under all scenarios (i.e. they are globally robust solutions based on the new robust optimality criterion). By applying multiple robustness rules together, the DMs can make risk-conscious decisions in the context of building design decision-making. However, in this thesis, comparing various robust solution sets aims to cast light on the behaviour of the new robustness indicator – and not to point out the most effective rule or combination of rules, or identify a single, best-performing design solution.

Table 4.7. Number of solutions (for the described problem formulation).

Type of solutions	Number of solutions	
	Design space	Region of interest
Feasible (under all scenarios)	1,280	51
Nominal optimum	217	22
Optimum under at least one scenario	322	36
Optimum under all scenarios (globally robust)	68	19
Minimax	242	35
Minimax regret	256	35
Max-min	45	3

Focusing on the hypothetical region of interest (illustrated in figure 4.8), figure 4.12 shows all feasible robust solutions that are obtained from the application of the new indicator as well as of the three existing rules. Out of the 51 total feasible solutions, 35, 35 and 3 solutions are calculated to be robust according to the minimax, minimax regret and max-min rule, respectively. These are sorted (in descending order) in terms of their level of robustness (i.e. the number of scenarios under which they are Pareto optimal) and are denoted with a black circle. A red circle with a cross indicates that the solution does not appear in the solution set that is derived from the application of the new robust optimality criterion. If the solution remains Pareto optimal under all (162) scenarios, it is denoted with a black rhombus. All 19 globally robust design solutions appear in the solution sets that are derived from the application of the minimax and minimax regret rules, with only 3 of them being robust based on the max-min rule.

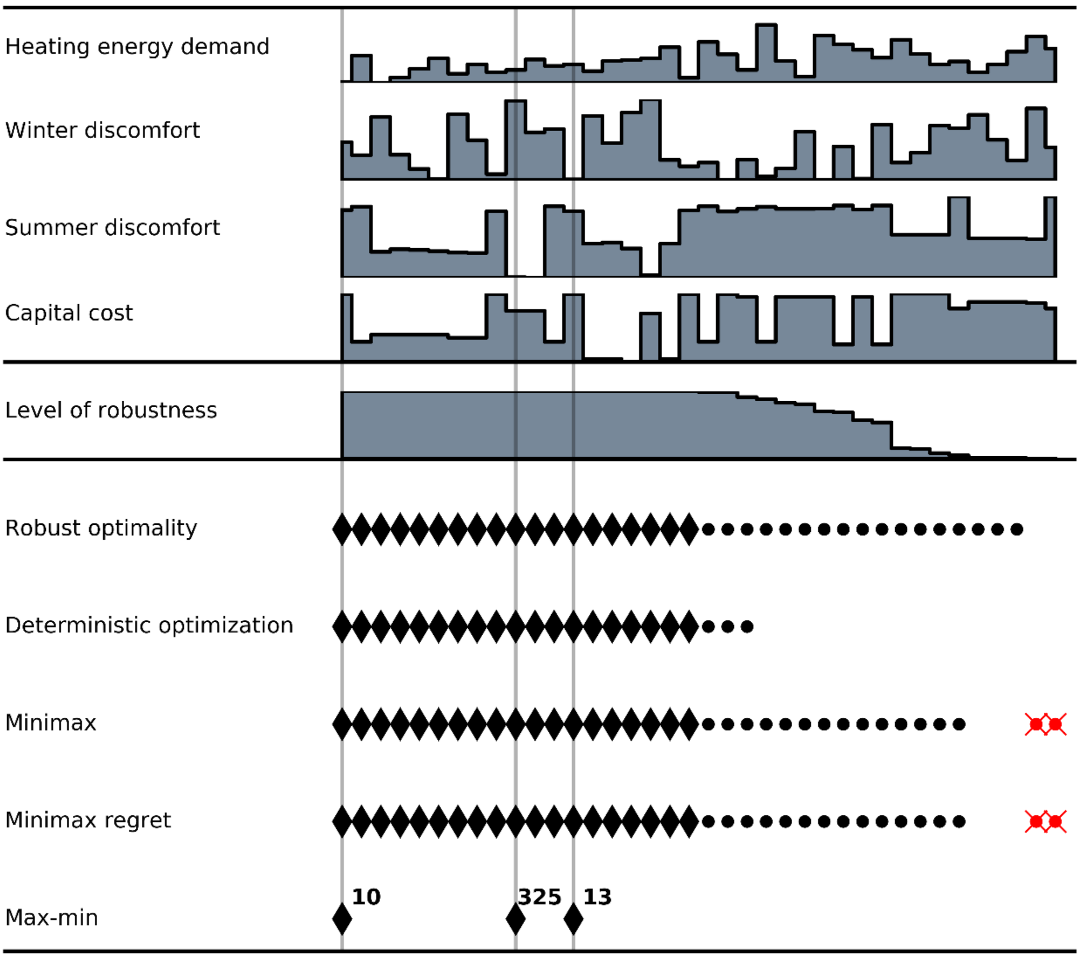

Figure 4.12. Feasible robust solutions as resulted from different robustness indicators.

Solutions no. 10, 13 and 325 are the 3 globally robust solutions that are also found to be robust according to the minimax, minimax regret and max-min rules. As already discussed in section 4.2, solutions no. 10 and 13 fully comply with the Passivhaus Standard, both including heavyweight (concrete) wall and roof constructions. They also comprise the lowest value of overhang depth and highest WWR. They thus refer to the same construction, but different heating setpoint (19 and 22 °C, respectively). Not surprisingly, solution no. 10 results in lower heating energy demand, but higher winter discomfort (as displayed in figure 4.12). Solution no. 325 includes a window construction that violates the requirements of the Passivhaus Standard (its U-value is higher than the maximum allowable value), as well as the highest value of overhang depth and lowest WWR. Comparing it with solution no. 10 that includes the same heating setpoint, it leads to higher heating energy demand and winter discomfort, but lower summer discomfort and capital cost (as the cost of its window construction is two times lower, compared with the one that meets the Passivhaus Standard).

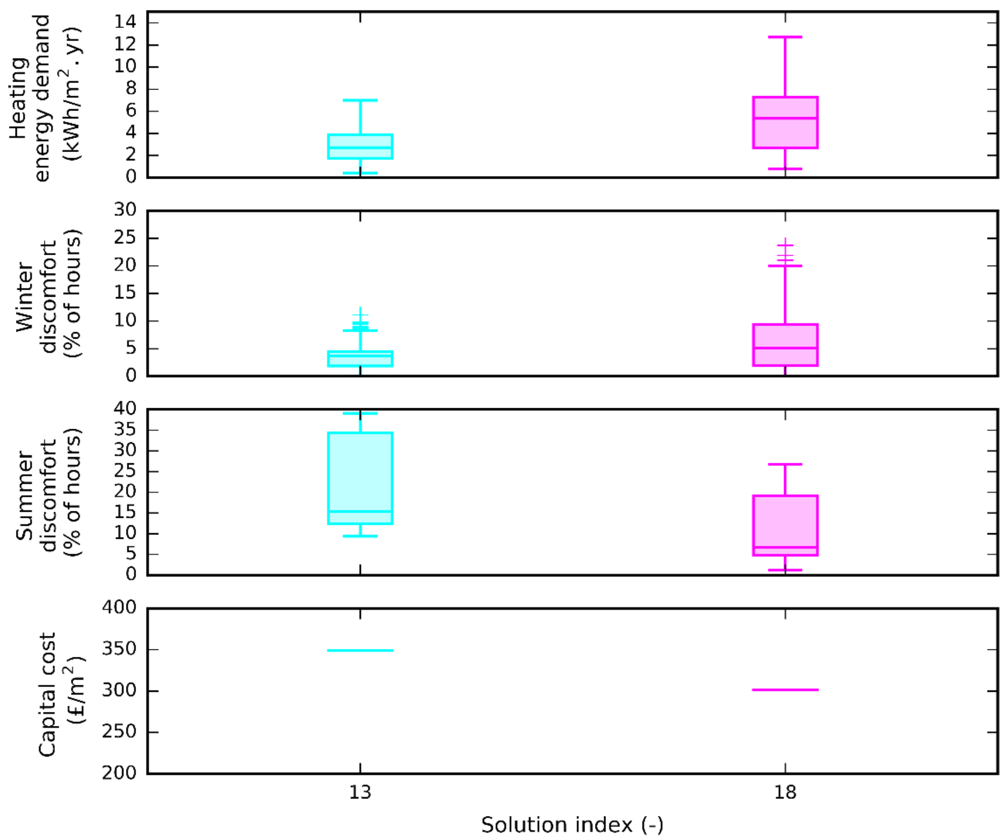

Figure 4.13. The box plots of solutions no. 13 and 18.

Figure 4.12 implies that the solution sets that are derived from the application of the minimax and minimax regret rules are similar (for the examined building and given problem formulation) to the solution set that results from the implementation of the new robustness indicator. The figure also suggests that the max-min rule results in a robust solution set that differs from the other three sets, which indicates that the other three robustness indicators do not necessarily result in solutions that limit the range of performance. This can also be observed in figure 4.13 that illustrates the boxplots of solution no. 13 (which is robust according to all indicators) and solution no. 18 (which does not remain robust under the max-min criterion). Although solution no. 18 is robust according to the minimax and minimax regret rules as well as the robust optimality criterion, it results in the highest range of heating energy demand among all 51 feasible solutions. This observation needs to be taken into account during decision-making, the further discussion of which is, however, out of the scope of this thesis.

4.4 Summary

Chapter 4 described the application of the suggested framework for robust building design optimization to a 'test cell', with the objective of exploring the behaviour of the novel robustness indicator prior to its use within a real-world context (in chapter 5), as discussed in chapter 1. The examined test cell is a single-zone office building with a simple and widely used geometry that allows for the smooth implementation of the framework, therefore drawing attention to the behaviour of the new robust optimality criterion (introduced in chapter 3).

Robust solutions were identified using the new criterion, with their performance being then analysed. As both epistemic and aleatoric uncertainties were taken into account, solution analysis revealed how the test cell may behave in real life. A wide range of objective function values was observed, resulting from both the differences in design solutions and performance scenarios. Comparing the distributions of objective values when aleatoric uncertainties are incorporated in the building design problem with the distributions of the deterministic objective values revealed the risk of unsatisfactory performance due to the effect of aleatoric uncertainties, and consequently the critical importance of assessing robustness within the context of building design exploration problems. This was also revealed by the comparison between the number of nominal optimum solutions (as derived from the deterministic Pareto ranking) and the number of robust solutions (as resulted from the application of the robust optimality criterion). Scatter, box and radar plots elucidated the relationship between robust solutions and the four design objectives, which can inform decision-making.

In order to gain a better understanding of the behaviour of the new robust optimality criterion, robust solutions were compared with the solutions that were obtained from the application of existing robustness rules (minimax, minimax regret and max-min). The solution sets that were derived from the application of the minimax and minimax regret rules were similar (for the examined building and given problem formulation) to the solution set that resulted from the application of the robust optimality criterion. The max-min rule produced a solution set that differed from the other sets, implying that the robust optimality criterion (so as other robustness rules in the literature) may not result in solutions that minimise the range of performance. By applying multiple robustness rules together, the DMs can improve the confidence in their decisions in the context of building design exploration and decision-making, with the selection of a single robustness indicator for addressing a given design problem being dependent on their (risk) preferences – which is, however, out of the scope of this thesis.

Chapter 5

Real-world building – Example application

Chapter 5 describes the application of the new robust optimization framework to the design optimization of a real-world building. The potential of the robust optimality criterion to support design exploration under uncertain conditions within a real-world context is elucidated by analysing the solution set that is derived from the application of the criterion.

5.1 Description of the building

A new community centre that will be constructed in London is used as a case study building. This incorporates a shop, café, visitor space and third-party offices. Since it comprises a variety of building uses (and thus of thermal zones and requirements), it is considered to be suitable for demonstrating the potential of the suggested approach in the case of complex real-life problems. As part of the design exploration process, three alternative forms are considered, as illustrated in figures 5.1, 5.2 and 5.3. These were conceived by the design team based on the brief that was agreed with the client. Their treated floor area is 935 m^2, 665 m^2 and 760 m^2, respectively.

Figure 5.1. Real-world building – Form A (source: Eco Design Partnership ©).

Figure 5.2. Real-world building – Form B (source: Eco Design Partnership ©).

Figure 5.3. Real-world building – Form C (source: Eco Design Partnership ©).

5.2 Application of the robust optimization framework

This section will focus on the application of the proposed robust design optimization framework (introduced in chapter 3) to the example building described in section 5.1. The implementation of the five steps to solving a robust optimization problem (shown in figure 3.1) will be discussed in sections 5.2.1 to 5.2.5.

5.2.1 Uncertainty quantification

The rationale behind uncertainty quantification was described in section 3.1.1, with the design variables and variable values that are defined in the case of the community centre being summarised in table 5.1. Compared with the test cell that was examined in chapter 4, the only difference lies in the handling of the building form. Three pre-defined designs (A, B and C, Figures 5.1 – 5.3) are considered here, these expressing the conceptual ideas that were triggered by the brief (that was agreed with the client) and emerged from the collaborative brainstorming of the design team members.

Table 5.1. List of design variables and variable values.

Subcategories	Variables	Variable values	References
Form	Form (-)	1) A	Eco Design Partnership ©
		2) B	
		3) C	
Construction	External wall construction (W/m^2K) [22, 23]	1) HW-PH (0.140)	(IBO 2009, International Passive House Association 2018)
		2) LW-PH (0.143)	
		3) HW-PL (0.342)	(Neufert *et al.* 2012, UK Government 2013a)
		4) LW-PL (0.342)	
	Roof construction (W/m^2K)	1) HW-PH (0.146)	(IBO 2009, International Passive House Association 2018)
		2) LW-PH (0.144)	
		3) HW-PL (0.243)	(Neufert *et al.* 2012, UK Government 2013a)
		4) LW-PL (0.239)	
	Window construction (W/m^2K)	1) PH (0.780)	(IBO 2009, International Passive House Association 2018)
		2) PL (2.129)	(Neufert *et al.* 2012, UK Government 2013a)
	Infiltration rate (ac/h)	1) PH (0.050)	(CIBSE 2006, McLeod *et al.* 2014)
		2) PL (0.500)	(CIBSE 2006, ATTMA 2010)
Systems and operation	Heating setpoint (°C)	1) 19	(BRE 2015, International Passive House Association 2018)
		2) 20	
		3) 21	
		4) 22	
		5) 23	

22 HW/LW denotes the thermal mass of each construction (heavyweight and lightweight construction, respectively). PH/PL signifies the standard each construction complies with (the Passivhaus Standard and the Building Regulations Part L, respectively).

23 The U-value of each construction option is provided (in W/m^2K).

Table 5.2 summarises the considered performance variables and variable values (as described in section 3.1.1 and applied to the test cell in chapter 4).

Table 5.2. List of performance variables and variable values.

Subcategories	Variables	Variable values	Description/ References
Weather	Weather file	1) 1979	Cold year: maximum heating degree days (CIBSE 1979)
		2) TRY	Typical year (CIBSE 2016)
		3) DSY 3	Hot year: long, less intense warm spell (CIBSE 2016)
Occupancy	Occupant density (persons/m^2)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	(BRE 2015)
Construction (actual performance)	External wall construction (W/m^{2}K)	1) Fast response	Nominal values refer to the design variable values of table 5.1. The lower and upper bounds represent possible variations in the response of the thermal mass. The considered variations in the thermal properties of individual material layers depending on their general category (Clarke *et al.* 1990) are included in tables A.3, A.4 and A.5 of appendix A.
		2) Nominal	
		3) Slow response	
	Roof construction (W/m^{2}K)	1) Fast response	
		2) Nominal	
		3) Slow response	
	Infiltration rate (ac/h)	1) Nominal - 50%	(MacDonald 2002)
		2) Nominal	See table 5.1
		3) Nominal + 50%	(MacDonald 2002)

5.2.2 Exhaustive search

Since this thesis makes use of an exhaustive search, the total number of solutions (m) and the total number of scenarios (n) result from the exhaustive combination of the defined design variable values (table 5.1) and performance variable values (table 5.2), respectively. m hence equals 960 (3 forms x 4 external wall constructions x 4 roof constructions x 2 glazing types x 2 infiltration rates x 5 heating setpoints), and n equals 162 (3 weather files x 2 occupant densities x 3 external wall constructions (actual performance) x 3 roof constructions (actual performance) x 3 infiltration rates (actual performance)). This results in 155,520 combinations (960 design solutions x 162 performance scenarios) and associated building performance simulations (BPS).

5.2.3 Building performance simulation

The modelling process was described in section 3.1.3. In summary, the geometry of designs A, B and C is firstly built (figure 5.4, 5.5. and 5.6, respectively) in SketchUp (Trimble Navigation 2016) using its OpenStudio plug-in (U.S. Department of Energy 2015) and following the drawings and information that were provided by the design team. The 3D models are then imported into EnergyPlus (U.S. Department of Energy 2016a), where any additional data is defined prior to running all simulations.

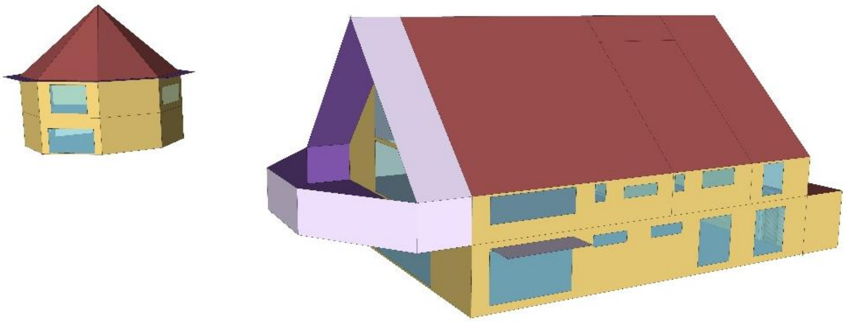

Figure 5.4. Real-world building – Form A – The SketchUp model.

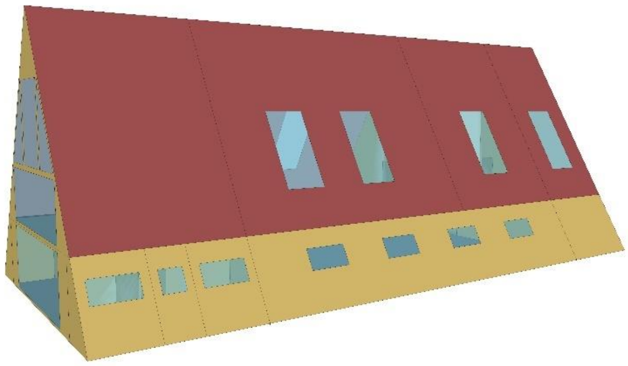

Figure 5.5. Real-world building – Form B – The SketchUp model.

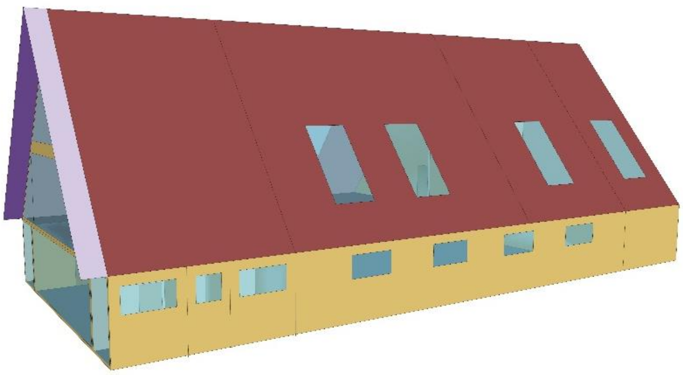

Figure 5.6. Real-world building – Form C – The SketchUp model.

The models are multi-zone buildings consisting of 18, 14 and 14 zones, respectively (appendix B). The difference in the number of zones stems from the vagueness of the brief and thus the uncertainty in problem formulation that must be further examined in future work. The zones incorporate a shop, café (main space and kitchen), visitor space and third-party offices, along with their secondary spaces (e.g. internal circulation).

16, 11 and 11 respectively of the aforementioned zones are mechanically conditioned during working hours (as the remaining zones are storage rooms). Winter heating and ventilation are supplied to zones by the Ideal Loads Air System of EnergyPlus (U.S. Department of Energy 2016b), which also enables (sensible) heat recovery when the zone exhaust air temperature is more favourable than the outdoor air temperature. The outdoor air flow is 0.01 m^3/s per person for all conditioned zones (BRE 2015), with the exception of the kitchen of the café (where it is 0.025 m^3/s per person (BRE 2015)), and all toilets (where it is 5 ac/h (CIBSE 2006)). In summer, all zones are naturally ventilated (during working hours). Note that, working hours vary from one building use to another based on the brief (but are the same for all three models), these also affecting their secondary spaces (e.g. internal circulation):

- Shop: every day between 9:00 and 18:00
- Café: every day between 11:00 and 21:00
- Visitor space: every day between 9:00 and 18:00
- Third-party offices: on weekdays between 9:00 and 17:00

Table 5.3. List of fixed parameter values in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for different building uses.

Object	Field	Value			
		Shop	Café	Visitor space	Offices
People	People per Zone Floor Area (persons/m^2)	0.1169	0.2	0.1256	0.111
	Sensible Heat Fraction	0.5	0.61	0.61	0.5935
Lights	Watts per Zone Floor Area (W/m^2)	13	3.5	5	9
ElectricEquipment	Watts per Zone Floor Area (W/m^2)	25[24]	0[24]	5.4	11.77
	Fraction Latent	0	0	0	0.75

[24] These values are updated by the client, as electric equipment is known.

Table 5.3 displays the internal loads (occupancy, lighting and electrical equipment), for these building uses, based on the activity database of the NCM (BRE 2015). The internal loads of any secondary spaces are similarly informed by the NCM. Tables 5.4, 5.5 and 5.6 demonstrate the schedules of these objects in EnergyPlus, as proposed by the NCM for shops, café and visitor spaces, respectively. Table 3.6 in section 3.1.3.1 demonstrates the corresponding schedules for office spaces.

Table 5.4. List of Schedule:Compact objects in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for shops.

Activity Level	People	Lights	Electric Equipment
Through: 12/31 For: AllDays Until: 24:00 140	Through: 12/31 For: AllDays Until: 09:00 0 Until: 10:00 0.8 Until: 12:00 1 Until: 14:00 0.8 Until: 17:00 1 Until: 18:00 0.8 Until: 24:00 0	Through: 12/31 For: AllDays Until: 09:00 0 Until: 18:00 1 Until: 24:00 0	Through: 12/31 For: AllDays Until: 09:00 0.048 Until: 18:00 1 Until: 24:00 0.048

Table 5.5. List of Schedule:Compact objects in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for café.

Activity Level	People	Lights	Electric Equipment
Through: 12/31 For: AllDays Until: 24:00 110	Through: 12/31 For: AllDays Until: 11:00 0 Until: 12:00 0.2 Until: 14:00 1 Until: 15:00 0.8 Until: 20:00 1 Until: 21:00 0.8 Until: 24:00 0	Through: 12/31 For: AllDays Until: 11:00 0 Until: 21:00 1 Until: 24:00 0	Through: 12/31 For: AllDays Until: 11:00 0.0567 Until: 21:00 1 Until: 24:00 0.0567

Table 5.6. List of Schedule:Compact objects in EnergyPlus, as determined by the activity database of the NCM (BRE 2015) for visitor spaces.

Activity Level	People	Lights	Electric Equipment
Through: 12/31 For: AllDays Until: 24:00 140	Through: 12/31 For: AllDays Until: 09:00 0 Until: 10:00 0.2 Until: 11:00 0.8 Until: 12:00 1 Until: 14:00 0.4 Until: 16:00 1 Until: 18:00 0.4 Until: 24:00 0	Through: 12/31 For: AllDays Until: 09:00 0 Until: 18:00 1 Until: 24:00 0	Through: 12/31 For: AllDays Until: 09:00 0.0447 Until: 18:00 1 Until: 24:00 0.0447

Since each run takes 89, 65 and 63 seconds[25] for form A, B and C respectively, 3,125 hours are needed to complete the experiment. However, thanks to a bespoke (Java) script that supports concurrent processing, 20 simulations are run in parallel, with the total computational time of BPS thus being 156 hours – that is, 6.5 days. Simulation results are exported to a CSV, which contains the predicted values for heating energy demand, winter thermal discomfort and summer thermal discomfort. Values have been cross-checked to validate the three models (form A, B and C), with table B.2 (appendix B) showing the results for a solution that complies with the Passivhaus Standard and a solution that just complies with the Building Regulations (under a given scenario). Thanks to a bespoke (Python) script and the Spon's price book (AECOM 2015), the capital cost of each design solution is also calculated and added to the CSV file.

5.2.4 Robust optimization

Robust design solutions are here identified with the help of the new robust optimality criterion, which suggests that, *a robust solution is one that remains Pareto optimal regardless of the uncertainty in the predicted building performance* that is due to any

[25] The discrepancy in runtime is mainly attributed to the difference in the number of zones and associated heat transfer surfaces.

uncertain conditions. That is, a solution x^* is robust, if there exists no x in the solution set X which decreases a criterion $f_i(x,u)$ without causing an increase in at least one other criterion, under any scenario u in the uncertainty set U:

$$f_i(x,u) > \ f_i(x^*,u) \text{ for at least one } i \in I,\, I = \{1, \dots, 4\}$$
$$\forall\, x \in X,\, X = \{x_1, \dots, x_{960}\} \text{ and } \forall\, u \in U,\, U = \{u_1, \dots, u_{162}\} \tag{5.1}$$

Table 5.7 summarises the four optimization objectives (as described in chapter 3 and applied to the test cell in chapter 4), as well as the metrics that are used to quantify the performance of each solution, in the case of the example building. Since this is a multi-zone building, both winter and summer thermal discomfort criteria express the total discomfort hours (the sum across all conditioned zones) divided by the total occupied hours (the sum across all conditioned zones), converted to a percentage.

Table 5.7. The four optimization objectives and the applied metrics.

Design objective	Metric	Reference
Heating energy demand	kWh/m^2.yr	EnergyPlus (U.S. Department of Energy 2016a)
Winter thermal discomfort	% of total occupied hours that PMV < -0.5	
Summer thermal discomfort	% of total occupied hours that acceptability < 80%	
Capital cost	£/m^2	Spon's price book (AECOM 2015)

5.2.5 Solution analysis

Solution analysis aims to assist the DMs in understanding how the designed building may behave and ultimately making informed design decisions. This is here achieved by visualising the performance results of candidate design solutions and investigating possible what-if scenarios which are informed by the requirements of regulations and the (hypothetical) preferences of different stakeholders. Analysis is divided into: the distribution of the predicted objective values across the range of design solutions and performance scenarios; an analysis of the Pareto optimality of design solutions; an investigation of the relationship between uncertainty and solution robustness; and an investigation into the impact of the preferences of the DMs.

Distribution of performance

Figures 5.7 to 5.10 show the distribution of the predicted values for each optimization objective. Each distribution reflects the 155,520 simulations which resulted from the exhaustive combination of the defined 960 solutions and 162 scenarios. By including the complete range of (predicted) performance values across the entire design space and uncertain conditions, such distributions can reveal how the building may behave in real life, in the light of both epistemic and aleatoric uncertainties.

The minimum heating energy demand is 0 kWh/m^2.yr (figure 5.7). This is associated with a solution that complies with the Passivhaus Standard and includes heavyweight wall and roof constructions, and a heating setpoint of 19 °C. Uncertain conditions include the hot weather year, the high value of occupant density and internal gains, the slow response of thermal mass and the lower than expected (or nominal) infiltration rate. The highest value is 66 kWh/m^2.yr. This refers to a solution that is compliant with the Building Regulations and includes heavyweight wall and roof constructions, and a heating setpoint of 23 °C. Uncertain conditions include the cold weather year, the lowest occupant density and internal gains, the fast response of thermal mass and the higher than expected infiltration rate. The lowest value is associated with form B and the highest with form A. Note that, solution analysis is here performed on a building level. Future work could focus on how to extend analysis to a zone level, in order to provide the design team with feedback on the zones that drive such values.

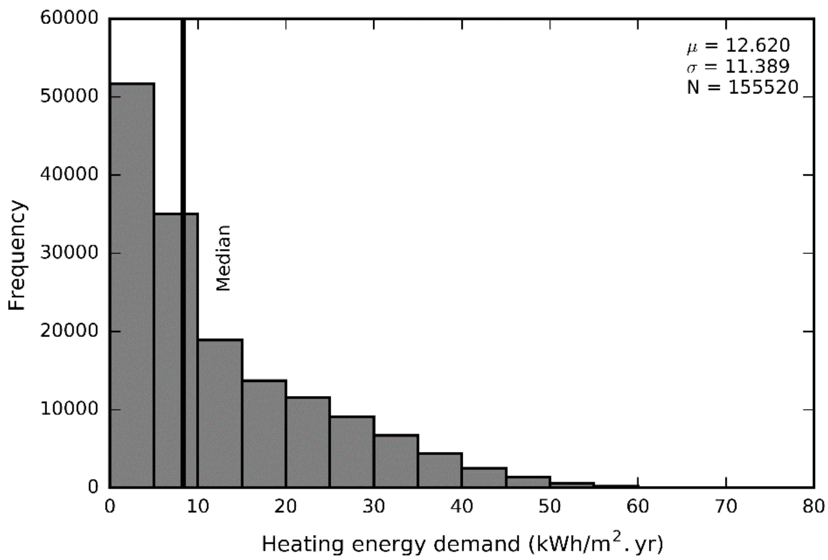

Figure 5.7. The histogram of predicted values for heating energy demand.

The minimum winter discomfort is 0% (figure 5.8). This results from a solution that includes Passivhaus wall, roof and window constructions and infiltration rate as well as a heating setpoint of 23 °C. Uncertain conditions are identical to those resulting in the lowest predicted heating energy demand value. The maximum winter discomfort is 58% and is associated with a solution that complies with the Building Regulations and comprises a heating setpoint of 19 °C. Given that winter heating is supplied by an ideal loads air system which is guaranteed to maintain the temperature setpoint (as it adds heat at 100% efficiency), this high percentage of winter thermal discomfort is attributed to the low heating setpoint (19 °C). Uncertain conditions are identical to those leading to the highest heating energy demand value as these detrimentally affect air temperature – and therefore thermal comfort. Both values are derived from form A and heavyweight wall and roof constructions.

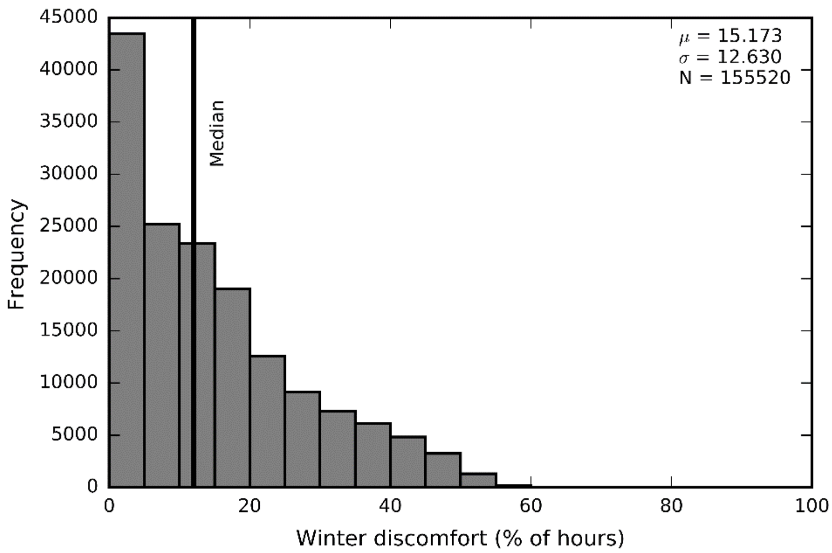

Figure 5.8. The histogram of predicted values for winter thermal discomfort.

The minimum summer discomfort is 7% (figure 5.9). As expected, this is associated with a design solution that complies with the Building Regulations as the less airtight the building is, the less prone to summer discomfort it will be. Uncertain conditions comprise the cold weather year, the lowest occupant density and internal gains, the slow response of thermal mass and the higher than expected infiltration rate. The maximum discomfort is 55% and results from a solution that meets the requirements of the Passivhaus Standard and thus has airtight constructions. Uncertain conditions are identical to those resulting in the lowest predicted heating energy demand value.

Both percentages are associated with heavyweight wall and roof constructions, with the lowest percentage resulting from form A and the highest from form C.

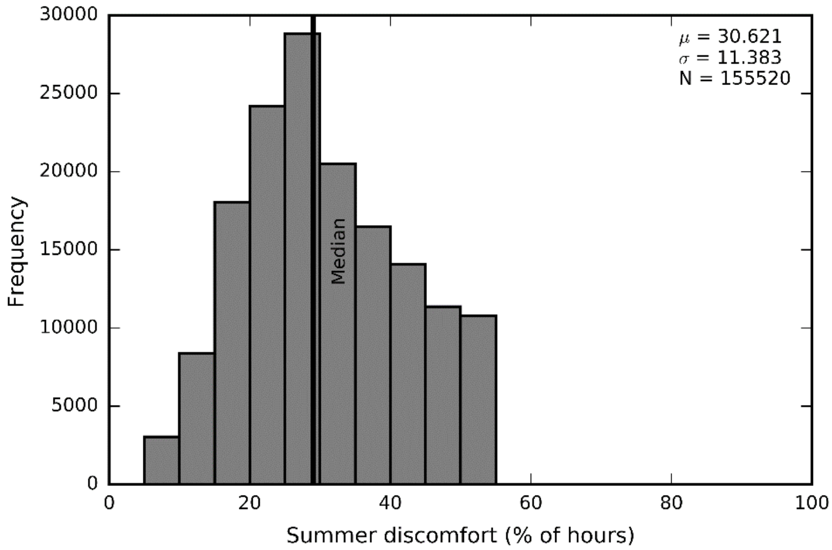

Figure 5.9. The histogram of predicted values for summer thermal discomfort.

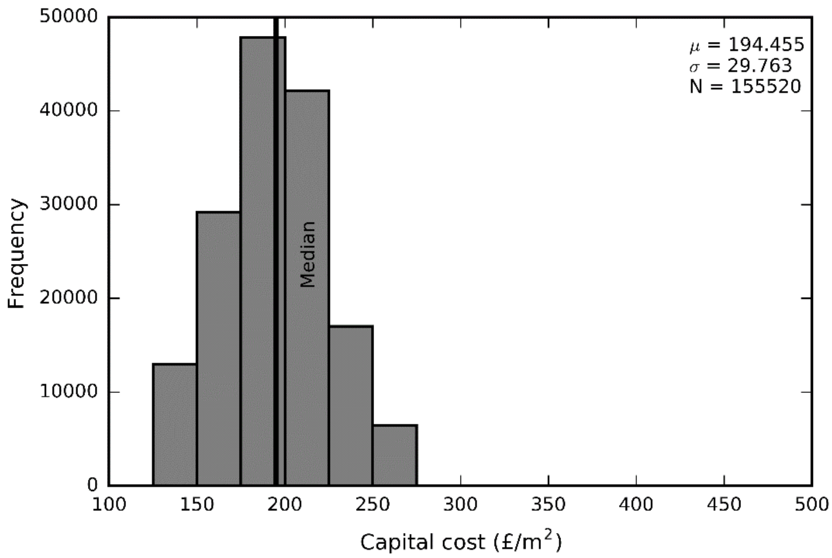

Figure 5.10. The histogram of predicted values for capital cost.

Finally, the minimum capital cost is 127 £/m^2 (figure 5.10) and is associated with the same design solution that leads to the lowest percentage of summer discomfort hours. The maximum cost value is 269 £/m^2. This refers to a solution that is compliant with the Passivhaus Standard and includes lightweight wall and roof constructions. Both values are derived from form A. Note that these values are observed under all (162) performance scenarios, as capital cost is not affected by the natural variability in the behaviour of the uncertain conditions. As in this thesis capital cost refers to the cost of the elements of the building envelope that are included in optimization (and not of the HVAC system), these values are also observed under any heating setpoint.

The distributions of the objective values across the range of solutions and scenarios, reveal the possible range of performance for the example building due to the effect of epistemic and aleatoric uncertainties. Such distributions can make the DMs aware of the risk of unsatisfactory performance and hence support risk-conscious decisions.

Pareto optimality

Table 5.8 provides the DMs with feedback on the Pareto optimality of the 960 design alternatives under different performance scenarios. This information can support the DMs in gaining a better understanding of the performance of candidate solutions and, hence, making informed design decisions. It can also inform them of the risk of sub-optimality due to the random nature of aleatoric uncertainties (as discussed in section 2.5). Out of the 960 candidate solutions, 521 solutions are Pareto optimum under at least one scenario (out of the 162 considered scenarios). 229 of them are found to be optimum under the nominal (or deterministic) value of the uncertain conditions, with only 110 of them, however, remaining optimum under all scenarios – that is, being globally robust based on the new robust optimality criterion. Note that, these values are obtained from the trade-off between all four objective functions.

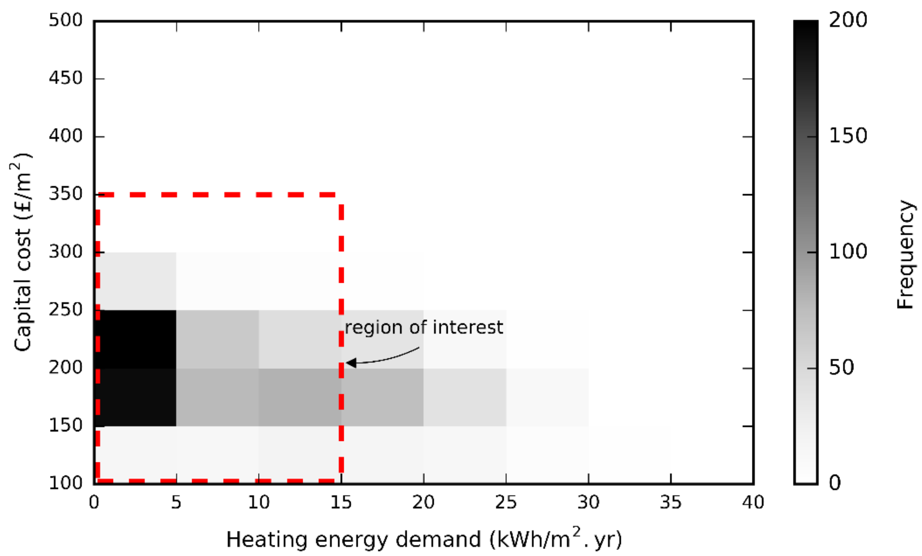

Figure 5.11. Restricted (hypothetical) region of interest in the deterministic objective space. The shading signifies the number of design solutions in each region of the figure.

Table 5.8. Number of solutions (for the described problem formulation).

Type of solutions	Number of solutions	
	Design space	Region of interest
Feasible (under all scenarios)	960	426
Nominal optimum	229	151
Optimum under at least one scenario	521	203
Optimum under all scenarios (globally robust)	110	56

The risk of sub-optimality – or even infeasibility – of candidate design solutions due to aleatoric uncertainties can be elucidated by restricting the (hypothetical) region of interest in the objective space. For instance, the DMs may consider 15 kWh/m^2.yr and 350 £/m^2 as the maximum values for heating energy demand and cost, respectively (figure 5.11). Out of the 751 feasible solutions in the deterministic objective space (i.e. in the case of no aleatoric uncertainties), 426 solutions remain feasible under all (162) scenarios. 151 of them are optimal under the nominal conditions, with 56 of them remaining optimal under all scenarios. Restricting the objective space thus halved the number of globally robust solutions (as this dropped from 110 to 56), this showing the effect of constraint functions on solution optimality. 203 solutions are optimal under at least one scenario (including the 56 solutions that are 100% robust).

As discussed in section 2.1, the generation of form (also called massing) expresses the design concept that is conceived by the design team as a response to the given problem. Such a concept affects how the building looks, as well as how it functions, therefore commonly preceding the definition of any construction and operation variables. In order to eliminate the risk of selecting a building form that is sensitive to aleatoric and/or epistemic uncertainties, the new robust optimality criterion can be used by the DMs to compare all (three) candidate building forms with respect to their degree of robustness. In more detail, in addition to the two steps that were presented in section 3.1.4.3 (i.e. for applying the new criterion), the DMs also need to count the number of solutions for which each form is Pareto optimum under one or more scenarios (with the number of scenarios being dependent on the (risk) preferences of the DMs).

Figure 5.12 illustrates the frequency of each form – that is, A (green), B (blue) and C (red) – across the 521 solutions that are Pareto optimum under at least one scenario (left) and the 110 solutions that remain optimal under all 162 scenarios (right), in the design space. No candidate form appears to be optimal (under at least one scenario) for all the 320 design solutions that are associated with each form. However, form A remains optimal under at least one scenario for 270 solutions and under all scenarios for 98 solutions. Form B ranks second, as it is optimal under at least one scenario for 182 solutions and under all scenarios for only 12 solutions. Form C is optimal under at least one scenario for 69 solutions, but is never globally robust.

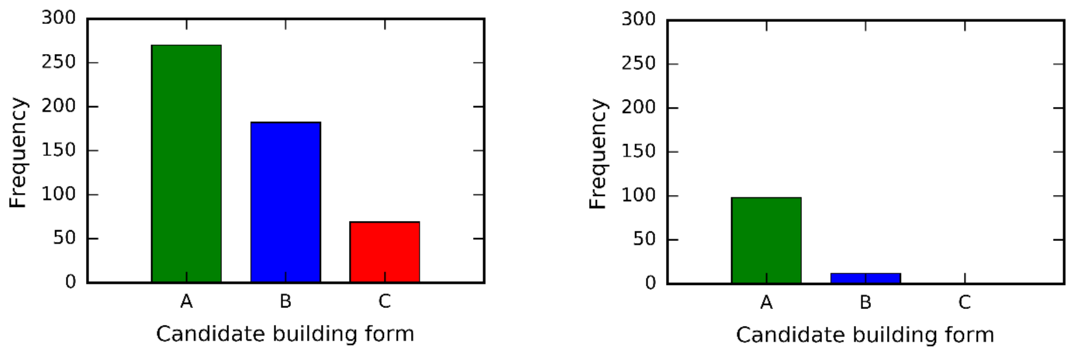

Figure 5.13. The form frequency across the 521 solutions that are optimum under at least one scenario (left) and the 110 solutions that are globally robust (right), in the design space.

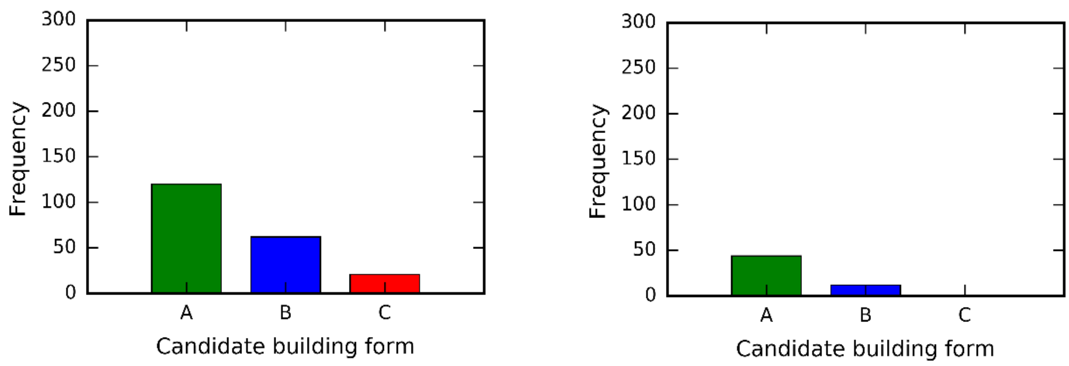

Figure 5.12. The form frequency across the 203 solutions that are optimum under at least one scenario (left) and the 56 solutions that are globally robust (right), in the region of interest.

Figure 5.13 illustrates the frequency of each form across the 203 solutions that are optimum under at least one scenario (left) and the 56 solutions that remain optimum under all 162 scenarios (right), in the region of interest (that is shown in figure 5.11). Form A remains optimal under at least one scenario for 120 solutions and under all scenarios for 44 solutions. Form B ranks second, as it is optimal under at least one scenario for 62 solutions and under all scenarios for 12 solutions. Form C is optimal under at least one scenario for 21 solutions, but does not remain optimal under all scenarios for any of these solutions.

The comparison of the three building forms with respect to their degree of robustness indicates the following ranking: form A ranks first; form B second; and form C third. That is, form C tends to be dominated by the other forms, which can be attributed to its fully glazed façade that results in a higher number of summer discomfort hours. A detailed zone-level analysis could assist the DMs in further explaining this ranking and informing the form generation process, which is out of the scope of this thesis.

Relationship between uncertainty and robustness

As discussed in section 3.1.5, useful information can be obtained from the analysis of sub-optimal solutions, as this can assist the DMs in gaining a better understanding of the solution characteristics as well as the uncertain conditions that may trigger sub-optimality. Figure 5.14 shows the radar plots of solutions no. 0, 320 and 640[26], which belong to the 203 solutions that are optimal under at least one scenario, in the region of interest. Even though solutions no. 0 and 320 remain optimal under all scenarios, solution no. 640 remains optimal under 85 (out of the 162) scenarios, therefore not appearing at the globally robust solution set. As the radar plots display the predicted objective values of each design solution under each performance scenario, they can reveal the design characteristics but also the uncertain conditions that result in such a lack of robustness, thus assisting the DMs in making risk-conscious decisions.

The three solutions have identical construction as well as operation variable values (heavyweight external wall and roof constructions that satisfy the requirements of the Passivhaus Standard; window constructions and infiltration rates that also comply with the Passivhaus Standard; and a heating setpoint of 19 °C), but different building forms (A (green), B (blue) and C (red), respectively). The danger of sub-optimality for solution no. 640 is hence related to the design characteristics of form C. The radar plots display 27 (out of the 77) scenarios under which the solution is sub-optimal. In particular, out of the 54 displayed scenarios that all include the hot weather year, the

[26] The number refers to the solution “index” and as such, its magnitude does not imply a rank/ order of optimality.

solution is sub-optimal under scenarios no. 108 to 134 (that include the highest value of occupant density and hence the highest internal gains). As indicated by the figure, this is due to the fact that solution no. 640 (this referring to form C) is dominated by the other two solutions, as their performance is always better (under these scenarios).

Figure 5.14. The radar plots of solutions no. 0, 320 and 640.

These radar plots also indicate the impact of performance scenarios (that is, sources of aleatoric uncertainty) on each optimization objective, therefore assisting the DMs in gaining an understanding of the conditions that can cause unsatisfactory performance.

The displayed scenarios appear to have a greater impact on heating energy demand and winter discomfort, than summer discomfort – and no impact on capital cost.

Preference articulation

As also discussed in section 3.1.5, the new robust optimization framework allows for the *a posteriori* articulation of preferences, which are expressed as constraints to the formulated problem. For example, the DMs may wish to further restrict the described region of interest in the objective space, by defining 10% as the maximum allowable value for winter thermal discomfort. In order for a solution to be considered feasible, no more than 10% of total occupied hours (within the winter period) should hence be outside the comfort zone (under any scenario). Such a constraint drops the number of feasible solutions that are optimum under at least one scenario from 203 to 66, with 41 of them being associated with form A, 20 with form B and the remaining 5 with form C (figure 5.15). Globally robust solutions are decreased from 56 to 21, with 17 of them being associated with form A and the remaining 4 with form B.

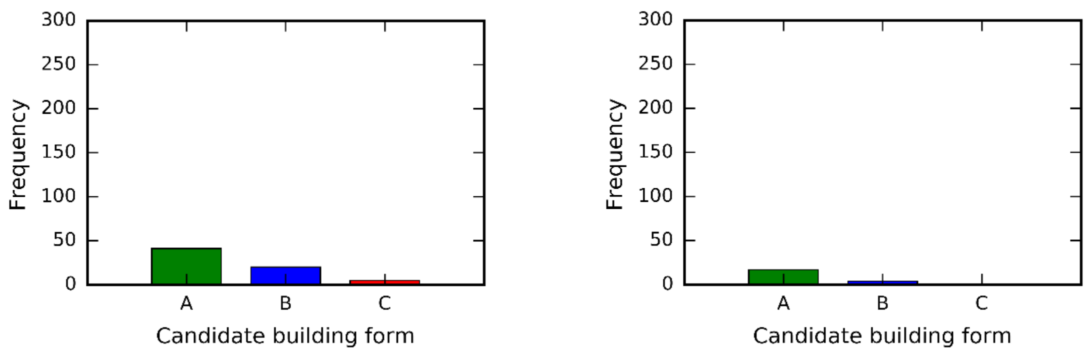

Figure 5.15. The form frequency across the 66 solutions that are optimum under at least one scenario (left) and the 21 solutions that are globally robust (right), in the (updated) region of interest.

As already observed in figures 5.12 and 5.13, form C is never globally robust, as it is dominated by the other two forms under the majority of performance scenarios. This can be attributed to its fully glazed façade that results in a higher number of summer discomfort hours compared to the other two forms – especially to form A, whose West façade has a much lower WWR (section 3.2). This can also be seen in table 5.9, which displays the objective values for solutions no. 3, 323 and 643 (all belonging to the 66 solutions that are optimum under at least one scenario in the updated region of interest) under the scenario that results in the highest percentage of summer discomfort (for all three solutions). Such solutions include identical construction and operation variable values, but different forms (A, B and C, respectively). The low Pareto frequency for solution no. 643 (that is, the low number of scenarios under which the solution is Pareto optimal) is hence related to the design characteristics of form C and, in particular, its fully glazed façade. Such information can support the DMs in making robust decisions during the design process, and ultimately designing a building that performs well with respect to the considered objectives and constraints in the light of different sources of uncertainty – with form A being here more likely to reduce the risk of sub-optimality.

Table 5.9. The predicted objective values under the scenario that results in the highest percentage of summer discomfort for 3 (out of 66) solutions that are optimum under at least one scenario, in the (updated) region of interest. Note that, such solutions include identical construction and operation variable values, but different forms (A, B and C, respectively).

Solution index	Design objective				Pareto frequency
	Heating energy demand ($kWh/m^2.yr$)	Winter discomfort (% of hours)	Summer discomfort (% of hours)	Capital cost ($£/m^2$)	
3	1.235	0.172	45.854	177.752	162
323	1.072	1.900	53.279	191.921	161
643	1.730	1.922	55.053	188.803	50

The scatter plot in figure 5.16 can assist the DMs in gaining a better understanding of the relationship between the 21 globally robust solutions (marked with a rhombus) and the four objectives. Note that, objective values express the predicted performance of the building under the nominal uncertain conditions. Table 5.10 displays such values, with table 5.11 then displaying the combinations of design variable values that led to these objective values. 9 of the 21 solutions fully comply with the Passivhaus Standard, with solutions no. 2, 3 and 4 (form A) only comprising heavyweight constructions and solutions no. 27 (form A) and no. 347 (form B) only lightweight constructions. The remaining (12) globally robust solutions include either one or two elements (wall, roof and/or window) that do not comply with the Passivhaus Standard. However, note that, their infiltration rate always meets the requirements of the Passivhaus Standard. 22 °C is the most commonly encountered value for the heating setpoint, whereas 19 °C and 20 °C never appear in the robust solution set (as they result in a greater than 10% winter thermal discomfort, this showing the impact of the heating setpoint on comfort).

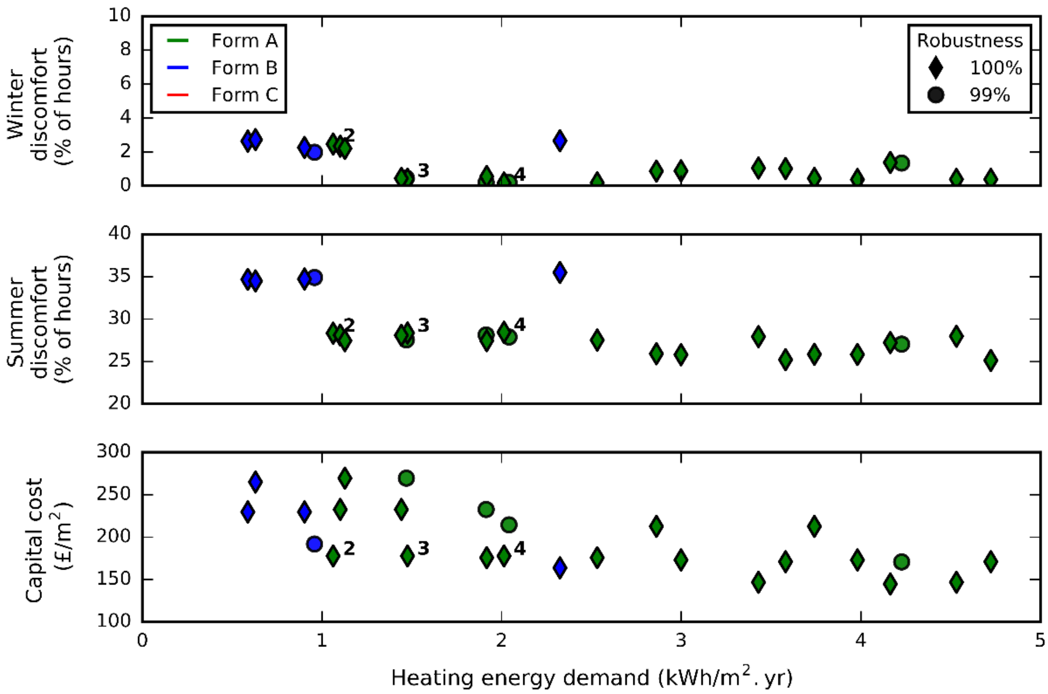

Figure 5.16. The trade-offs between the four optimization objectives under the nominal conditions.

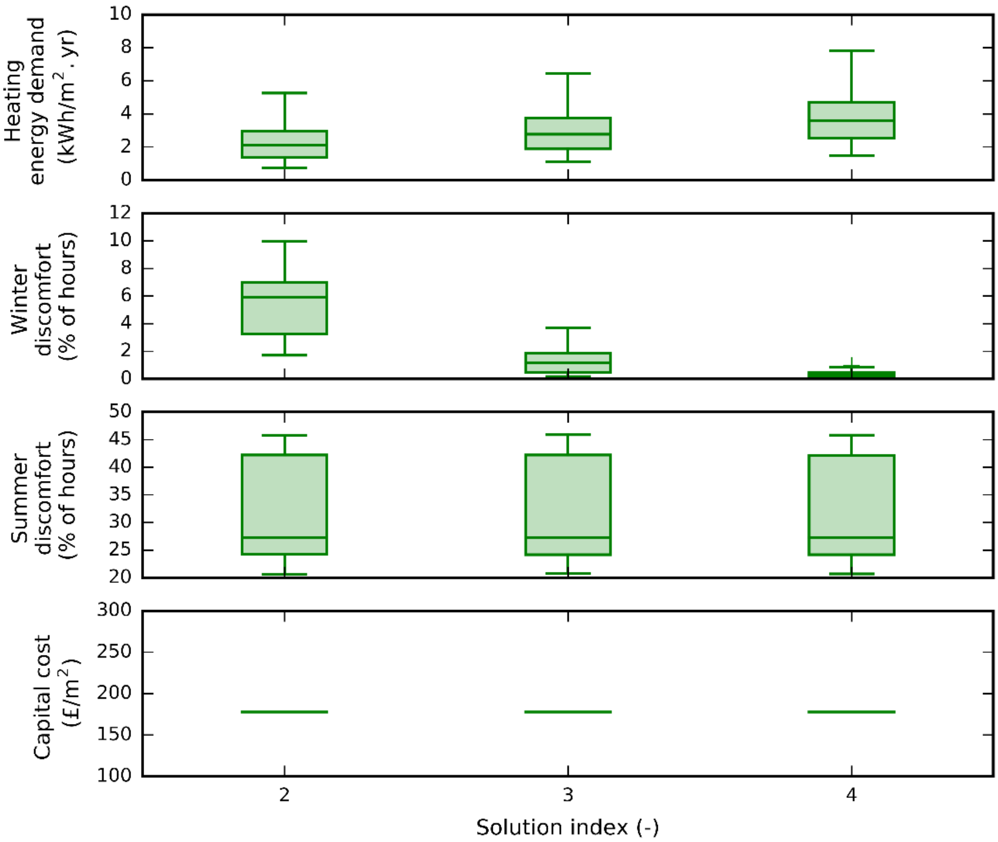

Figure 5.17. The box plots of compatible (for a hypothetical what-if scenario) solutions.

Table 5.10. The predicted objective values under the nominal conditions for the 21 solutions that remain optimum under all (162) scenarios, in the (updated) region of interest. Note that, the solution index does not imply a rank/ order of optimality – in fact, these solutions are all equal in terms of their level of robustness.

Solution index	Design objective			
	Heating energy demand (kWh/m^2.yr)	Winter discomfort (% of hours)	Summer discomfort (% of hours)	Capital cost (£/m^2)
2	1.062	2.469	28.349	177.752
3	1.477	0.396	28.353	177.752
4	2.014	0.172	28.444	177.752
7	1.102	2.345	28.120	232.674
8	1.442	0.439	28.102	232.674
13	2.999	0.883	25.814	173.047
14	3.981	0.380	25.822	173.047
18	2.862	0.871	25.913	212.587
19	3.741	0.439	25.855	212.587
27	1.127	2.213	27.462	269.424
43	1.917	0.555	27.452	175.798
44	2.532	0.180	27.517	175.798
53	3.581	1.027	25.224	171.093
54	4.723	0.392	25.126	171.093
83	3.431	1.051	27.936	146.812
84	4.533	0.384	27.987	146.812
123	4.163	1.382	27.222	144.858
327	0.587	2.637	34.681	229.547
328	0.903	2.269	34.710	229.547
347	0.630	2.729	34.489	264.886
403	2.324	2.664	35.480	163.681

Since the robust optimality criterion provides the DMs with the flexibility to specify their desired level of robustness, figure 5.16 also shows (using a circle) the 5 design solutions which are 99% robust – if, for example, the DMs decide to accept 1% of ‘rejects’ (as discussed in section 3.1.4). Apart from solution no. 323 (table 5.9) which includes form B, the remaining solutions include form A – this again suggesting that form A is more likely to reduce the risk of sub-optimality in the light of uncertainty.

Table 5.11. The combinations of design variable values for the 21 solutions that remain optimum under all (162) scenarios, in the (updated) region of interest. HW/LW denotes the thermal mass of the construction (heavyweight and lightweight, respectively). PH/PL signifies the standard each construction complies with (Passivhaus Standard and Building Regulations Part L, respectively).

Solution index	Form	Construction				Operation
	Form (–)	Wall construction (–)	Roof construction (–)	Window construction (–)	Infiltration rate (–)	Heating setpoint (°C)
2	A	HW-PH	HW-PH	PH	PH	21
3	A	HW-PH	HW-PH	PH	PH	22
4	A	HW-PH	HW-PH	PH	PH	23
7	A	LW-PH	HW-PH	PH	PH	21
8	A	LW-PH	HW-PH	PH	PH	22
13	A	HW-PL	HW-PH	PH	PH	22
14	A	HW-PL	HW-PH	PH	PH	23
18	A	LW-PL	HW-PH	PH	PH	22
19	A	LW-PL	HW-PH	PH	PH	23
27	A	LW-PH	LW-PH	PH	PH	21
43	A	HW-PH	HW-PL	PH	PH	22
44	A	HW-PH	HW-PL	PH	PH	23
53	A	HW-PL	HW-PL	PH	PH	22
54	A	HW-PL	HW-PL	PH	PH	23
83	A	HW-PH	HW-PH	PL	PH	22
84	A	HW-PH	HW-PH	PL	PH	23
123	A	HW-PH	HW-PL	PL	PH	22
327	B	LW-PH	HW-PH	PH	PH	21
328	B	LW-PH	HW-PH	PH	PH	22
347	B	LW-PH	LW-PH	PH	PH	21
403	B	HW-PH	HW-PH	PL	PH	22

As the scatter plot in figure 5.16 displays the predicted values of the four objectives under the nominal uncertain conditions only, it must be used in conjunction with the box plots in figure 5.17 in order to reveal the possible effect of aleatoric uncertainties on objective values. In particular, the box plots illustrate the distributions of possible objective values for solutions no. 2, 3 and 4. Given a (hypothetical) what-if scenario in which the DMs wish to construct a building which complies with the Passivhaus

Standard but also minimises capital cost, these are the only globally robust solutions – due to the fact that lightweight constructions result in a higher capital cost (table 5.10). Since they refer to the same construction but different heating setpoint (21, 22 and 23 °C, respectively), they lead to (almost) identical summer discomfort hours, with their lowest percentage (21%) being observed in the case of the slow response of thermal mass (for wall and roof constructions), the higher than expected infiltration rate, the cold weather year and the lowest value of occupant density (and internal heat gains). The highest percentage is 46% and results from the fast response of thermal mass, the lower than expected infiltration rate, the hot weather year and the highest value of occupant density (and internal heat gains). As indicated by figure 5.17, these solutions also result in an identical capital cost that is equal to 178 £/m^2 under all scenarios (as this is not affected by the variability in the behaviour of the uncertain conditions). As expected, the lower the setpoint, the lower the heating energy demand but also the higher the winter thermal discomfort. It is worth noting that solution no. 4 (which has a heating setpoint of 23 °C) results in a negligible range of winter thermal discomfort, this demonstrating the impact of the heating setpoint on occupant comfort.

The parallel coordinates plot in figure 5.18 can further assist the DMs in gaining an understanding of the relationship between these 21 globally robust solutions and the (four) design objectives. By displaying the combination of design variable values for each solution, this plot can support the DMs in obtaining a deeper understanding of the problem and identifying any 'commonality principles' among solutions – that is, any properties that are likely to ensure robust optimality. For instance, all solutions include an infiltration rate that satisfies the requirements of the Passivhaus Standard, with the majority of them including form A. The plot can also reveal the characteristics that are likely (for the given problem) to trigger sub-optimality, therefore assisting the DMs in minimising risk in the decision-making process. For example, in this region of interest, no globally robust solution includes form C, as this would result in a higher percentage of summer thermal discomfort compared to the other two forms, and thus a higher risk of sub-optimality. No globally robust solution has a heating setpoint of 19 or 20 °C, as this would result in a higher than 10% winter thermal discomfort under most of the scenarios, and consequently violate one of the defined constraint functions.

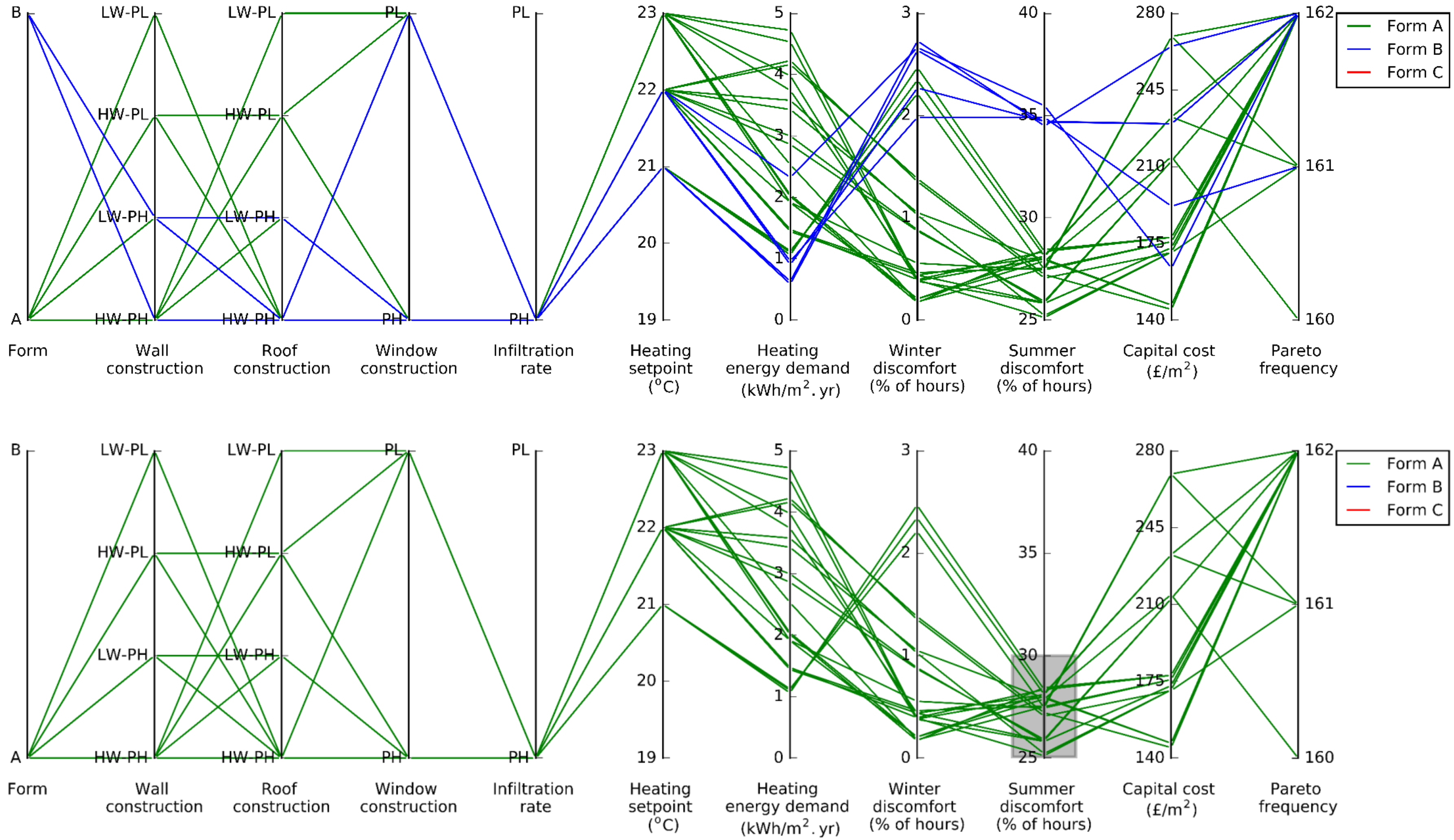

Figure 5.18. The parallel coordinates plot of feasible solutions that are at least 99% robust (top). The DMs can further restrict their region of interest (bottom).

The plot also provides the DMs with the opportunity to update their region of interest (denoted with a grey rectangle) and interactively relate their preferred region in the objective space with the region in the decision space. For instance, if the DMs would wish to obtain a solution that results in a lower than 30% summer thermal discomfort under nominal conditions, they should select a solution that comprises form A, as the four globally robust solutions that include form B (in blue) are infeasible. In order to assess feasibility under all scenarios, the DMs must also use a radar plot (such as the one in figure 5.14), which comprehensibly displays the predicted objective values of each solution under each scenario, hence assisting the DMs in making risk-conscious design decisions.

Finally, the parallel coordinates plot illustrates the Pareto frequency of each solution (that is, the number of scenarios under which a solution is Pareto optimal). Given that the applied exhaustive search method supports the re-focusing of the design problem as a post-processing step (section 3.1.5), the DMs are able to update their preferred degree of robustness. For example, they may decide to tolerate sub-optimality under one or two scenarios and select one of the design solutions which are 99% robust – that is, they have a Pareto frequency that is equal to 160 or 161. By providing the DMs with the opportunity to update and explore their region of interest, this including their desired level of robustness, such a plot can assist the DMs in gaining an understanding of what influences robustness and ultimately making informed design decisions.

5.3 Summary

Chapter 5 described the application of the new robust optimization framework to the design of a community centre, with the objective of demonstrating the potential of the new robust optimality criterion within a real-world context (as discussed in chapter 1). The five-step framework can support the DMs in formulating a design problem that is subject to design and performance uncertainties, assessing the optimality of candidate design solutions with respect to multiple objectives and ensuring their optimality under plausible uncertain conditions, with the assistance of the robust optimality criterion. The criterion can thus assist the DMs in not only minimising the values of multiple objective functions, but also dealing with any possible fluctuations that are caused by the variability in the behaviour of any uncertain conditions and therefore increasing the confidence in the predicted objective values.

Solution analysis demonstrated the potential of the new robust optimality criterion to reveal the possible impact of uncertainties on the predicted performance of candidate design solutions and hence reduce risk in decision-making. Radar plots were used to communicate in a comprehensible manner the predicted objective values of candidate solutions under different performance scenarios and point out the conditions that are likely to result in an unsatisfactory performance. Parallel coordinates plots were used to show the combinations of design variable values for robust solutions and indicate the design characteristics that are likely to make a building form immune to aleatoric uncertainties. Such plots were also used to demonstrate the ability of the new robust optimality criterion to support the *a posteriori* articulation of preferences, therefore enabling the DMs to update and explore their region of interest, this including their desired level of robustness – based on how large risks they are willing to take.

Chapter 6

Discussion and conclusions

6.1 Discussion

Despite the uniqueness of each building project, a number of generally-applied stages are suggested by the Royal Institute of British Architects (RIBA) (Sinclair 2013), in an effort to organise the procedure of briefing, designing, constructing and operating buildings. Zooming in on the concept and developed design stages, the RIBA Plan of Work (Sinclair 2013) mentions that these ‘may require a number of iterations of the design’, without however providing further guidance about the steps that should be followed by stakeholders to explore the design space and obtain a successful solution.

Building performance simulation (BPS) can support the identification of a satisfactory solution by providing rapid, quantitative feedback on the performance of the defined design alternatives (Clarke and Hensen 2015). Integrating BPS in design exploration can thus support the designers in meeting the requirements of the brief that has been agreed with the client, as well as complying with the building regulations. However, the common trial-and-error process of identifying an ‘optimum’ design solution may be misleading and time-consuming (mainly in the case of a large design space), this revealing the need for a more efficient exploration method (Wang *et al.* 2005).

This need has led to the integration of optimization into building design exploration over the last few years, as it supports the identification of solutions that best satisfy objective and constraint functions (Machairas *et al.* 2014). Optimization is therefore described as the process of identifying the best solution – or set of solutions – with respect to one or more objective and constraint functions. Accounting for multiple objectives can moderate the decision bias that characterises the conventional one- and two-objective problems, as it can provide the decision makers (DMs) with additional trade-offs that increase the understanding of the consequences of decisions (Kollat *et al.* 2011). Pareto optimization can support the DMs in resolving multiple, conflicting objectives and finding non-dominated solutions, without having to determine weights that hinder the *a posteriori* articulation of any stakeholder preferences (Evins 2013). Given that the capabilities of optimization algorithms can affect the optimized trade-offs (Wetter and Wright 2003), selecting a suitable algorithm is critical to finding the Pareto front for a given problem. Probabilistic optimization algorithms are fast in their convergence (especially if a high level of confidence is not necessary) but are subject to the number of objective and constraint functions (ur Rehman *et al.* 2017). They are also not guaranteed to find the global optimum (Brownlee and Wright 2015), hence being accompanied with an inherent uncertainty in optimization results.

Accounting for uncertain factors (such as weather variations, the occupant behaviour and randomness of thermal properties) is crucial in analysing complex problems and informing decisions (Helton *et al.* 2010), although it further increases the complexity of calculating and visualising trade-offs (Tian *et al.* 2018). In more detail, (even small) perturbations in uncertain factors are able to affect performance prediction and shift nominal optimal solutions to sub-optimal, or even infeasible solutions that fail to meet any stakeholder preferences and/or the requirements of regulations (Ben-Tal *et al.* 2009). Including uncertainty analysis (UA) in BPS and optimization is thus essential for demonstrating the consequences of decisions with a greater confidence (Gokhale 2009). Despite its benefits though, it is not regarded as standard practice in building design exploration (Tian *et al.* 2018), which can be partly attributed to the lack of tools that deal with the various sources of uncertainty and can thus eliminate the associated risks in decision-making (Martani 2015).

Robust optimization couples optimization and UA, acting as a decision support tool that accounts for the possibility that the nominal values of uncertain parameters may never occur, as a result of the randomness in their nature (Hopfe 2009). Combining such methods enables optimum, risk-conscious decisions, as optimization can ensure the identification of solutions that minimise the objective function values, and UA can improve the confidence in the optimality of solutions by evaluating their performance under a number of possible performance scenarios (Hopfe *et al.* 2012). Although robust optimization has been used over the last few years in other fields such as structural design (Doltsinis and Kang 2004, Martinez-Frutos *et al.* 2016), it is still not widely used in building energy studies, this suggesting the need for further investigation and implementation in building design optimization problems (Nguyen *et al.* 2014).

It is hence still ambiguous how to quantify uncertainty and assess robustness, which is revealed by the existence of multiple definitions of robustness in the literature and the discrepancy in the types of uncertainty that are accounted for as well as their handling (Walsh *et al.* 2013). The majority of existing studies adopt a probabilistic handling of uncertainty, assuming that the probability of each uncertain value occurring is known and evaluating solutions upon the probability density functions of their performance indicators (Van Gelder *et al.* 2014). These probabilistic formulations of robustness are, however, infeasible if there is no adequate information on the probability of occurrence of each uncertain input value, this being the case for uncertainties such as the weather.

A scenario-based approach can be alternately used when there are uncertainties that are 'largely unquantifiable in probabilistic terms in the context of prediction' (Dessai and Hulme 2004). Wald's rule (or minimax) (Wald 1945); Savage's rule (or minimax regret) (Savage 1951); and range (or max-min) are common scenario-based methods, which are used in situations where uncertainties cannot be quantified in probabilistic terms (Whalen and Churchill 1971). However, these robustness indicators may not be comprehensible to a non-specialist audience (Huang and Du 2007). In addition to this, their behaviour within multi-objective problems remains unknown, as they have not been extended to problems where multiple functions need to be minimised due to the entailed (computational) complexity (Rysanek and Choudhary 2013).

Finally, existing robustness indicators appear to be rather conservative (Ehrgott *et al.* 2014). Specifying the desired level of conservatism is, however, a fundamental step for assessing robustness (Hussain *et al.* 2016), this being subject to the state of mind of the DMs and in particular the risks they are willing to take (Whalen and Churchill 1971). Although each classical decision rule represents a different state of mind that may express the perspective of the DMs, they do not offer a control of the level of conservatism and therefore of the degree of robustness, calling for a more flexible definition of robustness, which supports the articulation of the (risk) preferences of the

DMs. Given that a large number of scenarios may be needed to adequately capture uncertainties, a rationale must be developed for the selection of scenarios in order to keep the computational cost low when assessing robustness (Bertsimas *et al.* 2011).

To sum up, additional studies are required to demonstrate how uncertainties must be quantified and how robustness must be assessed within the context of building design exploration. The literature review uncovered the need for a more flexible definition of robustness that enables the articulation of any stakeholder preferences. It also revealed the need to extend such a definition to multi-objective problems, as design solutions are commonly assessed with respect to only one or two criteria due to the associated computational complexity, this however restricting the number of optimization trade-offs and consequently the exploration of the design space.

6.2 Conclusions

The issues that were summarised in section 6.1 were addressed in this thesis through the development of a robust building design optimization framework, which can assist designers in handling building design problems that are exposed to uncertainties. This was achieved by meeting the objectives that were defined in section 1.2, with the main conclusions drawn being here presented (directly responding to such objectives).

- To investigate the different sources of uncertainty during the building design process and how they are quantified.

Prior to developing a new framework for coupling optimization and UA, the different sources of uncertainty and how these are quantified, were investigated. Although the detailed classification of the different sources of uncertainty may vary from case to case due to the fact that there is still not a single, widely-applied categorisation, their analysis is reported (Paté-Cornell 1996, Dessai and Hulme 2004, Helton *et al.* 2006, Der Kiureghian and Ditlevsen 2009) to be most commonly performed based on their reducibility (that is, their capability of being reduced). In this way, uncertainties are divided into two principal categories: *epistemic*, ‘if the modeller sees a possibility of reducing them by gathering more data’, and *aleatoric*, ‘if he/she does not foresee the possibility of reducing them’ (Der Kiureghian and Ditlevsen 2009).

In more detail, in the context of building design exploration, epistemic uncertainties emerge from the lack of detailed information on the form, construction and operation of the building, this resulting in a (high) number of uncertain design parameters, and thus in a (broad) range of possible performance outcomes. While proceeding to more developed stages of the design process, however, the amount of design information increases thanks to the decisions that are taken by the DMs in order to successfully complete their building project. In this way, as the design progresses, the size of the design space – i.e. the number of solutions that need to be explored – decreases, this resulting in the gradual elimination of epistemic uncertainties. On the contrary, the increase in the design detail does not lead to the elimination of aleatoric uncertainties which stem from the assumptions that are taken with regard to uncertain conditions (such as the weather) that are random in their nature, hence reducing the confidence in BPS results and the robustness in decision-making.

Any uncertain design parameters (i.e. sources of epistemic uncertainty) referring to building form, construction and operation that should be explored during the building design process, were presented. Any uncertain conditions (i.e. sources of aleatoric uncertainty) that can greatly affect building performance and should hence be taken into account to ensure satisfactory performance, were also described, these reflecting the three main sources that were identified in the literature (Ramallo-González *et al.* 2015): weather variations, occupant behaviour and randomness of thermal properties. With regard to their quantification, uncertain design parameters were found to have a uniform distribution – if there are no preference weights and therefore each solution (i.e. combination of design parameter values) has equal chance of being chosen – and uncertain conditions to have a normal distribution (de Wilde and Tian 2009).

- To develop an approach to formulating a multi-objective design problem that is exposed to uncertain conditions – this referring to the definition of design solutions, uncertain conditions, design objectives and constraints.

In order to define the values of uncertain design parameters, the new robust building design optimization framework recommends using the limiting values of building standards, and in particular of the Passivhaus Standard (International Passive House Association 2018) and Building Regulations Part L (UK Government 2013a). Each aleatoric uncertainty is advised to be expressed by a nominal value and two limiting values that represent ‘extreme’ – but possible – conditions, this providing a rationale for restricting the number of scenarios and hence keeping the computational cost low when assessing robustness later (Bertsimas *et al.* 2011). To eliminate any modelling uncertainty, an exhaustive search method is adopted by the framework to define all possible solutions (i.e. combinations of design parameter values) and scenarios (i.e. combinations of uncertain conditions). Given that all candidate design solutions are known, their Pareto optimality (within the defined problem) will be certain, as there is no doubt about the convergence behaviour of the search method – as might be the case for an optimization algorithm that could potentially fail to find the global optimum (Wetter and Wright 2004). As an exhaustive search method supports the evaluation of all solutions prior to the assessment of their optimality, its computational performance is not affected by the number of optimization objectives and constraints, thus enabling the identification of design solutions that are Pareto optimum with respect to multiple criteria (four in this study: heating energy demand; winter thermal discomfort; summer thermal discomfort; and cost).

The constraints of the design problem represent the criteria that a design option needs to meet in order to be considered feasible. In this thesis, the building regulations and guides and possible stakeholder preferences are taken into account for the formulation of the design problem and, in particular, the specification of any constraint functions. To avoid the risk of ‘cognitive hysteresis’ (Gettys and Fisher 1979), in this thesis, the application of constraints to the objective functions is posterior to the implementation of optimization; i.e. it is part of solution analysis. This disburdens the exploration of the design space of the bias that characterises the highly constrained problems, where the resulted solution set is limited by the initial conceptions of the DMs (Reed *et al.* 2013). These conceptions may however change along the way, with even small shifts being able to modify the resulted solution set (Robinson *et al.* 2016) and thus exclude well-performing solutions from exploration. Not applying a constrained optimization method also bolsters the direction of the search towards the truly optimum (Farmani and Wright 2003). However, note that, the framework that is presented in this thesis can also support the *a priori* application of constraints to the objective functions – in case the DMs are confident that the defined constraints will not change later on.

- To investigate existing robustness indicators and how they assess robustness.

Prior to introducing the new robust optimality criterion, existing robustness indicators and how they assess robustness in the light of uncertain conditions, were investigated. Two main approaches to the robustness assessment of design solutions were found in the literature, these advocating the probabilistic or not handling of uncertainties. In probabilistic analysis, the probability of all uncertain values occurring is known and the robustness assessment of solutions is based on the probability density function of performance indicators (Van Gelder *et al.* 2014). In non-probabilistic analysis, the probability of occurrence of uncertain values is unknown (or at least not defined with certainty), this hindering the probabilistic treatment of output distributions (Rysanek and Choudhary 2013).

A probabilistic approach is thus infeasible if there is an inadequacy of information on the probability of occurrence of uncertain values, this being the case for any aleatoric uncertainties such as the weather. Scenario analysis is proposed in the literature when there are uncertainties which are unquantifiable in probabilistic terms, with scenarios representing plausible combinations of uncertain values (Dessai and Hulme 2004). It is however reported that existing robustness indicators are not always comprehensible to a non-specialist audience (Huang and Du 2007), with their complexity increasing with the increase in the number of (objective and constraint) functions, this hindering their use in multi-objective formulations – which are however necessary to reflect the multi-dimensionality of real-life problems (Rysanek and Choudhary 2013). Another drawback of existing indicators is the lack of flexibility in specifying the degree of robustness of solutions, this being however vital for expressing the risk preferences of the DMs (Hussain *et al.* 2016).

- To develop a new indicator for evaluating the robustness of design solutions and identifying optimum solutions that are insensitive to the behaviour of the considered uncertain conditions, while supporting the articulation of the (risk) preferences of the DMs.

This thesis introduced the robust optimality criterion to support robustness assessment in the context of building design exploration and decision-making. The new robustness indicator couples optimization and UA to provide the DMs with a set of globally robust solutions; that is, solutions that remain Pareto optimal regardless of the uncertainty in the predicted building performance that is due to the variability in the behaviour of any uncertain conditions – these reflecting the three main sources of aleatoric uncertainty that were found in the literature (Ramallo-González *et al.* 2015): weather variations, occupant behaviour and randomness of thermal properties. Given that each aleatoric uncertainty is expressed by a nominal value and two 'extreme' – but possible – values, globally robust solutions may be regarded as conservative solutions by the DMs, due to the fact that they need to preserve their optimality even under 'extreme' conditions. Since such a (worst-case) combination of extreme conditions has a low probability of occurring, a small number of 'rejects' could be allowed, the magnitude of which needs to be decided by the DMs in line with their (risk) preferences. In contrast to existing robustness indicators, the robust optimality criterion supports the DMs in determining that number of 'rejects' and hence the degree of robustness of candidate solutions. As an example, the DMs may decide to tolerate sub-optimality under one or two scenarios. Given that the applied exhaustive search method enables the re-focusing of the design problem as a post-processing step, such a preference can be effortlessly translated into a constraint function during solution analysis.

- To explore the behaviour of the new robustness indicator.

The robust optimality criterion was applied to the design optimization of a 'test cell', this being a single-zone office building in London, with the objective of exploring the behaviour of the new robustness indicator – prior to its use within a real-world context. Robust solutions were identified using the new criterion, with their performance being then analysed. As both epistemic and aleatoric uncertainties were taken into account, solution analysis revealed how the test cell may behave in real life. A wide range of objective function values was observed, resulting from both the differences in design solutions and performance scenarios. The distributions of the objective values when aleatoric uncertainties are incorporated in the building design problem, were compared with the distributions of the deterministic objective values. This comparison revealed the risk of unsatisfactory performance due to the effect of aleatoric uncertainties, and consequently the importance of assessing robustness in the context of building design exploration problems. The discrepancy between the number of nominal optimum solutions (as derived from the deterministic Pareto ranking) and the number of robust solutions (as resulted from the application of the robust optimality criterion), also revealed the need for robustness assessment. Scatter, box and radar plots elucidated the relationship between robust solutions and the four design objectives, which can inform decision-making.

In order to gain a better understanding of the behaviour of the new robust optimality criterion, robust solutions were compared with the solutions that were obtained from the application of existing robustness rules (minimax, minimax regret and max-min). The solution sets that were derived from the application of the minimax and minimax regret rules were similar (for the examined building and given problem formulation) to the solution set that resulted from the application of the robust optimality criterion. The max-min rule produced a solution set that differed from the other sets, implying that the robust optimality criterion (so as other robustness rules in the literature) may not result in solutions that minimise the range of performance. By applying multiple robustness rules together, the DMs can improve the confidence in their decisions in the context of building design exploration and decision-making, with the selection of a single robustness indicator for addressing a given design problem being dependent on their (risk) preferences – which is, however, out of the scope of this thesis.

- To demonstrate the potential of the new robustness indicator in a real-world context.

The robust optimality criterion was also applied to the design optimization of a real-world building, this being a new community centre that will be constructed in London, with the objective of demonstrating the potential of the new robustness indicator to support design exploration and decision-making under uncertain conditions in a real-world context. Solution analysis demonstrated the potential of the robust optimality criterion to reveal the possible impact of uncertainties on the predicted performance of candidate design solutions and hence reduce risk in decision-making. Radar plots were used to communicate in a comprehensible manner the predicted objective values of candidate solutions under different performance scenarios and point out the conditions that are likely to lead to an unsatisfactory performance. Parallel coordinates plots were used to illustrate the combinations of design variable values for robust solutions and indicate the design characteristics that are likely to make a building form immune to aleatoric uncertainties. Such plots were also used to highlight the ability of the robust optimality criterion to support the *a posteriori* articulation of preferences, therefore enabling the DMs to update and explore their region of interest, this including their desired level of robustness – based on how large risks they are willing to take.

6.3 Contribution to knowledge

This thesis introduced a robust building design optimization framework for handling building design problems that are exposed to uncertainties. The framework comprises five main steps, which can assist stakeholders in exploring the design space in the light of different sources of uncertainty, and obtaining a solution that performs satisfactorily with respect to the considered objectives and constraints: a) uncertainty quantification; b) exhaustive search; c) BPS; d) robust optimization; and e) solution analysis. The application of these steps to the design optimization of a real-world building indicated that the framework can assist practitioners in designing buildings that are optimal in the defined objectives and robust to the inherent uncertainties.

In particular, by incorporating BPS and multi-objective optimization, the framework enables stakeholders to efficiently explore the design space (this being informed by the project brief and building standards) and reduce the uncertainty in the selection of an optimum design solution. By making use of an exhaustive search method (to assess all candidate solutions) that is independent of the number of objective and constraint functions, the framework can provide stakeholders with several optimization trade-offs, which can reveal the consequences of design decisions. Given that an exhaustive search method is guaranteed to find the global optimum, the framework also reduces the uncertainty in optimization results (that accompanies optimization algorithms).

By coupling multi-objective optimization and UA, the framework assists stakeholders in quantifying uncertain conditions and assessing the robustness of design solutions under such conditions, therefore demonstrating the consequences of decisions with a greater confidence and reducing risks in decision-making (such as failing to meet the requirements of the building standards). Robustness assessment is performed with the help of a novel robustness indicator, called robust optimality criterion, which ensures the Pareto optimality of solutions under all uncertain conditions. In contrast to existing robustness indicators, the robust optimality criterion offers a control of the degree of robustness, which supports the articulation of the (risk) preferences of the DMs during solution analysis. That is, it provides the DMs with the flexibility to define their desired Pareto frequency; the more risk-averse they are, the higher the number of performance scenarios for which the design solution is Pareto optimal should be.

By using scatter plots and parallel coordinates plots as part of its last step (i.e. solution analysis), the framework disseminates the degree of robustness of candidate solutions in a user-friendly manner, hence enabling the DMs to explore their region of interest based on how large risks they wish to take. Given that the applied exhaustive search method supports the re-focusing of the design problem as a post-processing step, the DMs are able to effortlessly update their preferred degree of robustness. This can assist them in gaining an understanding of what influences robustness and ultimately making risk-conscious decisions. Since the robust optimality criterion supports multi-objective optimization, it provides the DMs with robust solutions that are optimal with respect to a range of objective and constraint functions, thus assisting them in solving complex real-world problems that are exposed to various sources of uncertainty.

6.4 Limitations and suggestions for future research

This thesis adopted a worst-case approach to quantifying the aleatoric uncertainty in the behaviour of uncertain conditions, this implying that each uncertainty is expressed by a nominal value and two limiting values that signify extreme conditions. Adopting a rationale for restricting the number of values was vital for using an exhaustive search (selected here to enable the exploration of all possible solutions), as computational load increases exponentially with the number of values. In the future, commonly applied optimization algorithms (such as NSGAII) could be used to support the assessment of the optimality of solutions under a greater number of uncertain conditions – however, taking into account that such algorithms are not guaranteed to find the global optimum. Conclusions regarding modelling uncertainty could be drawn from the comparison of the solution sets that are resulted from the application of an exhaustive search and an optimization algorithm to the same design problem.

Using an optimization algorithm could also support the exploration of a larger design space at a much lower run-time (but also at the risk of not finding the global optimum), compared to an exhaustive search. Defining a larger design space would be necessary to enable the exhaustive generation and aesthetic evaluation of alternative forms which were out of the scope of this thesis. These are however inextricably linked to the form-finding approach that characterises the parametric design tools often used by designers during concept design stages. To provide rapid feedback on the performance of design alternatives, the application of the robust building design optimization framework may be automated in the future through the development of a plug-in for parametric design tools. By integrating uncertainty analysis, multi-objective optimization and robustness assessment into parametric design tools, such a plug-in could support the performance-based evaluation of design alternatives during concept design stages.

This thesis also proposed an approach to quantifying the (epistemic) uncertainty in the choice of building form, construction and operation. In particular, the selected design parameters represent sources of epistemic uncertainty that, according to the literature, can greatly influence performance prediction and should therefore attract the attention of stakeholders during the design exploration process. In the future, sensitivity analysis could be part of the robust building design optimization framework, in order to enable a customised list of influential design parameters (based on the mapping from analysis inputs to analysis outputs). Focusing on the definition of their values, this is informed by the project brief and building standards, with the final selection being dependent on the preferences of stakeholders that are expressed during solution analysis. Interactive (parallel coordinates) plots could be created in the future to support the instantaneous articulation of preferences and expeditious exploration of the design space.

The application of the framework to the design optimization of the real-world building revealed discrepancies between candidate building forms (such as the difference in the number of zones), this showcasing the vagueness of the project brief and therefore the uncertainty in problem formulation that should be further investigated in future work. The literature review also revealed the uncertainty in defining the design optimization problem, as several performance indicators and metrics are available (as an example, either the ASHRAE Standard 55-2013 or the British Standard 15251:2007 may be used to assess comfort). Conclusions regarding the uncertainty in problem formulation and how this affects solution robustness, could be drawn from the comparison of the solution sets that are resulted from the application of the robust optimality criterion when considering different combinations of objectives and constraints.

Finally, this thesis focused on exploring the design space (i.e. generating and evaluating alternative design options), rather than on selecting the (single) design that would be refined later on in the design process. Such a selection is dependent on the preferences of the different stakeholders, hence requiring their active involvement in the decision-making process. Stakeholder preferences also play an important role in indicating the most effective robustness indicator or combination of indicators for addressing a given design problem, as this is dependent on their risk perception. However, in this thesis, the reason for applying multiple robustness indicators together was not to select the best-performing indicator among them, but to cast light on the behaviour of the new robust optimality criterion within the context of building design exploration. Note that, solution analysis was here performed on a building level. Future work could focus on how to extend analysis to a zone level to provide designers with feedback on the zones that are likely to trigger unsatisfactory performance, therefore assisting them in making more risk-conscious decisions.

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Appendices

Appendix A – Construction materials

Table A.1. Material layers of external wall constructions: thermophysical properties (CIBSE 2006) and costs (AECOM 2015).

			HW-PH	LW-PH	HW-PL	LW-PL[27]
Layer 1 (outermost)	Material		Plaster	Shingles	Plaster	Shingles
	Thermophysical properties	Thickness (m)	0.013	0.010	0.013	0.010
		Thermal conductivity (W/mK)	0.220	0.120	0.220	0.120
		Density (kg/m^3)	800	510	800	510
		Specific heat capacity (J/kgK)	840	1260	840	1260
	Cost (£/m^2)		12.190	35.480	12.190	35.480
Layer 2	Material		EPS[28]	Battens[29]	EPS	Battens
	Thermophysical properties	Thickness (m)	0.225		0.085	
		Thermal conductivity (W/mK)	0.033		0.033	
		Density (kg/m^3)	15		15	
		Specific heat capacity (J/kgK)	1450		1450	
	Cost (£/m^2)		17.390	12.250	9.290	12.250
Layer 3	Material		Concrete	Chipboard	Concrete	Chipboard
	Thermophysical properties	Thickness (m)	0.180	0.012	0.180	0.012
		Thermal conductivity (W/mK)	1.300	0.140	1.300	0.140
		Density (kg/m^3)	2000	600	2000	600
		Specific heat capacity (J/kgK)	840	1700	840	1700
	Cost (£/m^2)		23.320	9.470	23.320	9.470
Layer 4	Material			Wool insulation		Wool insulation
	Thermophysical properties	Thickness (m)		0.190		0.075
		Thermal conductivity (W/mK)		0.039		0.039
		Density (kg/m^3)		25		25
		Specific heat capacity (J/kgK)		1800		1800
	Cost (£/m^2)			52.270[30]		20.690

[27] HW/LW denotes the thermal mass of each construction (heavyweight and lightweight construction, respectively); PH/PL signifies the standard each construction complies with (the Passivhaus Standard (International Passive House Association 2018) and the Building Regulations Part L (UK Government 2013a), respectively).
[28] Expanded polystyrene board.
[29] In EnergyPlus (U.S. Department of Energy 2016a), this layer is simulated as an air gap.
[30] The cost of timber studs is also included.

			HW-PH	LW-PH	HW-PL	LW-PL[27]
Layer 5	Material			Chipboard		Chipboard
	Thermophysical properties	Thickness (m)		0.012		0.012
		Thermal conductivity (W/mK)		0.140		0.140
		Density (kg/m^3)		600		600
		Specific heat capacity (J/kgK)		1700		1700
	Cost (£/m^2)			9.470		9.470
Layer 6	Material			Vapour barrier		Vapour barrier
	Thermophysical properties	Thickness (m)				
		Thermal conductivity (W/mK)				
		Density (kg/m^3)				
		Specific heat capacity (J/kgK)				
	Cost (£/m^2)			2.480		2.480
Layer 7	Material			Wool insulation		Battens (services)
	Thermophysical properties	Thickness (m)		0.050		
		Thermal conductivity (W/mK)		0.039		
		Density (kg/m^3)		25		
		Specific heat capacity (J/kgK)		1800		
	Cost (£/m^2)			6.500[31]		3.500
Layer 8 (innermost)	Material			Plaster (board)		Plaster (board)
	Thermophysical properties	Thickness (m)		0.013		0.013
		Thermal conductivity (W/mK)		0.210		0.210
		Density (kg/m^3)		700		700
		Specific heat capacity (J/kgK)		1000		1000
	Cost (£/m^2)			19.530		19.530
Total cost (£/m^2)			52.900	147.450	44.800	112.870

[31] The cost of battens is also included.

Table A.2. Material layers of roof constructions: thermophysical properties (CIBSE 2006) and costs (AECOM 2015).

			HW-PH	LW-PH	HW-PL	LW-PL
Layer 1 (outermost)	Material		Shingles	Shingles	Shingles	Shingles
	Thermophysical properties	Thickness (m)	0.010	0.010	0.010	0.010
		Thermal conductivity (W/mK)	0.120	0.120	0.120	0.120
		Density (kg/m^3)	510	510	510	510
		Specific heat capacity (J/kgK)	1260	1260	1260	1260
	Cost (£/m^2)		50.190	50.190	50.190	50.190
Layer 2	Material		Battens	Battens	Battens	Battens
	Thermophysical properties	Thickness (m)				
		Thermal conductivity (W/mK)				
		Density (kg/m^3)				
		Specific heat capacity (J/kgK)				
	Cost (£/m^2)		17.500	17.500	17.500	17.500
Layer 3	Material		Breather membrane	Breather membrane	Breather membrane	Breather membrane
	Thermophysical properties	Thickness (m)				
		Thermal conductivity (W/mK)				
		Density (kg/m^3)				
		Specific heat capacity (J/kgK)				
	Cost (£/m^2)		1.890	1.890	1.890	1.890
Layer 4	Material		Fibreboard	Chipboard	Fibreboard	Chipboard
	Thermophysical properties	Thickness (m)	0.019	0.012	0.019	0.012
		Thermal conductivity (W/mK)	0.082	0.140	0.082	0.140
		Density (kg/m^3)	350	600	350	600
		Specific heat capacity (J/kgK)	1300	1700	1300	1700
	Cost (£/m^2)		9.880	9.470	9.880	9.470

			HW-PH	LW-PH	HW-PL	LW-PL
Layer 5	Material		EPS	Wool insulation	EPS	Wool insulation
	Thermophysical properties	Thickness (m)	0.200	0.190	0.110	0.125
		Thermal conductivity (W/mK)	0.033	0.039	0.033	0.039
		Density (kg/m^3)	15	25	15	25
		Specific heat capacity (J/kgK)	1450	1800	1450	1800
	Cost (£/m^2)		13.460	59.920	10.290	42.170
Layer 6	Material		Concrete	Chipboard	Concrete	Chipboard
	Thermophysical properties	Thickness (m)	0.200	0.012	0.200	0.012
		Thermal conductivity (W/mK)	1.300	0.140	1.300	0.140
		Density (kg/m^3)	2000	600	2000	600
		Specific heat capacity (J/kgK)	840	1700	840	1700
	Cost (£/m^2)		21.880	9.470	21.880	9.470
Layer 7	Material			Vapour barrier		Vapour barrier
	Cost (£/m^2)			2.480		2.480
Layer 8	Material			Wool insulation		Battens (services)
	Thermophysical properties	Thickness (m)		0.050		
		Thermal conductivity (W/mK)		0.039		
		Density (kg/m^3)		25		
		Specific heat capacity (J/kgK)		1800		
	Cost (£/m^2)			6.500		3.500
Layer 9 (innermost)	Material			Plaster (board)		Plaster (board)
	Thermophysical properties	Thickness (m)		0.013		0.013
		Thermal conductivity (W/mK)		0.210		0.210
		Density (kg/m^3)		700		700
		Specific heat capacity (J/kgK)		1000		1000
	Cost (£/m^2)			16.990		16.990
Total cost (£/m^2)			114.800	174.410	111.630	153.660

Table A.3. Variations in the thermal properties of non-hygroscopic materials due to the impact of 1% moisture content (MacDonald 2002).

	Variation (non-hygroscopic materials)	
Thermal properties	Fast response	Slow response
Thermal conductivity (W/mK)	Nominal + 5%	Nominal - 5%
Density (kg/m^3)	Nominal - 13%	Nominal + 13%
Specific heat capacity (J/kgK)	Nominal - 4%	Nominal + 4%

Table A.4. Variations in the thermal properties of inorganic-porous materials due to the impact of 4% moisture content (MacDonald 2002).

	Variation (inorganic-porous materials)	
Thermal properties	Fast response	Slow response
Thermal conductivity (W/mK)	Nominal + 15%	Nominal - 15%
Density (kg/m^3)	Nominal - 4%	Nominal + 4%
Specific heat capacity (J/kgK)	Nominal - 19%	Nominal + 19%

Table A.5. Variations in the thermal properties of organic-hygroscopic materials due to the impact of 7% moisture content (MacDonald 2002).

	Variation (organic-hygroscopic materials)	
Thermal properties	Fast response	Slow response
Thermal conductivity (W/mK)	Nominal + 25%	Nominal - 25%
Density (kg/m^3)	Nominal - 11%	Nominal + 11%
Specific heat capacity (J/kgK)	Nominal - 8%	Nominal + 8%

Table A.6. Material layers of internal wall, foundation slab, internal floor, and internal door constructions: thermophysical properties (CIBSE 2006) and costs (AECOM 2015).

			Internal wall	Foundation slab	Internal floor	Internal door
Layer 1 (outermost)	Material		Plaster (board)	Granular filling	Plaster (board)	Plywood
	Thermophysical properties	Thickness (m)	0.013	0.150	0.013	0.012
		Thermal conductivity (W/mK)	0.210	0.360	0.210	0.130
		Density (kg/m^3)	700	1840	700	500
		Specific heat capacity (J/kgK)	1000	840	1000	1600
	Cost (£/m^2)		19.530	28.780	16.990	15.280
Layer 2	Material		Metal studs	Cement screed	Air (services)	Air
	Thermophysical properties	Thickness (m)	0.050	0.050	0.300	
		Thermal conductivity (W/mK)		1.400		
		Density (kg/m^3)		2100		
		Specific heat capacity (J/kgK)		650		
	Cost (£/m^2)		5.750	19.000		
Layer 3	Material		Plaster (board)	Vapour barrier	Concrete	Plywood
	Thermophysical properties	Thickness (m)	0.013		0.200	0.012
		Thermal conductivity (W/mK)	0.210		1.300	0.130
		Density (kg/m^3)	700		2000	500
		Specific heat capacity (J/kgK)	1000		840	1600
	Cost (£/m^2)		19.530	2.480	21.880	15.280
Layer 4	Material			EPS		
	Thermophysical properties	Thickness (m)		0.200		
		Thermal conductivity (W/mK)		0.033		
		Density (kg/m^3)		15		
		Specific heat capacity (J/kgK)		1450		
	Cost (£/m^2)			13.460		

			Internal wall	Foundation slab	Internal floor	Internal door
Layer 5	Material			Vapour barrier		
	Cost (£/m^2)			2.480		
Layer 6 (innermost)	Material			Concrete		
	Thermophysical properties	Thickness (m)		0.200		
		Thermal conductivity (W/mK)		1.300		
		Density (kg/m^3)		2000		
		Specific heat capacity (J/kgK)		840		
	Cost (£/m^2)			21.880		
Total cost (£/m^2)			44.810	88.080	38.870	30.560

Appendix B – Modelling the case study buildings

Test cell

Table B.1 shows the performance values (as predicted in EnergyPlus (U.S. Department of Energy 2016a)) for a solution that fully complies with the Passivhaus Standard (no. 10) and a solution that only complies with the Building Regulations (no. 1170), in the case of the examined test cell. Note that, values refer to nominal uncertain conditions (i.e. the nominal values for (wall and roof) constructions, infiltration rate and occupant density as well as the TRY weather file). Both solutions include the highest WWR, the lowest value of overhang depth, heavyweight wall and roof constructions and a heating setpoint of 19 °C. As expected, solution no. 10 leads to a lower heating energy demand and winter thermal discomfort compared to solution no. 1170 – as the U-values of its external wall, roof and window constructions as well as its infiltration rate are lower – but higher summer thermal discomfort and capital cost.

Table B.1. The predicted objective values under the nominal conditions for a solution that fully complies with the Passivhaus Standard (no. 10) and a solution that only complies with the Building Regulations (no. 1170), in the case of the examined test cell.

Solution index	Design objective			
	Heating energy demand ($kWh/m^2.yr$)	Winter discomfort (% of hours)	Summer discomfort (% of hours)	Capital cost (£/m^2)
10	0.409	35.043	16.595	348.959
1170	12.789	73.988	10.177	251.157

Real-world building

Table B.2 similarly shows the predicted performance values under nominal uncertain conditions for a solution that fully complies with the Passivhaus Standard (no. 0, 320 and 640) and a solution that only complies with the Building Regulations (no. 290, 610 and 930), in the case of each of the three candidate forms (A, B and C, respectively) for the examined real-world building. Solutions include heavyweight wall and roof constructions and a heating setpoint of 19 °C. As expected, solutions no. 0, 320 and 640 lead to a lower heating energy demand and winter thermal discomfort compared to solutions no. 290, 610 and 930, but higher summer thermal discomfort and capital cost.

Table B.2. The predicted objective values under the nominal conditions for a solution that fully complies with the Passivhaus Standard (no. 0, 320 and 640) and a solution that only complies with the Building Regulations (no. 290, 610 and 930), in the case of each of the three candidate forms (A, B and C, respectively) for the examined real-world building.

Solution index	Form	Design objective			
	Form (–)	Heating energy demand (kWh/m^2.yr)	Winter discomfort (% of hours)	Summer discomfort (% of hours)	Capital cost (£/m^2)
0	A	0.536	10.140	28.366	177.752
290	A	13.504	42.283	16.176	125.784
320	B	0.216	12.140	34.876	191.921
610	B	8.910	38.310	26.512	144.172
640	C	0.484	14.000	38.478	188.803
930	C	11.011	39.522	27.141	142.257

Figures B.1, B.2 and B.3 show the zoning diagrams for forms A, B and C, respectively. Note that, colours indicate the outside boundary conditions for all space surfaces (that is, blue – external air; green – interior air; and brown – ground).

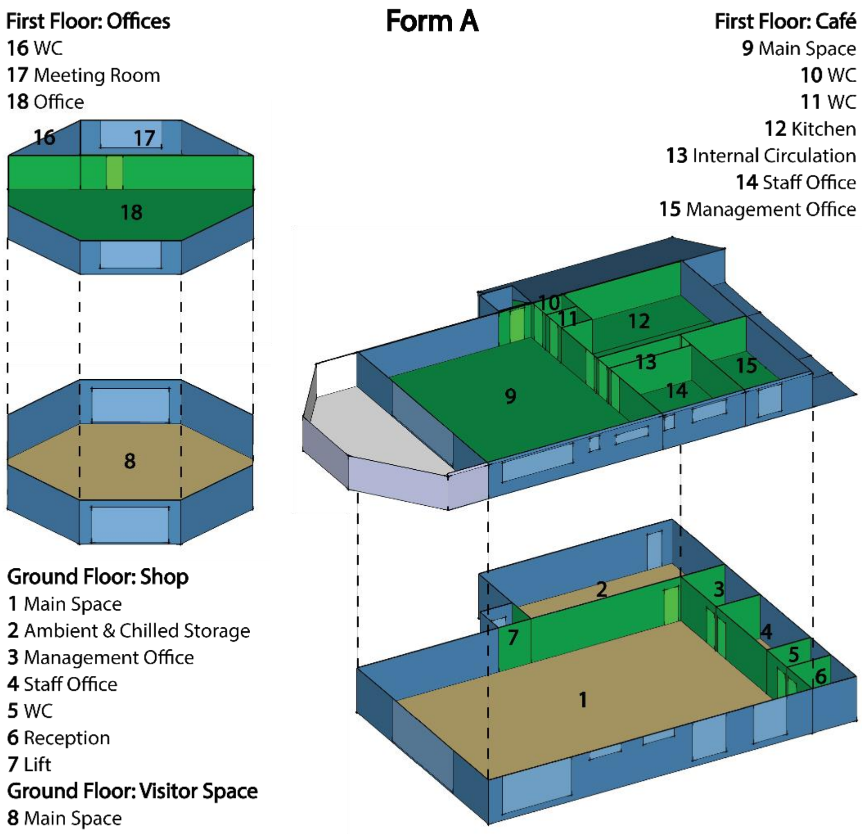

Figure B.1. Real-world building – Form A – The Sketchup model (zoning diagram).

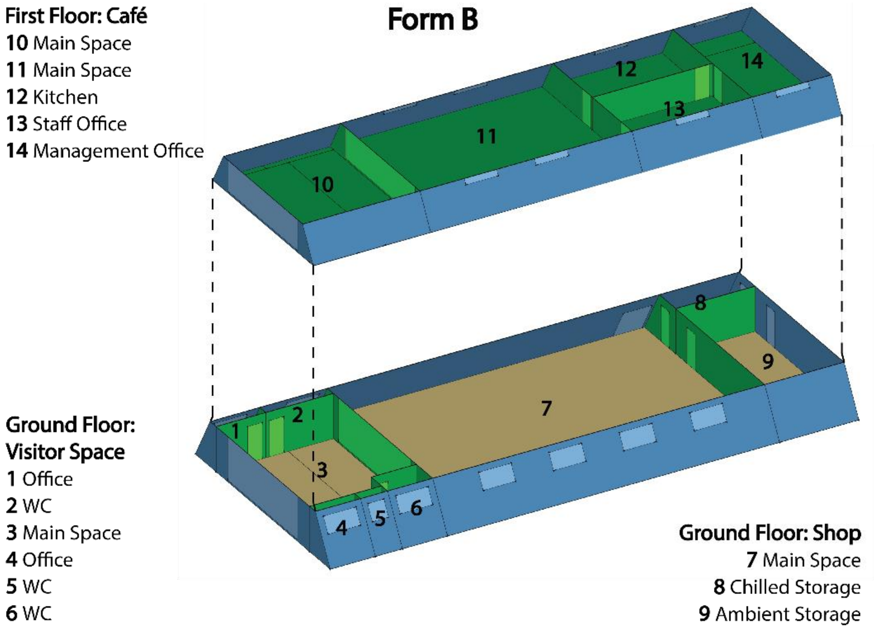

Figure B.2. Real-world building – Form B – The SketchUp model (zoning diagram).

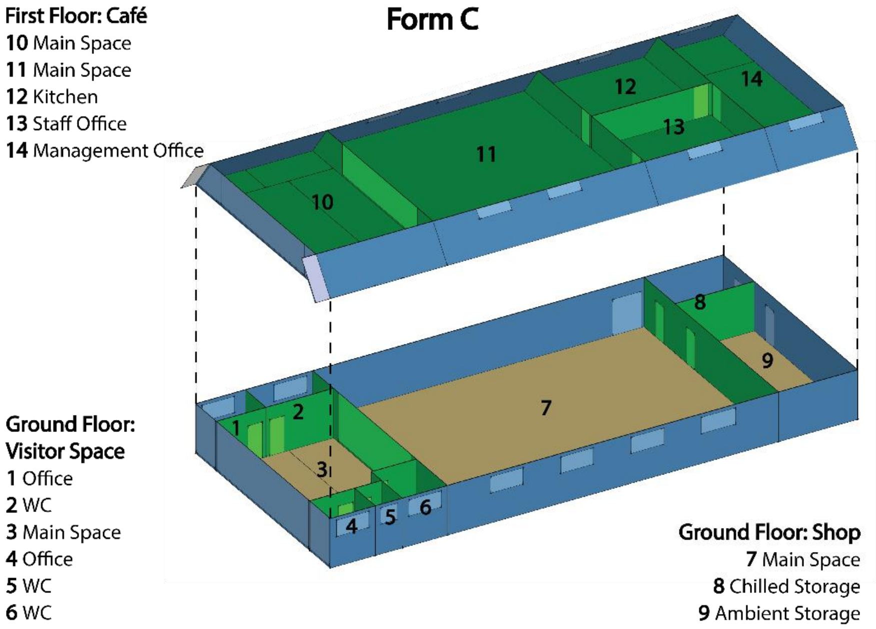

Figure B.3. Real-world building – Form C – The SketchUp model (zoning diagram).

Appendix C – List of publications

List of publications

Nikolaidou, E., Wright, J., and Hopfe, C.J., 2017. Robust building scheme design optimization for uncertain performance prediction. *In*: *BS2017, 15th Conference of International Building Performance Simulation Association, San Francisco, USA, August 7-9.*

Wright, J., Nikolaidou, E., and Hopfe, C.J., 2016. Exhaustive search; does it have a role in explorative design? *In*: *BSO2016, 3rd Building Simulation and Optimization Conference, Newcastle, UK, September 12-14*.

Nikolaidou, E., Wright, J., and Hopfe, C.J., 2015. Early and detailed design stage modelling using Passivhaus design; what is the difference in predicted building performance? *In*: *BS2015, 14th Conference of International Building Performance Simulation Association, Hyderabad, India, December 7-9*.

Nikolaidou, E., Wright, J., and Hopfe, C.J., 2015. The difference in early and detailed design stage building performance prediction for a Passivhaus building. *In*: *LoLo2015, 2nd Conference of London-Loughborough Centre, Loughborough, UK, April 22*.