Robust Building Scheme Design Optimization for Uncertain Performance Prediction

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Abstract

Design exploration is a vital part of the building design process that aims at identifying the best-performing design with regard to the requirements of the client and building regulations. Building performance simulation can support this "explorative" process, its potential however being restricted by the fact that all design parameters are subject to uncertainty. In addition, while the need for an efficient exploration of the design space has resulted in the integration of optimization into the design process, the majority of existing research treats uncertainty quantification and optimization as separate processes. Finally, candidate designs are commonly evaluated with respect to only one or two design criteria, while the multi-dimensionality of real-world problems calls for integrated design solutions that meet several – often-conflicting – objectives.

A new approach is thus developed that aims to help designers identify robust Pareto-optimal solutions that satisfy several design criteria, while remaining optimal regardless of the uncertainty in boundary conditions. Through its implementation to a real-world case-study building, the novel approach is found to be able to identify optimum solutions that preserve their optimality over the entire range of uncertain performance scenarios.

Introduction

Exploring the design space is a fundamental part of the building design process, but also a great challenge as several – often-conflicting – criteria and constraints need to be met simultaneously. Attaining a well-performing design solution thus presupposes the definition of several candidate solutions, and their evaluation with respect to a series of criteria such as aesthetics, functionality, cost, and sustainability (Prowler 2008). The experience of designers has traditionally played an important role in the assessment of candidate options and the selection of a suitable solution in the context of design decision-making. Although this procedure is inherently interactive so as to permit the integration of qualitative criteria (such as aesthetics) and stakeholder preferences (Geyer 2009), reliance on the intuition of the designers and/or rules of thumb should be minimised (Hillier *et al.* 1972). Further, although subjectivity is an integral part of the nature of the design process, it should be restricted and – to an extent – replaced by more objective methods of assessment, as subjectivity increases the risk that well-performing options will be eliminated.

Building performance simulation (BPS) can act as an objective guide that is able to assist designers fulfil the defined objectives and constraints, while ensuring the compliance with the building regulations. However, the commonly applied trial-and-error method of identifying an "optimum" design solution, can be misleading and time-consuming, this revealing the need for a more efficient exploration of the design space (Wang *et al.* 2005). This need has resulted in the integration of optimization into the building design process (Machairas *et al.* 2014), as it can help designers identify the solutions that best meet the objective function(s) and constraints. Optimization is therefore referred to as the process of identifying suitable design parameters x with respect to one or more objective functions $f(x)$ and constraints $g(x)$. Nevertheless, this process may prove to be complex due to the plethora of design parameters and possible values, and the uncertainty in the behaviour of boundary conditions.

Although some studies have focused on the integration of uncertainty analysis (UA) into BPS (Macdonald and Strachan 2001, de Wit and Augenbroe 2002, Hopfe and Hensen 2011), the majority of existing research treats UA and optimization as separate processes. However, Van Gelder et al. (2014) and Nix et al. (2015) describe approaches for probabilistic optimization, this implying the minimisation of both the mean and possible spread of predicted performance. Coupling UA and optimization is crucial in the context of robust decision-making (Hopfe *et al.* 2012), as optimization can help minimise the value of objective function(s), while UA can help ensure the optimality of candidate design solutions by examining their performance over a number of uncertain scenarios. In this way, using optimization and UA for exploring the design space can help increase the understanding of the relationship between the candidate designs and probable building performance, and support the identification of an optimal design solution.

Nevertheless, an optimal design solution may prove to be non-robust if its optimality is compromised by the considered uncertainty. In order to avoid this risk and to support building design decision-making, a new robust multi-objective optimization approach is suggested in this paper. The approach is demonstrated through its application to a real-world case-study building and the
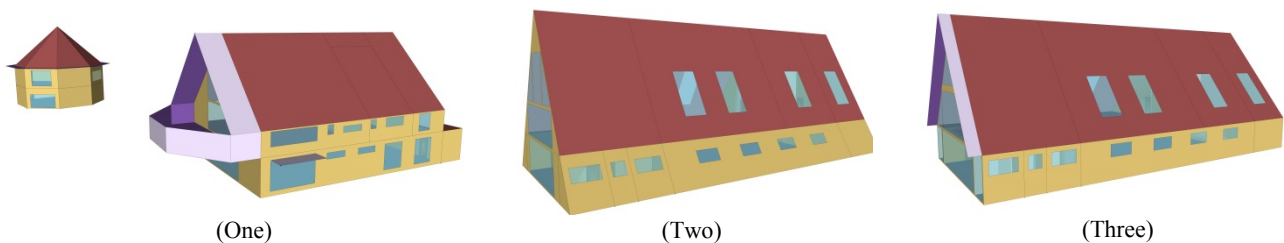
(One)   (Two)   (Three)

Figure 1. The three candidate forms for the case-study building (as conceived by the design team).

exploration of three candidate forms, all satisfying the aesthetical preferences of the client and the design team. An exhaustive search method is applied to generate all possible combinations of design and boundary condition variables, these representing the sources of uncertainty at the examined design stage.

Exhaustive search and optimization

Due to the fact that an exhaustive search evaluates all of the solutions, their analysis is unrestricted, this enabling an increase in the understanding of the relationship between the candidate design solutions and the design objectives, and thus support for decision-making (Wright *et al.* 2016). Given that all solutions are known, their optimality (within the defined problem) is certain, as there is no doubt about the "convergence" behaviour of the search method. In addition, its computational performance is unaffected by an increase in the number of design objectives, this providing the opportunity to identify design solutions that are optimum with respect to several criteria. For clarity, it should be noted that in this research, the exhaustive search is used to evaluate all solutions, with the identification of the optima being achieved through the Pareto ranking of the solutions, the post-processing being the optimization step of the approach. The selection of the optima during the post-processing, is also based on a new definition of robustness, which is that a robust optimal solution is one that remains Pareto-optimal regardless of the uncertainty in the predicted building performance.

A significant limitation of an exhaustive search is however that computational load increases exponentially with the number of design solutions and uncertain conditions. Despite the valuable help that is provided by concurrent processing, limiting the number of variables and their assigned values is crucial for the feasibility of the suggested approach. In this study, this is performed with the help of the preferences of the client and the design team, and the requirements of the building standards, these helping reduce the size of the search space through the elimination of the infeasible solutions (Nikolaidou *et al.* 2015).

Methodology

In order to support design exploration under uncertainty and enhance robustness in design decision-making, a new approach is developed and applied to a real-world case-study building and the evaluation of three candidate forms. An exhaustive search is initially used to generate all possible combinations of variables, these representing the influential – as identified in the literature – input

uncertainties at the examined design stage. The resulting set of design options and boundary conditions are post-processed to identify robust Pareto-optimum designs that minimise the value of four design criteria (underheating; overheating; heating energy demand; and capital cost) regardless of the uncertainty in boundary conditions, and given the potential design solutions that are related to the construction and operation of the building – those to be specified later on in the design process.

Case-study building and performance simulation

As a proof of concept, the suggested approach to design support under uncertainty is applied to a real-world case-study building. This is a new community centre that is planned to be constructed in the UK, incorporating a shop, café, visitor space, and third party offices. A fundamental step prior to the implementation of this novel approach is the creation of the three models that represent the candidate building forms as conceived by the architects involved in the project, all satisfying the requirements of the client's brief. These three models (figure 1) act as the baseline designs around which the design parameters that are related to the construction and the HVAC system operation of the building vary, in an effort to include design uncertainty in the exploration of alternative design solutions. The variation of the input parameters is performed within a certain range, these having been heavily derived from building standards and influenced by the real-world consideration of the design parameters. Since an exhaustive search method is used to explore the design solution space and thus all possible combinations of parameter values are evaluated, the choice of the initial values of the design parameters used at the start of the search is not important.

The performance of the three models is simulated using EnergyPlus (U.S. Department of Energy 2016a), this being a detailed thermal simulation program that has been widely reviewed and validated. Despite its notable features and capabilities, the fact that it is a console-based program that operates by reading input and writing output as text files, it does not support the expeditious creation of the geometry of the models. A third-party graphical user interface is thus required for the creation of the three candidate forms. In this study, SketchUp (Trimble Navigation 2016) is used as a massing tool for the reason that it provides a user-friendly environment for the three-dimensional representation of the models. In addition, it provides the opportunity of adding the OpenStudio plug-in (U.S. Department of Energy 2015) to the existing list of toolbars, this supporting whole building simulation using EnergyPlus.

In this way, the geometry of the three models is created in SketchUp with the help of the OpenStudio plug-in, in order to ensure the successful translation of building spaces into thermal zones. OpenStudio can also help confirm that each zone is an enclosed as well as convex[1] space. The three models are subsequently refined in EnergyPlus where the remaining input details (objects) are specified. In particular, the fields that are associated with the materials and the construction of the building are filled based on real-world products and typical constructions. Internal gains and the corresponding schedules are also defined, these referring to loads from people, lights, and electric equipment. With regard to (winter) heating and air conditioning, an ideal loads air system is used, this being the only conditioning component that is specified. As the air unit is considered ideal and its efficiency is thus fixed to 100%, the output

Table 1. Variables and assigned values.

Type	Variable	Number of options	Values
Design	Building form	3	1. One 2. Two 3. Three
	Wall construction	4	1. HW-PH 2. HW-PL 3. LW-PH 4. LW-PL
	Roof construction	4	1. HW-PH 2. HW-PL 3. LW-PH 4. LW-PL
	Infiltration rate	2	1. PH (0.05 ach) 2. PL (0.50 ach)
	Glazing type	2	1. PH 2. PL
	Heating setpoint	3	1. 19°C 2. 21°C 3. 23°C
	Heat recovery	2	1. On 2. Off
	Humidification	2	1. On 2. Off
Performance	Occupant density	2	1. 100% 2. 50%
	Weather file	2	1. CIBSE TRY 2. CIBSE DSY

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[1] A zone is considered convex when any straight line passing through it intercepts no more than two surfaces.

of the energy analysis should be treated with caution, taking into account that it does not incorporate any system energy losses, but it only reflects the heating energy demand for the specified conditions. Finally, as in summer period the building is naturally ventilated, there is no need for a cooling and/or air conditioning system under summertime operation, and thus there are no cooling loads.

Definition of the search space

At the examined (early) design stage, the geometry of the building as well as the design parameters that are associated with its construction and operation are still under investigation. Starting with form, three candidate designs are explored (figure 1), these representing the conceptual ideas that emerged from the collaborative brainstorming of the design team. These forms are not the only possible designs that satisfy the requirements of the project brief, but they are three feasible alternatives that are also in line with the aesthetical preferences of the architects, thus also satisfying qualitative measures. The existence of multiple designs that meet the project prerequisites stems from the fact that form-making is a design problem that does not have a single correct answer, as it is affected not only by the conditions of the project itself but also by the cognitive schema of the architects. That is, addressing a form-making problem is significantly influenced by the knowledge, experience, and the aesthetics of the architects, and thus inherently connected with their subjective interpretation of project information and its translation into building form.

Hence, although the design team commonly comprises of individuals from different backgrounds (architectural, structural, mechanical etc.), architects tend to have a more active role at the early stages of the building design process. This is due to the fact that the early design phases are associated with the exploration of alternative building forms, this commonly preceding the definition of the structural and mechanical elements that compose the building. However, in accordance with the integrated approach to the design process that was launched in the 1990's, the involvement of all stakeholders is vital for the successful accomplishment of the design process (Zimmerman 2006). At the early design stages, the collaboration of all stakeholders is essential not only for defining the candidate forms, but also for developing possible construction and operation scenarios, these representing the sources of design uncertainty – that will be eliminated later on in the design process.

The design variables that have been considered can be found in table 1, these constituting influential – as identified in the literature – design parameters. As all the solutions have equal chance of being selected, the variables are treated as having a uniform probability distribution, with their possible values having been specified with the help of building standards and guides, as well as real-world consideration. In addition to building form, 7 design variables have been selected due to their effect on the design criteria: wall construction; roof construction; infiltration rate; glazing type; heating

setpoint; heat recovery; and humidification. With respect to the wall and roof constructions, 4 types have been selected for each element, with two options complying with the Approved Document L2A of the UK Building Regulations for new buildings other than dwellings (UK Government 2013) and the remaining two options with the Passivhaus Standard (Mead and Brylewski 2010) (referred in the table as PL and PH, respectively). The two options that are compliant with each building standard have similar U-values but different thermal weights (heavyweight (HW) and lightweight (LW) constructions), this helping assess the impact of thermal mass on optimum performance.

The values of the infiltration rate and the glazing type have also been chosen based on the requirements of the two standards, while Spon's Architects' and Builders' price book (AECOM 2015) has been consulted to ensure that all constructions consist of commercial products. In addition, it helped link each design solution to the capital cost of the building envelope, this constituting one of the optimization criteria. Heating setpoint values have been defined based on CIBSE Guide A (CIBSE 2006), while on/off values have been included for both heat recovery and humidification, these being only applied during the occupied hours of the (winter) heating period. Further, "enthalpy" is the selected type of heat recovery, this indicating that "there is latent and sensible heat recovery whenever the exhaust air enthalpy is more favourable than the outdoor air enthalpy" (U.S. Department of Energy 2016b).

Considering the variation in building performance due to the uncertainty in boundary conditions, 2 more variables have been added to the list of input uncertainties, these referring to the occupancy profile and weather template. 2 values have been assigned to each variable to represent possible scenarios for the occupant density and weather data, respectively. More specifically, the two weather files that have been used in this study correspond to the test reference year (TRY) and the design summer year (DSY) as provided by CIBSE (2009) (for the same location), with the first file being used for ensuring the compliance with the UK Building Regulations Part L (UK Government 2013), and the latter for investigating the risk of overheating.

Since an exhaustive search method is used to explore the design space, a total number of 9216 simulations need to be run (3 buildings forms x 4 wall constructions x 4 roof constructions x 2 infiltration rates x 2 glazing types x 3 values for heating setpoint x 2 values for heat recovery x 2 values for humidification x 2 occupancy profiles x 2 weather files).

Design objectives

Having run the 9216 simulations using EnergyPlus (U.S. Department of Energy 2016a) as a simulation engine, the resulting set of design solutions and boundary conditions are post-processed – with the help of programming – to identify robust Pareto-optimum designs that minimise the value of four objectives (underheating; overheating; heating energy demand; and capital cost).

With respect to thermal comfort, Fanger's PMV model is used to assess the indoor environment of the building during the occupied winter/ conditioned period, with the underheating hours indicating the period of time that the PMV is less than -0.5. Fanger's thermal comfort model cannot however be used to evaluate the environmental conditions during the free-running summer mode, as it is not widely acceptable in the case of naturally ventilated buildings due to the notable discrepancies that have been observed between its predictions and the actual comfort temperatures in free-running buildings (de Dear and Brager 2002). Hence, the adaptive model of ASHRAE Standard 55 (ASHRAE 2013) is used to investigate the acceptability of indoor temperatures for the occupied summer/ non-conditioned period, with the overheating hours expressing the period of time that less than 80% of the occupants find the thermal environment acceptable.

The heating energy demand is calculated in kWh per m^2 to express the normalised per floor area space heating demand, this being a result of the EnergyPlus (U.S. Department of Energy 2016a) simulation. Capital cost is similarly normalised to indicate the cost of the building envelope per floor area. A bespoke model has been implemented to calculate the capital cost of all candidate design solutions, with the cost values of individual materials having been specified upon Spon's price book (AECOM 2015).

Approach to robust design exploration and decision-making under uncertainty

There are two sources of uncertainty associated with the building design process: uncertainty in the choice of an optimum design solution (that is, the choice of building form, construction, and operation); and uncertainty in the performance of the selected design solution (in this study, this being due to the uncertainty in the weather conditions and occupant density). The optimization process described here reduces the uncertainty in the selection of an optimum solution, and ensures that the solution remains optimal regardless of the uncertainty in the building performance prediction.

Having created the candidate building forms and defined the range of the unknown parameters, an exhaustive search is used to generate all possible combinations of design solutions and uncertain boundary conditions. Given the computational demands of the exhaustive search method, the performance of the candidate design solutions have been simulated concurrently in order to limit the computation time. The new approach to robust decision-making that is applied to all solutions is:

1. For each combination of the specified uncertain boundary conditions (4 in this paper), find the Pareto set of design solutions.

2. For each design solution (i.e. combination of design parameter values), count the number of uncertain scenarios for which the solution is Pareto optimal. If this equals the total number of boundary condition scenarios, the robustness of the solution with respect to the performance uncertainty is maximum, as the design remains

optimal regardless of the considered boundary conditions.

This approach can thus support robust decision-making, as it compares and ranks candidate solutions based on an objective metric that evaluates their optimality and its insensitivity to the uncertain boundary conditions, this replacing the subjective intuition of the decision-makers (DMs). However, as the suggested approach provides the DMs with a set[2] of robust optimum design alternatives, their preferences play an important role in the selection of a suitable design solution. Preferences for a specific solution may also be critical for the definition of form, this explaining the bottom-up character of the approach. As an example, a bias for a lightweight construction that complies with the UK Building Regulations Part L (UK Government 2013) may imply that there is a single form that can be selected, this being the only alternative that is Pareto optimal and insensitive to the uncertain boundary conditions for this type of construction. Even in the case that there are no solid preferences for a particular option, the suggested approach can help reveal the implications of potential decisions through the investigation of what-if scenarios. Answers can hence be given to questions such as how a change in construction (e.g. from Part L to Passivhaus) affects the design objective function(s).

However, according to the traditional design process, geometry commonly precedes the remaining elements of the building. In this case, design process begins with the definition of the form, this subsequently informing the additional elements that assemble the building. This top-down approach to design thus implies that the selection of form goes ahead of the definition of the construction and operation parameters. However, in order to eliminate the risk of selecting a building form that is sensitive to the uncertain boundary conditions for all possible design options, robustness relating to performance uncertainty should be examined.

The robustness of the optimized form in relation to the design parameters (construction and operation options), can be examined by adding a third step to the robust decision-making process:

3. For each form that has been found (from the previous steps) to be optimum and insensitive to the uncertain boundary conditions for at least one design option[3], count the number of design solutions for which the form is Pareto optimal. If this is equal to the total number of design options, the robustness of the form concerning the design uncertainty is maximum, as the form remains optimal regardless of the combination of design parameter values.

The selection of a particular building form can also be informed through the application of classical decision rules that provides the DMs with additional information on the performance of candidate building forms and thus supports decision-making (Rysanek and Choudhary 2013). For a design problem where all design objectives are to be minimised, the applied decision rules are:

a. Minimin criterion. Select the candidate form with the minimum payoff[4].

b. Laplace's criterion. Select the candidate form with the minimum average payoff.

c. Wald's criterion. Select the candidate form with the least worst payoff.

d. Savage's criterion. Select the candidate form with the least worst opportunity loss.

The goal of the first rule (a.), is to minimise payoff without any regard for risk, with the DMs thus having to spot the minimum payoff for each candidate form – and each design objective – and subsequently the minimum of those. The second decision rule (b.), aims to reduce average payoff, with the minimum average value being similarly identified. However, as indicated by Zang *et al.* (2005), the goal of robust design is not only to minimise the value of the objective function(s), but also to reduce the variation (spread) in performance that is triggered by the different sources of uncertainty. Taking into account the risk of the worst performance, Wald's criterion (c.), aims to minimise the least worst payoff, with the DMs having to identify the worst performance for each candidate form, and then the minimum of those. Finally, the aim of Savage's criterion (d.), is to minimise the opportunity loss, this implying the implementation of the following steps: identify the minimum payoff for all candidate forms; subtract it from each payoff to calculate opportunity loss (regret); find the maximum value for each building form; and select the minimum of those.

Results and Discussion

The three-stage process described here has been applied to the example building optimization problem. The first two stages treat the building form as a design variable, and identify design solutions that are Pareto optimal for each uncertain boundary (performance) condition; the robust solutions are the solutions that are Pareto optimal for all the uncertain boundary conditions. The solution frequency across the uncertain performance conditions for the case-study building is illustrated in figure 2. Out of the 2304 design solutions that have been evaluated (768 for each candidate building form), 2105 solutions were found to always be dominated and therefore sub-optimal, while the remaining 199 were optimal for at least one uncertain performance scenario.

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[2] This is due to the existence of multiple design criteria and the intention for design freedom and flexibility.

[3] Some candidate forms may prove to be sub-optimum and/or sensitive to the uncertain boundary conditions for all design options. In this case, they are excluded from any further exploration at the upcoming stages.

[4] Payoff here refers to the performance outcome of the building form assuming a specific combination of design options and uncertain boundary conditions.
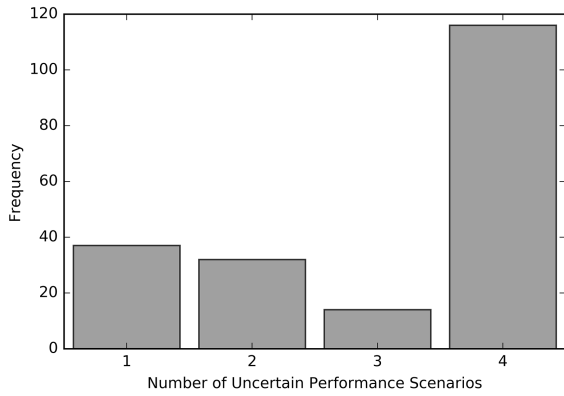
Figure 2. The solution frequency across the uncertain performance conditions for the case-study building.

Figure 3. The form frequency across the 116 optimum and insensitive to boundary conditions solutions.

More specifically, 37 solutions were optimal for one uncertain scenario; 32 for two; 14 for three; and 116 for all four performance scenarios (these 116 being the robust Pareto-optimal solutions). Figure 3 illustrates the frequency of each form across the 116 design solutions. As indicated in the figure, form one (green) remains optimal for 62 design options; form two (blue) for 42; and form three (red) for 12. No single form is optimal for all of the optimized solutions.

However, even though this histogram can inform the DMs about the frequency that each form is optimal, it cannot give an idea of the output variation due to the input uncertainties, and/or the relationship between the considered design objectives. This information can be provided in figure 4 that demonstrates the trade-off
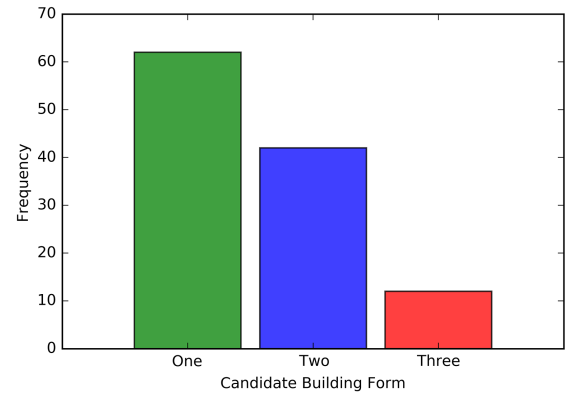
between the four conflicting objectives (underheating; overheating; heating energy demand; and capital cost). Note that, even though more than two objectives have been considered, trade-offs are still visualised two-dimensionally as scatter plots for the pairs of the four objectives – and for all the design options and uncertain boundary conditions. Each circle represents one design solution (out of the 2304 total solutions), while each star symbolises one robust optimum solution (out of the 116 robust solutions). In addition, as four uncertain boundary conditions are considered in this study, the number of the illustrated (in figure 4) circles and stars are quadruple (i.e. four possible performance outcomes are attributed to each design solution). Green, blue, and red colours are used to denote the candidate form that the performance
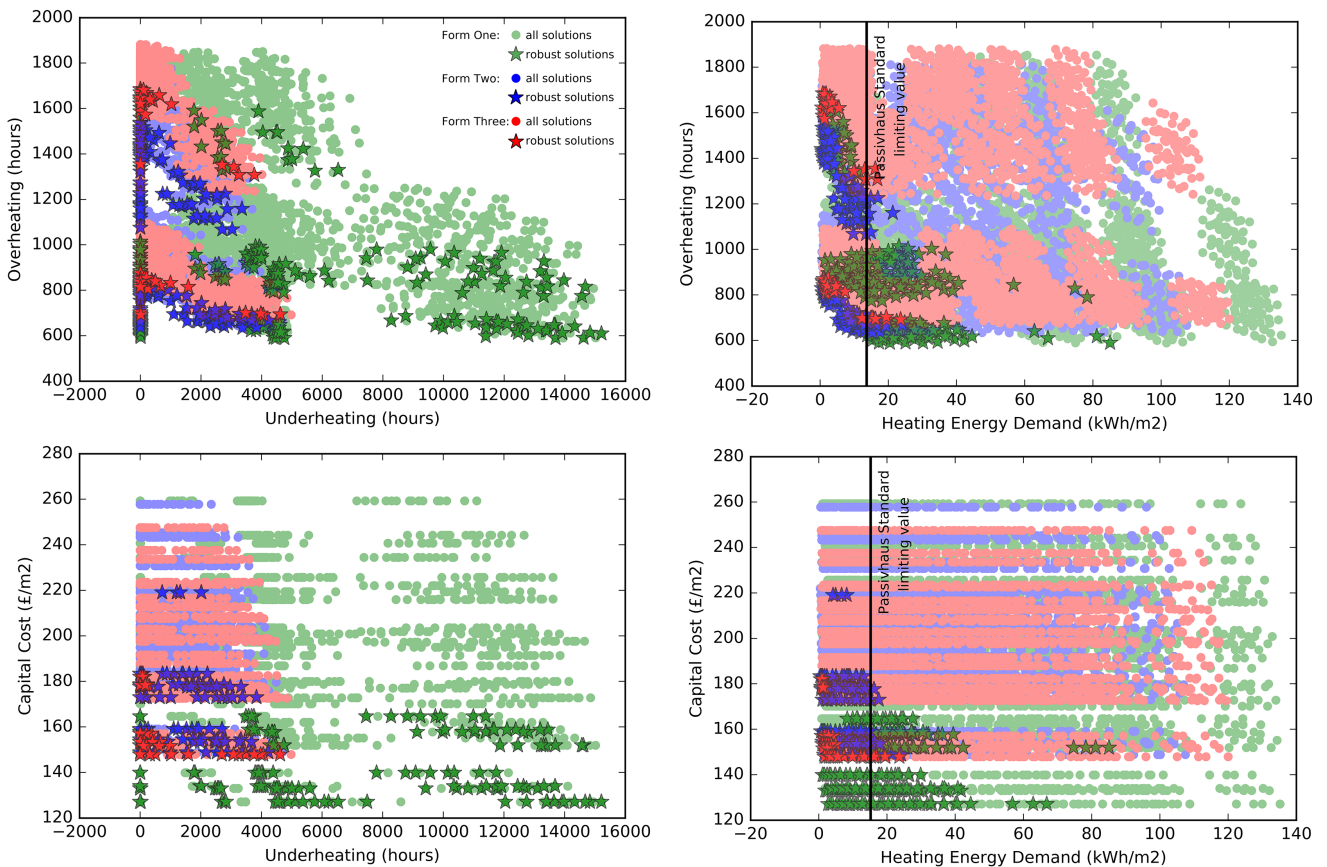

Figure 4. The trade-off between the four design objectives (in pairs).

outcome is associated with (form one, two, and three respectively, as displayed in figure 1).

In order to support decision-making, the output could be further analysed taking into consideration the classical decision criteria (Minimin; Laplace; Wald; and Savage). Starting with the Minimin criterion, attention should be paid to the minimum value of each objective function. As observed in the scatter plots of figure 4, the minimum value of underheating hours is 0, this occurring for several design solutions for all three candidate forms. With respect to overheating, the minimum value is only observed for form one and is approximately 590 hours (cumulatively for all building thermal zones), a value that is equivalent to the 3% of the total summer occupied hours. Form one also leads to the lowest capital cost (£127 per m^2 of floor area), while, along with the remaining two forms, it also results in almost net zero heating energy demand.

Focusing on Laplace's criterion, the minimum average value needs to be identified for each objective. Form two appears to result in the minimum average underheating hours as well as heating energy demand, while form one leads to the minimum average payoff for overheating and capital cost – for all the design options and uncertain boundary conditions. With respect to Wald's criterion, form two is associated with the least worst payoff for all objectives except for capital cost, for which the least worst value comes of form three. Similarly, concerning Savage's criterion, the least worst opportunity loss is provided by form two for all objectives excluding cost, for which the minimum regret results from form three. The ranking of the three candidate forms according to the aforementioned decision rules is displayed in table 2, this acting as an additional material that can assist the DMs in informing and guiding the design process.

Conclusions

In the context of design exploration and decision-making under uncertainty, a new approach has been developed, this being able to help the DMs assess the performance of candidate design solutions, and identify robust Pareto-optimum solutions that remain optimal regardless of the uncertainty in the behaviour of boundary conditions. By coupling optimization and UA, the suggested approach can thus provide the DMs with robust solutions that are optimum and insensitive to the performance scenarios that are associated with the considered design stage. As the resulting set of solutions are all optimum, it can also help reduce risk in decision-making while handling the multi-criteria nature of the building design process by simultaneously satisfying several design objectives.

This is also facilitated by the application of an exhaustive search method that – in contrast to many optimization algorithms – is not limited by the increased number of design objectives. In addition, given the fact that it provides the maximum possible information for analysis, it can also increase the understanding of the relationship between the design solutions and the design objectives, and thus inform the decision-making process. In an effort to limit the design space and therefore the computational load, design variables have been selected based on their influence – as resulted from the literature – on the design objectives, while their values have been informed by the project brief, the building standards and guides, and real-world consideration. Finally, in order to incorporate qualitative measures, predefined forms have been included to the explorative process, these being in accordance with the aesthetical preferences of the client and the design team.

The applicability of the new approach has been verified through its implementation to a real-world case-study building, this being a new community centre to be built in the UK. Out of a total number of 2304 design options, 116 solutions have been identified as being optimum and insensitive to the uncertain performance conditions, with more than half of them corresponding to the first (out of three) candidate forms. The application of four classical decision rules (Minimin; Laplace; Wald; and Savage) has provided additional information on the performance of the candidate forms. Even though there is not a form that is best-performing in all rules, the resulted ranking of the three candidate forms can inform – along with the subjective preferences of the designers and the relative importance of the four design objectives (underheating;

Table 2. The ranking of the three candidate forms according to the different decision rules.

| Candidate forms | Decision rules | | | | | | | | | | | | | | | |
| | Minimin | | | | Laplace | | | | Wald | | | | Savage | | | |
	Underheating	Overheating	Heating Energy Demand	Capital Cost	Underheating	Overheating	Heating Energy Demand	Capital Cost	Underheating	Overheating	Heating Energy Demand	Capital Cost	Underheating	Overheating	Heating Energy Demand	Capital Cost
One	1	1	1	1	3	1	3	1	3	2	3	2	3	2	3	2
Two	1	2	1	2	1	2	1	3	1	1	1	2	1	1	1	2
Three	1	3	1	3	2	3	2	2	2	3	2	1	2	3	2	1

overheating; heating energy demand; and capital cost) – the decision-making process. Further research is required to investigate the implications of stakeholder preferences and decisions, as well as the limitations of the problem definition at the different design stages.

Acknowledgements

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