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A methodology for performance robustness assessment of low-energy buildings using scenario analysis

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Abstract

Uncertainties in building operation and external factors such as occupant behavior, climate change, policy changes etc. impact building performance, resulting in possible performance deviation during operation compared to the predicted performance in the design phase. Multiple low-energy building configurations can lead to similar optimal performance under deterministic conditions, but can have different magnitudes of performance deviation under these uncertainties. Low-energy buildings must be robust so that these uncertainties do not result in significant variations in energy use, cost and comfort. However, these uncertainties are rarely considered in the design of low-energy buildings and hence, the decision making process may result in designs that are sensitive to uncertainties and might not perform as intended. Therefore, to reduce this sensitivity, performance robustness assessment of low-energy buildings considering uncertainties should be assessed in the design phase. The probability of occurrences of these uncertainties are usually unknown and hence, scenarios are essential to assess the performance robustness of buildings. Therefore, a non-probabilistic robustness assessment methodology, based on scenario analysis, is developed to identify robust designs. Maximum performance regret calculated using the minimax regret method is used as the measure of performance robustness. In this approach, the preferred robust design is based on optimal performance and performance robustness.

The proposed methodology is demonstrated using a case study with a policymaker as the decision maker. The proposed methodology can be used by designers and consultants to aid decision makers in the design phase to identify robust low-energy building designs that deliver preferred performance in the future operation.

Keywords: Robust design; low-energy buildings; future scenarios; occupant behavior; performance assessment; robustness assessment; design decision making

Highlights

- A novel methodology for performance robustness assessment is proposed.
- Multi-criteria assessment is carried out using predicted performance and robustness.

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- The minimax regret method is used to identify robust designs.
- A multi-criteria decision making strategy is implemented to select robust designs.

1. Introduction

Energy efficiency and CO_2 emission reductions in buildings are typically achieved by improving building insulation levels, using energy efficient technologies and integrating renewable energy technologies in the built environment [1–3]. Considering the high economic efforts required for the implementation of these measures in the built environment, it is important to ensure that these measures deliver the preferred performance over the building's life span. However, in conventional design practice, building performance is predicted based on a set of assumptions about building operation. Many uncertainties arise in the operation of a building such as household size and their corresponding behavior and external factors, such as climate change and policy changes. These uncertainties in building operation, climate change and policies may influence the building performance, which could cause variations in energy use, operational costs and comfort. The potential impact of these uncertainties is very high in low-energy buildings [4,5] resulting in possible deviation during operation compared to the predicted energy performance in the design phase [6], and could also lead to thermal comfort issues such as overheating [7–11]. These uncertainties are rarely considered in the design of low-energy buildings and hence, the decision making process may result in designs that are sensitive to uncertainties [12,13] and might not perform as intended. To ensure intended performance, oversized energy systems are typically used in conventional design practice, which require high investment and operating costs [14,15]. Therefore, robust designs are essential to deliver preferred performance [14–16] at low costs and to attain robust designs, performance robustness taking into account these uncertainties should be assessed and considered during the design phase [17]. Performance robustness, in this work, is defined as the ability of a building to maintain the preferred performance under uncertainties arising from the building's operation and from external conditions.

1.1. Performance robustness assessment based on scenario analysis

In the building context, performance robustness assessment approaches are broadly categorized in two types – the probabilistic approach [18–20], where probabilities of uncertainties are assumed to be known, and the non-probabilistic approach [21–23], where probabilities of uncertainties are unknown. In many cases, the designer has limited or no information about the probability of the occurrence of uncertain situations, and it is thus difficult to quantify the associated risks. For instance, in most cases it is unknown during the design phase what type of households will occupy the building over its life span and what their corresponding behavior will be. Similarly, large uncertainties are associated with climate change projections [24,25]. In addition, it is difficult to probabilistically define uncertainties in the future economy such as electricity prices, policy changes etc. [22]. As such, one way to proceed is to use 'scenarios', which can be understood as formulated alternatives when probabilities of uncertainties are unknown [26,27] and can be used to integrate uncertainties into the performance robustness assessment [13,26]. Scenarios are used to present a range of possible alternatives so that the performance robustness of designs can be assessed based on how different designs perform in each of these alternatives [28]. For instance, using scenario analysis, the risk can be quantified based on an optimistic or a pessimistic approach using the best-case and the worst-case scenarios.

The non-probabilistic robustness assessment approach is typically used to identify robust designs through the use of scenarios. For instance, non-probabilistic decision rules have been implemented to identify robust building retrofits under technical and economic uncertainties by [22], and this research demonstrated that this approach was useful for scenario modelling and it allowed for easier identification of robust designs among other alternatives. Similarly, [21] carried out building performance robustness assessment considering scenarios dealing with uncertainties in user behavior. The preferred robust design using this method is more robust to user behavior but could result in very uncomfortable indoor temperatures, as observed in their previous study [29]. This overheating risk will be even higher in the future due to climate change [7,9,11,30] and hence, it is important to include uncertainties in climate change in the design process [31,32]. Climate change scenarios are included in performance robustness assessment by [11,23,33]. In the reported research, robustness assessment is carried out separately for user scenarios [21,23], technical and economic scenarios [22] and climate scenarios [11,23,33]. Furthermore, implemented robustness measures do not take all scenarios into account and the likely occurrence of any scenario is unknown in the future. In addition, a design that is robust to a scenario could be sensitive to other scenarios. As such, a performance robustness assessment considering all scenarios is essential. Different robustness assessment methods based on scenario analysis are compared to aid decision makers for selecting robust designs [34]. These methods include the max-min method, the best-case and worst-case method [13], and the minimax regret method [35] and it was found that the choice of a robustness assessment method heavily depends on the purpose and decision makers approach towards risk in decision making [34]. In this work, we implement a non-probabilistic robustness assessment approach based on scenario analysis that considers uncertainties in occupant behavior and external factors.

1.2. *Scope of this article*

It is clear from literature that there is a lack of a holistic methodology for performance robustness assessment considering future scenarios that aids decision makers in design decision support considering performance robustness among other performance indicators. In practice, the design decision making process is a complicated and difficult task, especially when it involves decision makers with multiple and conflicting performance requirements [36]. The difficulty of the decision making task increases significantly if uncertainties are also included, and this issue is rarely addressed in the building performance context [13]. It is important to assess robustness of designs considering multiple performance criteria under uncertainties arising from the building's operation (e.g. occupant behavior) and from external factors (e.g. weather conditions) in order to enhance confidence in design decisions [16]. Therefore, to bridge this methodological gap, this article proposes a computational methodology that integrates uncertainties in multi-criteria assessment using scenario analysis to quantify robustness and facilitate the selection of robust designs for decision makers. We implement multi-criteria performance assessment and multi-criteria decision making considering performance robustness and provide different methods of identifying robust designs using trade-off solutions and a multi-criteria decision making method. Furthermore, sensitivity analysis is carried out to identify the most influencing scenarios and to enable decision makers to take extra measures for reducing their influence. It is demonstrated how the proposed methodology can be used in the design process to identify robust designs and enhance design decision making. In this paper, the proposed methodology is applied to a case study for policymakers.

This paper is organized as follows. In Section 2, the steps of the proposed computational performance robustness assessment methodology are described. The minimax regret method used to identify robust designs in the present context is also discussed in Section 2. In Section 3, the proposed methodology is demonstrated using a case study for a policymaker as the decision maker. The details of design space, future scenarios and performance indicators for performance robustness assessment are described in this section. Multi-criteria assessment and multi-criteria decision making approaches to select robust designs for the policymaker are also discussed in this section. The practical use of the proposed methodology is discussed in Section 4. A summary of the methodology along with main conclusions are presented in Section 5.

2. Proposed computational performance robustness assessment methodology

2.1 Overview

The proposed computational performance robustness assessment methodology is shown in Figure 1. Each step is described below and in further detail in the following subsections.

Step 1: Identify decision makers and based on decision maker's preferences define the following:

1a. Building design space

1b. Future scenarios

1c. Performance and robustness indicators

Step 2: Set up a building performance simulation model and simulate the performance of the design space for future scenarios with defined performance indicators.

Step 3: Multi-criteria performance assessment: Carry out performance assessment considering multiple performance indicators and corresponding robustness evaluated using a robustness assessment method.

Step 4: Multi-criteria decision making: Select robust designs for decision makers by prioritizing the performance indicators based on decision maker preferences.

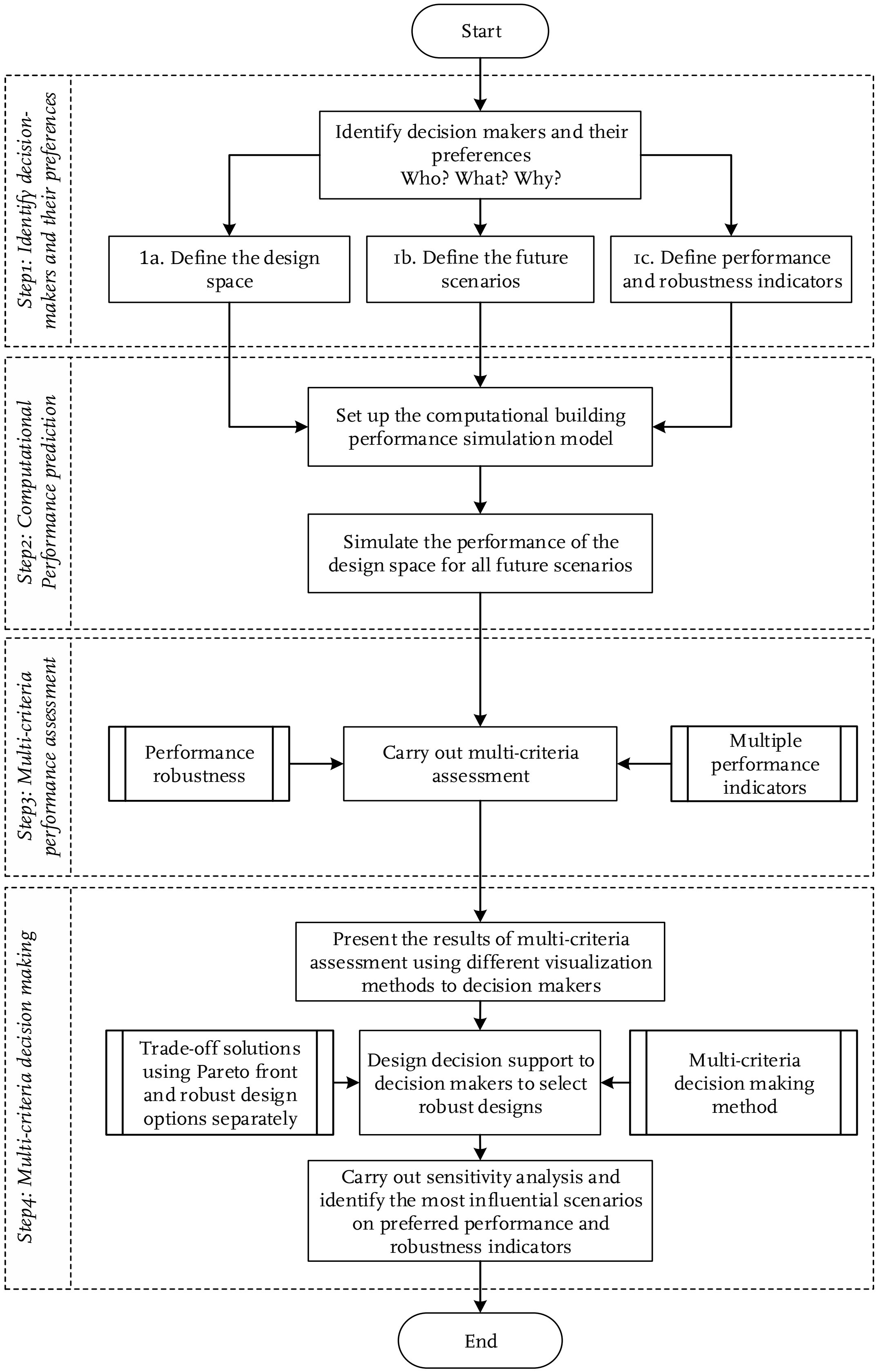

Figure 1 *Performance robustness assessment methodology.*

2.2 Detailed description of proposed methodology

Step 1: Identify decision makers and their preferences

The first step is to identify the end user of this methodology and their preferences. For instance, policymakers can use this methodology to define energy performance requirements in future building regulations to safeguard intended policy targets. They can also define policies considering performance robustness to support adaptations of current buildings to improve their performance robustness in order to extend their lifespan. Similarly, performance robustness is a relevant concern for homeowners, since they wish to ensure their preferred building performance over the building's lifespan. Energy performance contractors can benefit from performance robustness assessment by reducing the performance gap between predicted and actual operation. Similarly, by considering performance robustness, building designers and consultants can design and deliver more robust buildings, thus improving the satisfaction of their customers.

Step 1a: Define the building design space

The design space needs to be defined based on the requirements of the decision maker and on current and future building regulations such that the preferred design of a decision maker will also meet the criteria of building codes and regulations [37–40].

Step 1b: Define the scenarios

Scenarios need to be defined that consider all uncertain and influential parameters that can cause variations in the building's performance over its lifespan. Figure 2 provides an overview of scenarios that could be considered, e.g. different household sizes (referred as occupant scenarios) and their corresponding behavior (referred as usage scenarios) over the building's lifespan, external factors such as climate change (referred as climate scenarios) and policy changes such as feed-in-tariff prices (referred as policy scenarios). The combination of all these scenarios must be used in the performance robustness assessment as the likelihood of the occurrence of any of these scenarios is unknown. However, considering all scenarios results in very high computational cost, and thus a sampling strategy is desirable to find the smallest sample that represents all scenario combinations.

Step 1c: Define performance indicators

Define the performance indicators relevant to the decision makers. For instance, a policymaker prioritizes low or no CO_2 emissions associated with a building design, but not at the expense of high investment costs. In contrast, a homeowner prioritize designs with comfortable indoor environment at low investment and operating costs.

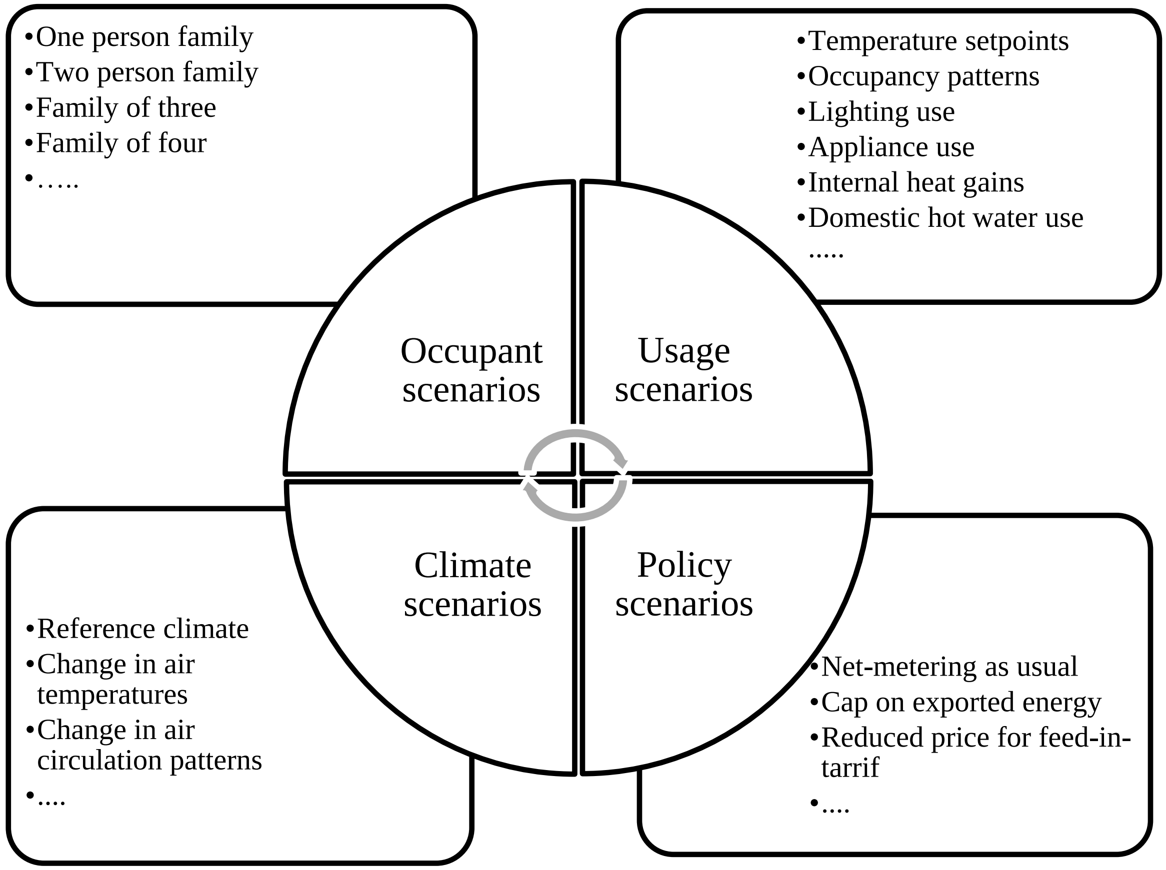

Figure 2 *Scenarios formulated based on uncertainties in (future) household size and range of occupant behavior, climate change and policy changes.*

Step 2: Performance prediction using building performance simulations

The performance of the design space is predicted for future scenarios by using a building performance simulation model. A detailed building and energy systems model used to predict thermal and energy performance of various designs is developed in TRNSYS [41]. The building and energy systems TRNSYS models are coupled with Mode Frontier [42] to carry out performance assessment of the design space for the formulated scenarios.

Step 3: Multi-criteria performance assessment

Step 3a: Multiple performance indicators

In practice, the decision maker with multiple performance requirements will be prepared to accept a trade-off solution. The decision maker will prioritize different performance indicators in the decision making process. For example, if the decision maker is a homeowner, then his/her design selection criteria will probably depend heavily on thermal comfort and operating and investment costs. This preference can be contrasted with, for example, a policymaker, who is more focused on CO_2 emissions.

All these performance indicators are compared against additional investment cost (design), which enables the decision maker to select a cost-optimal robust design or to accept a trade-off with respect to the other performance indicators and to the robustness of these performance indicators.

Step 3b: Performance robustness

In addition to predicted performance, performance robustness is also a primary criterion in the decision making process in this methodology. It is found that minimax regret method can be used if a decision maker is ready to accept certain risk as a trade-off [34], which is generally the case in residential buildings. For instance, a homeowner can accept designs with certain overheating hours as a trade off with operating costs and required additional investment cost. Therefore, the minimax regret method [35] is used for the performance robustness assessment in this study. This method is a combination of the minimax [43] and regret methods. This method has been widely used for robustness assessment in various fields [44–46] and has recently been used in the building performance context [22,34,47]. In this method, for a given scenario, performance regret is the performance difference between a design and the best performing design in that scenario. This is elaborated below. The maximum performance regret of a design across all scenarios is the measure of its robustness. The following steps are used to select the most robust design of a design space.

1. Assess the performance of designs (d_m) for all scenarios (S_n) using a performance indicator (PI).
2. Find the best performing design for each scenario by comparing the performance of all designs. In this work, we assume that the best performing (optimal) design is the one with the minimum performance for a scenario. For instance, as shown in Figure 3, designs d_m and d_i are the best performing (optimal) designs, among four designs, for scenarios S_1 and S_n respectively.

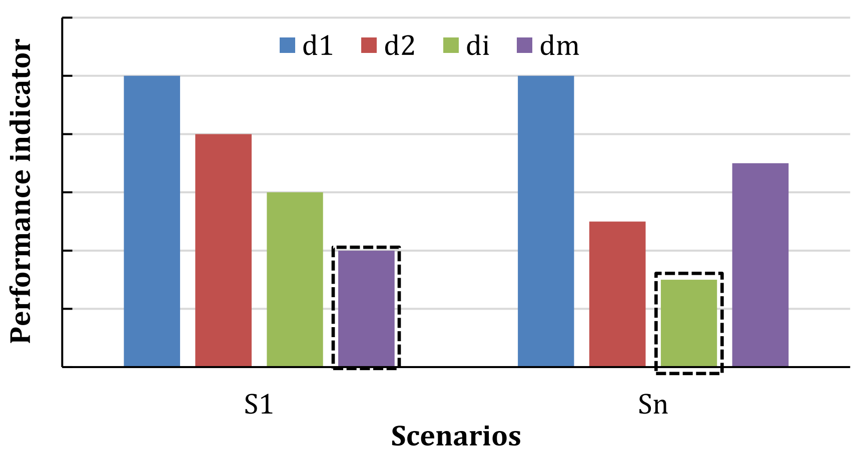

Figure 3 *Performance of various designs for scenarios S_1 and S_n with best performing /optimal designs indicated in dotted line.*

3. Calculate the regret (R) of a design for each scenario, as shown in Table 1. The regret is the performance difference between the design and the best performing design for a scenario. For instance, as shown in Figure 4, R_{11}, R_{21} and R_{i1} represent the performance regrets of designs d_1, d_2 and d_i respectively for scenario S_1. Similarly, R_{1n}, R_{2n} and R_{mn} represent the performance regret of designs d_1, d_2 and d_m respectively for scenario S_n. It is worth noting that designs d_m and d_i have zero regret for scenarios S_1 and S_n respectively.

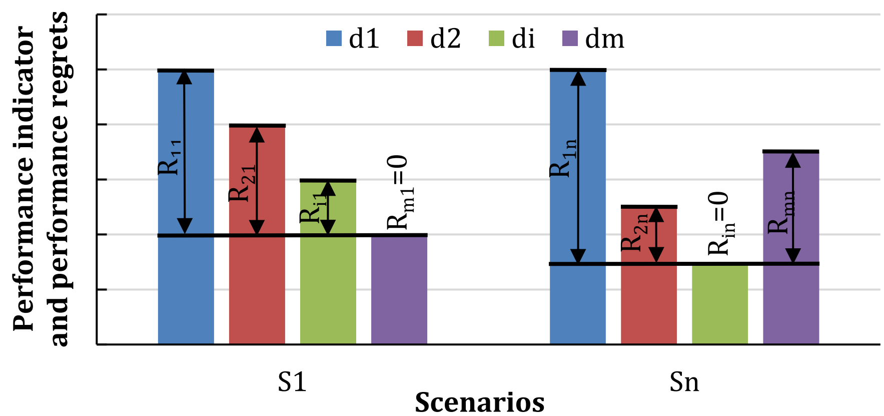

Figure 4 *Performance regret of various designs for scenarios S_1 and S_n.*

4. Find the maximum performance regret for each design across all scenarios. For instance, consider design d_m for scenarios S_1 and S_n (Figure 4), the maximum performance regret of design, d_m is R_{mn}.

5. The maximum performance regret is the measure of robustness; the lower the maximum performance regret, the higher the robustness. Therefore, the most robust design is the design with the lowest maximum performance regret, as shown in Table 1.

6. Repeat the steps 1-5 for other performance indicators.

Table 1 *Calculation of performance robustness of a design space across considered scenarios using the minimax regret method.*

	Scenarios					
Designs	**S_1**	**S_2**	**...**	S_j	**S_n**	
d_1	PI_{11}	PI_{12}	...	PI_{1j}	PI_{1n}	
d_2	PI_{21}	PI_{22}	...	PI_{2j}	PI_{2n}	
...	...	...	...	...	...	
d_i	PI_{i1}	PI_{i2}	...	PI_{ij}	PI_{in}	
d_m	PI_{m1}	PI_{m2}	...	PI_{mj}	PI_{mn}	
Minimum performance for each scenario (A)	$A_1 = \min (PI_{11}, PI_{21}, \ldots PI_{i1}, PI_{m1})$	$A_2 = \min (PI_{12}, PI_{22}, \ldots PI_{i2}, PI_{m2})$	...	$A_j = \min (PI_{1j}, PI_{2j}, \ldots PI_{ij}, PI_{mj})$	$A_n = \min (PI_{1n}, PI_{2n}, \ldots PI_{in}, PI_{mn})$	
	Performance regrets (R)					
	S_1	**S_2**	**...**	**S_j**	**S_n**	Maximum performance regret (**Rmax**)
d_1	$R_{11}=PI_{11}-A_1$	$R_{12}=PI_{12}-A_2$	...	$R_{1j}=PI_{1j}-A_j$	$R_{1n}=PI_{1n}-A_n$	$Rmax_1= \max (R_{11}, R_{12},\ldots R_{1n})$
d_2	$R_{21}=PI_{21}-A_1$	$R_{22}=PI_{22}-A_2$	...	$R_{2j}=PI_{2j}-A_j$	$R_{2n}=PI_{2n}-A_n$	$Rmax_2= \max (R_{21}, R_{22},\ldots R_{2n})$
...	...	...	...	...	...	...
d_i	$R_{i1}=PI_{i1}-A_1$	$R_{i2}=PI_{i2}-A_2$	...	$R_{ij}=PI_{ij}-A_j$	$R_{in}=PI_{in}-A_n$	$Rmax_i= \max (R_{i1}, R_{i2},\ldots R_{in})$
d_m	$R_{m1}=PI_{m1}-A_1$	$R_{m2}=PI_{m2}-A_2$	...	$R_{mj}=PI_{mj}-A_j$	$R_{mn}=PI_{mn}-A_n$	$Rmax_m=\max (R_{m1}, R_{m2},\ldots R_{mn})$
	The most robust design					min(Rmax)

Step 4: Multi-criteria decision making

Step 4a: Trade off solutions using Pareto front

In multi-criteria performance assessment considering multiple performance indicators, a set of Pareto optimal solutions is obtained, thus enabling decision makers to trade off among alternative design solutions based on their preferred choice of performance indicators and their corresponding robustness. This multi-criteria assessment enables different decision makers to choose robust designs from a large design space. Each decision maker could choose different robust designs in the same design space. It is difficult to visualize two or more performance indicators and corresponding performance robustness because doing so results in a multi-dimensional Pareto front. Hence, in this work, different visualization methods are presented to enhance the decision making process.

The design options of all Pareto solutions are compared to provide an overview of the different design options of the entire Pareto front to aid decision makers when choosing which design options lead to optimal performance and robust design.

Step 4b: Multi-criteria decision making (MCDM) method

To choose a robust solution from among a set of available solutions for all decision makers, we adopt the MCDM method based on the Savage criterion [35]. Using this method, a design score (0-1) is calculated [42] by normalizing the preferred performance and robustness indicators. The design that has the highest score is the most robust.

Step 4c: Sensitivity analysis

In order to provide additional information to decision makers about the influence of scenarios on Pareto solutions, sensitivity analysis is carried out using the statistical Mann-Whitney U test to identify the most influential scenarios [48]. The sensitivity index (*p*) determines whether the influence of two samples of a scenario (e.g. low and high IHG) on a performance indicator differ significantly from each other or not. In this study, scenarios in which $1-p>0.95$ are assumed to be sensitive [49].

3. Demonstration of methodology using a case study with a policymaker as the decision maker

Description of case study building

A semi-detached terraced house, a typical Dutch residence [37,50], was chosen as the case study building. It is a three-story building with a gross surface area of 124 m^2 and a treated floor area of 104 m^2 (for the building layout, see Figure a in the appendix). The building is constituted by heavyweight floor, wall and roof constructions. The external walls consist of brick (100 mm), air cavity (25 mm), insulation and brick (100 mm). The ground floor is made of wood (20mm), concrete (150mm) and insulation. The roof is comprised of wood (20mm), insulation, cast concrete (100mm), and roof tiles. The insulation thickness of external walls, ground floor and roof are varied to obtain different thermal resistance (Table 2) for different design options. Internal walls are made of gypsum board (12mm), insulation (75mm) and gypsum board (12mm). The insulation thickness of internal walls is the same for all design options. The south and north walls have identically sized windows of about 12m^2 on each façade, which is approximately a 40% window to wall ratio (WWR). In addition, the roof facing north has a window of 1.4 m^2, but this window is not considered while varying window to wall ratio for different designs (Table 2) since it is too small to yield significant results. Each of these windows is shaded by its own external shading device to reduce glare and overheating in summer. The building is ventilated using balanced mechanical ventilation with a heat recovery unit, with an efficiency of 90%. Heat recovery is bypassed when the room temperature (Ti) is greater than the heating setpoint and when the ambient temperature (T_a) is greater than room temperature. To reduce overheating during summer, natural ventilation (free cooling) by opening windows is used instead of mechanical cooling. Windows are opened when the room temperature is greater than the ambient temperature and when the ambient temperature is less than the maximum allowable adaptive temperature limits proposed by [51].

An ideal heating system is assumed for heating. However, to convert the heating energy demand to the equivalent amount of electricity, a heat pump with a coefficient of performance (COP) of 3.5 is used. The domestic hot water (DHW) needs are met by a standalone solar thermal collector system with an auxiliary heater. A storage tank of 200 liters with an auxiliary immersion heater of 2KW capacity is used in this study. It is an all-electric building and the total electricity consumption for heating, ventilation, DHW system, lighting, and appliances of the building is met by an onsite energy generation system. A photovoltaic system consisting of LG photovoltaic panels with a module efficiency of 18.3% and an Omnik inverter with a conversion efficiency of 97.5% were chosen for the onsite-energy generation system [52]. Each panel has a gross surface area of 1.64 m^2 and a peak capacity of 300 Wp. Both solar thermal collectors and photovoltaic panels are placed at a tilt angle of 43° facing south, which is also the slope of roof.

Step 1: Identify policymaker's preferences

The decision maker of this case study is a policymaker. The policymaker prefers a robust design that has low CO_2 emissions with low investment costs to enable the policy of providing subsidies for the implementation of CO_2 reduction measures for end users.

Step 1a: Define the building design space

Different design options, as shown in Table 2, are varied to form the design space. Some of the design options such as window type and insulation for roof, floor and wall are varied at the same time to form building envelope packages that meet different building codes and standards. For instance, P1 can meet the current Dutch building standards [39], P2 and P3 can meet Dutch nearly zero and zero energy building standards [37,53] and P5 can meet a Passive house standard.

Table 2 *Design parameter options considered in this study.*

Design parameter	Options				
Building envelope packages	***P1***	***P2***	***P3***	***P4***	***P5***
Rc-wall, m^2k/W	4.5	6	7	9	10
Rc-roof, m^2k/W	6	7	8	9	10
Rc-floor, m^2k/W	3.5	5	6	7	10
Windows U value, W/m^2K	1.43	1.01	0.81	0.68	0.4
WWR	[20, 40, 60]				

Infiltration, ach	[0.12, 0.24, 0.36, 0.48]
PV system, m^2	[3.2, 6.4, 9.6, 12.8, 16, 19.2, 22.4, 25.6, 28.8,32]
Solar DHW system, m^2	[0, 2.5, 5]

Other design options such as building airtightness and window to wall ratio (WWR) are varied as shown in Table 2 for all building envelope packages. Similarly, the size of PV panel is varied from $3.2m^2$ to $32m^2$. It should be noted here that the maximum size of PV system is limited by the available roof area on the south surface. Three sizes of solar domestic hot water system, as shown in Table 2, are considered for each building envelope package. In practice, it is generally the case that several design configurations (Table 2) lead to similar optimal performance under deterministic conditions, but these configurations can have significantly different magnitudes of performance deviation for formulated scenarios. Hence, preferred design is based on optimal performance and performance robustness.

Step 1b: Define future scenarios

Scenarios are defined considering uncertain and influential parameters that can impact CO_2 emissions of a building over its lifespan. The following occupant, usage and climate scenarios are considered in this study.

i. *Occupant scenarios*

Four occupant scenarios are formulated based on Dutch household statistics [54]. The first scenario, a single person, represents 37% of the Dutch households. The second scenario, a two-person family, accounts for 33% of the Dutch households, as shown in Figure 5. Similarly, for occupant scenarios 3 and 4, families of three and four persons occupy the building respectively. The main difference between these scenarios is the heat gain due to the number of occupants and their corresponding behavior in the building.

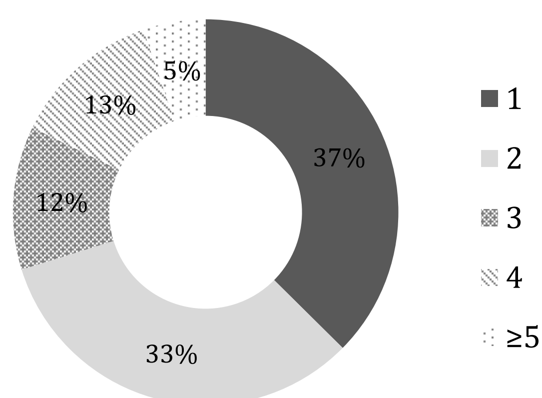

Figure 5 *Percentage of dwellings occupied by different household sizes.*

ii. Usage scenarios

For each of the occupant scenarios, usage scenarios are formulated based on energy usage in the building. These usage scenarios span very careful energy users to energy-wasting users, and cover different types of equipment with low to very high efficiencies. For instance, 1W/m² average electricity use for appliance represents very careful energy users and also highly efficient equipment.

Occupancy patterns, heating setpoint temperatures, lighting and appliance use, ventilation rates, domestic hot water consumption and shading control are varied for usage scenarios, as shown in Table 3. Occupancy patterns and the corresponding heating setpoints are chosen based on [55]. The evening occupancy profile represents 19% and the all-day occupancy profile accounts for 48% of the Dutch households respectively [55]. The heating setpoint temperature is varied form 18-22°C during occupied hours and reduced to 14-18°C during unoccupied hours, as shown in Table 3. Three scenarios are considered for average electricity use for lighting and appliances. Each scenario has a similar usage profile for occupancy pattern but differs in peak loads, resulting in different average electricity consumption. For the average scenario, electricity consumption for lighting [50,56] and appliances [57] is in line with average electricity consumption of Dutch households of about 3500 kWh for lighting and appliances [58]. Internal heat gains (IHG) due to lighting, appliances etc. is varied, in combination with appliance use and lighting use, from 2 to 6 W/m² based on [21,59]. Lighting, appliance use, and their corresponding internal heat gains are triggered in proportion to hourly occupancy profiles and reduced to base load (standby mode) when idle. Domestic hot water consumption is varied from 40 l/day to 100 l/day per occupant for different usage activities based on [59,60] and [61]. Examples of IHG and DHW profiles are given in appendix Figures b and c, respectively. A minimum ventilation rate of 0.9 ach, regardless of infiltration rates, is maintained in the building as decreed by Dutch building regulations, and the ventilation rate is increased up to 1.5 ach for the high usage scenario. Shading control (by occupants) of external shading devices of windows is implemented based on radiation levels on the façade and indoor temperature [62].

iii. Climate scenarios

Four scenarios for future climate change in the Netherlands, proposed in 2006 by the Dutch Royal meteorological institute [24], are used in this study. Climate change scenarios are based on global mean temperature rise and changes in atmospheric air circulation patterns in comparison to values in 1990. In these four climate change scenarios (Table 3), scenario G represents a moderate increase of global temperature of +1°C in 2050, whereas scenario W represents an extreme case of an increase of +2°C in 2050 relative to 1990. Scenarios G and W do not consider changes in air circulation patterns. In contrast, scenarios G+ and W+ include changes in air circulation patterns along with a rise in global mean temperature. In addition to climate change scenarios, a typical climate reference year, NEN 5060 [63], is considered (Table 3). This climate scenario is based on average months of 20 years of historical weather data. Hourly weather data generated for all climate scenarios is used in the simulations.

It is worth noting that some of the scenarios are varied together. For instance, internal heat gains due to lighting and appliances are varied in proportion with electricity use for lighting and appliances.

Table 3 *Summary of future scenarios considered in this study.*

Parameter	Options	References
Occupant scenarios		
Household size	[1, 2, 3, 4]	[54]
Usage scenarios		
Occupancy profile	Evening, All-day	[55]
Heating setpoint (occupied), °C	[18, 20, 22]	[55]
Heating setpoint (un-occupied) *, °C	[14, 16, 18]	[55]
Average electricity use for lighting, W/m²	[1,2,3]	[50,56,58]
Average electricity use for appliances, W/m²	[1,2,3]	[57,58]
Internal heat gains due to lighting and appliances (IHG)*, W/m2	[2, 3, 4, 5, 6]	[21,50,56–59]
Domestic hot water consumption (DHW), l/person per day	[40, 60, 100]	[59–61]
Ventilation, ach	[0.9, 1.2, 1.5]	[21]
Shading control ON if radiation is above, W/m² and if T_{indoor} >24°C	[250, 300, 350]	[62]
Shading control OFF if radiation is below*, W/m² and if T_{indoor} <24°C	[200, 350, 300]	[62]
Climate scenarios		
Reference climate and climate change	[NEN5060, G, W, G+, W+]	[24,63]

* This scenario is varied together with the previous scenario

Step 1c: Define performance indicators

The following performance indicators are used based on the policymaker's preferences:

i. *CO_2 emissions*

CO_2 emissions are calculated, as shown in equation 1, based on energy imports and exports by the building to and from the grid respectively.

$$CO_2 emissions = (El_{imp} \times f_{CO2,El}) - (El_{exp} \times f_{CO2,El}) \quad (1)$$

An emission factor of electricity ($f_{CO2,El}$) of 0.540 kgCO_2 per kWh of electricity is used to calculate CO_2 emissions due to electricity imports (El_{imp}) and avoided CO_2 emissions due to electricity exports (El_{exp}) [57]. Same emission factors are used for imported and exported electricity, as the exported electricity is assumed to replace equivalent electricity production by the grid. It is worth noting that the embodied emissions are not included in emissions calculation and thus CO_2 emissions in this study are only operational CO_2 emissions.

ii. Additional investment cost

Additional investment cost of a design is the sum of the investment cost of design options such as insulation packages, windows, solar DHW system and PV system. Fixed costs for all designs e.g. land, labor etc. are not considered, and thus only the costs that are incurred by varying design options compared to a design with no insulation and onsite renewable energy generation systems are considered. Hence, investment cost is referred to as additional investment in this work. The cost of the balanced mechanical ventilation system is the same for all design options and is therefore discarded in the calculations. The cost of the heat pump is calculated based on the peak heating load of a design. A range of investment costs for different design options is tabulated in Table a in the appendix.

Step 2: Performance prediction using building performance simulations

The building model, developed in TRNSYS, is divided into three thermal zones to enable the calculation of the temperature and energy demand of each zone. The living room and kitchen on the ground floor form the first zone, three bedrooms and bathrooms on the first floor constitute the second zone, and the attic on the second floor is the third zone. Ventilation, PV and solar DHW system models were also built in TRNSYS. The performance of the design space (Table 2) should be assessed for all scenarios (Table 3), however, all scenario combinations lead to 29160 scenarios, and the performance assessment of the entire design space for all these scenarios is computationally very expensive. To reduce the computational time and associated costs, we use a sampling strategy. A sample that has similar performance in all scenario combinations is selected based on convergence i.e., mean performance [64]. However, for performance robustness assessment, the performance range or distribution is vital in order to select the sample size. It is assumed that extreme scenarios (low-high scenarios) can cause this performance range. Hence, predicted performance and maximum performance regret of few designs is compared for all scenario combinations and combinations of low-high scenarios, to evaluate if low-high scenario combinations are sufficient for performance robustness assessment for the policymaker. Figure 6 shows a comparison of predicted performance and performance regrets of CO_2 emissions of three designs for all scenario combinations and of low-high scenario combinations. The three designs (designs A-B) have building envelope packages of P1, P2 and P5 with corresponding PV systems of 32 m², 25.6 m² and 16 m² respectively. In addition, infiltrations rates of designs A-B are 0.48 ach, 0.36 ach and 0.12 ach respectively. The three designs have a WWR of 40% and a solar DHW system of 2.5 m².

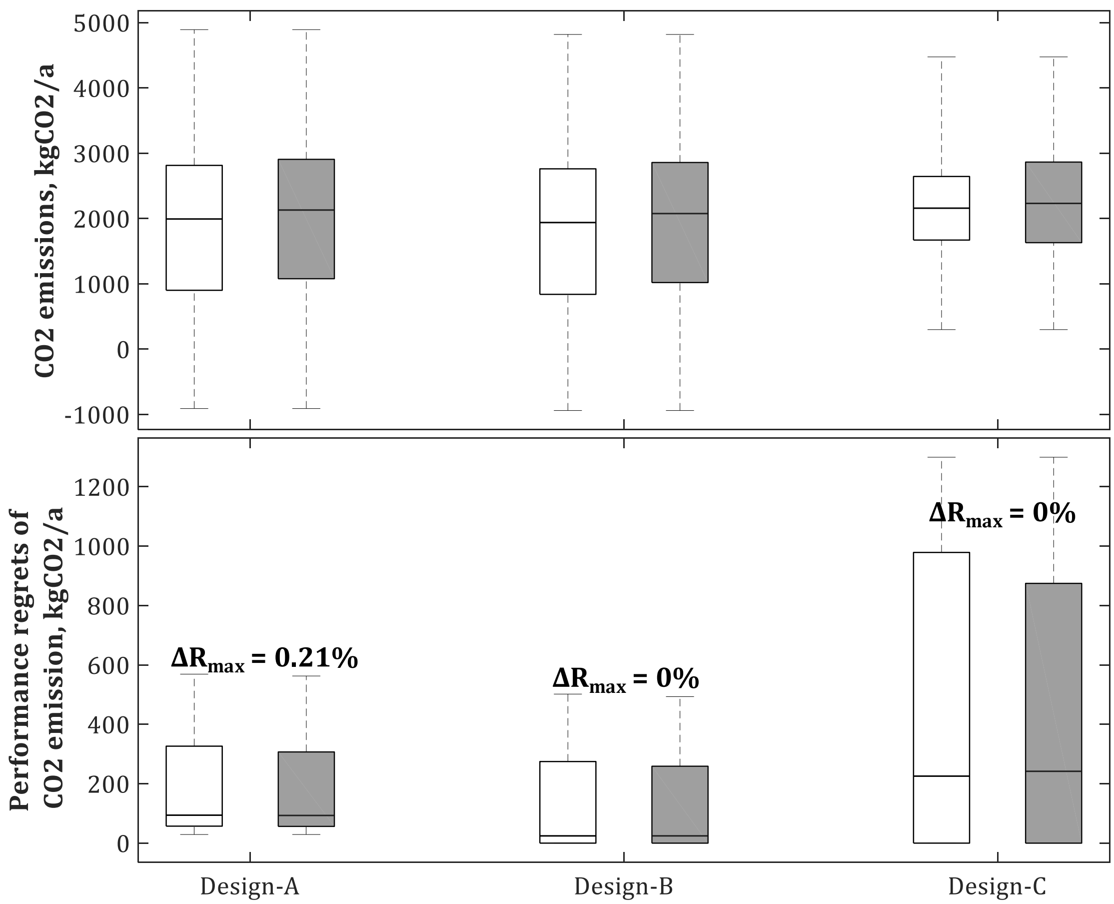

Figure 6 *Comparison of predicted performance and performance regrets of CO_2 emissions of three designs for combinations of all scenarios and low-high scenarios. The white box represents low-high scenario combinations and grey box represents all scenario combinations.*

It can be observed from Figure 6 that the range of predicted performance and performance regrets with low-high scenario combinations is similar to that of all scenario combinations. In comparison to all scenario combinations, the relative deviation of maximum performance regret (ΔR_{max}) of low-high scenario combinations is close to 0% for all performance indicators of three designs. Furthermore, both combinations of scenarios yield the same robust design i.e. design-B, which has better predicted performance and the lowest maximum performance regret compared to the other two designs. Therefore, low-high scenario combinations are sufficient for performance robustness assessment in this case study, when policymaker is the decision maker. Performance robustness assessment of the design space is carried out with low-high scenario combinations, which reduces computational time by about 98% compared to assessing all scenario combinations. The performance details of the design space are discussed in the next section.

Step 3&4: Multi-criteria performance assessment and multi-criteria decision making

i. Trade off solutions using a Pareto front

Figure 7 shows additional investment costs, CO_2 emissions and the corresponding performance robustness (maximum performance regret) of the design space for policymaker. The additional investment cost required for a design is shown on the X-axis to allow the decision maker to trade off additional investment cost with predicted performance and performance robustness of the design. Each bubble represents a median value of CO_2 emissions of a design across the considered scenarios, and the bubble size depicts the maximum performance regret of CO_2 emissions. The smaller the bubble size, the more robust is the design. In this work, the median value of a performance indicator across the considered scenarios is used to represent the predicted performance. The designs with CO_2 emissions less than or equal to zero are carbon neutral designs, and negative emissions are avoided emissions by the design. Pareto front, indicated in red color, is calculated considering additional investment costs, CO_2 emissions and maximum performance regret of CO_2 emissions as objectives.

The policymaker prioritizes a design with low CO_2 emissions and the lowest maximum performance regret, and can trade off with additional investment cost. It can be observed from Pareto front that the designs in the additional investment cost ranging from 18-26 k€ result in high CO_2 emissions and corresponding maximum performance regret (bigger bubble size), and are thus not preferred robust designs. Conversely, the designs in the additional investment cost range of 31-39 k€ result in low CO_2 emissions and smaller bubble size, and are thus more robust and more preferred designs. However, these designs incur high additional investment costs. Therefore, the preferred robust design of the policymaker depends on the required additional investment cost of the design. This is elaborated further by comparing few designs (Figure 8) that are selected from Pareto front in different additional investment cost ranges (Figure 7). The details of these selected Pareto designs are tabulated in Table 4.

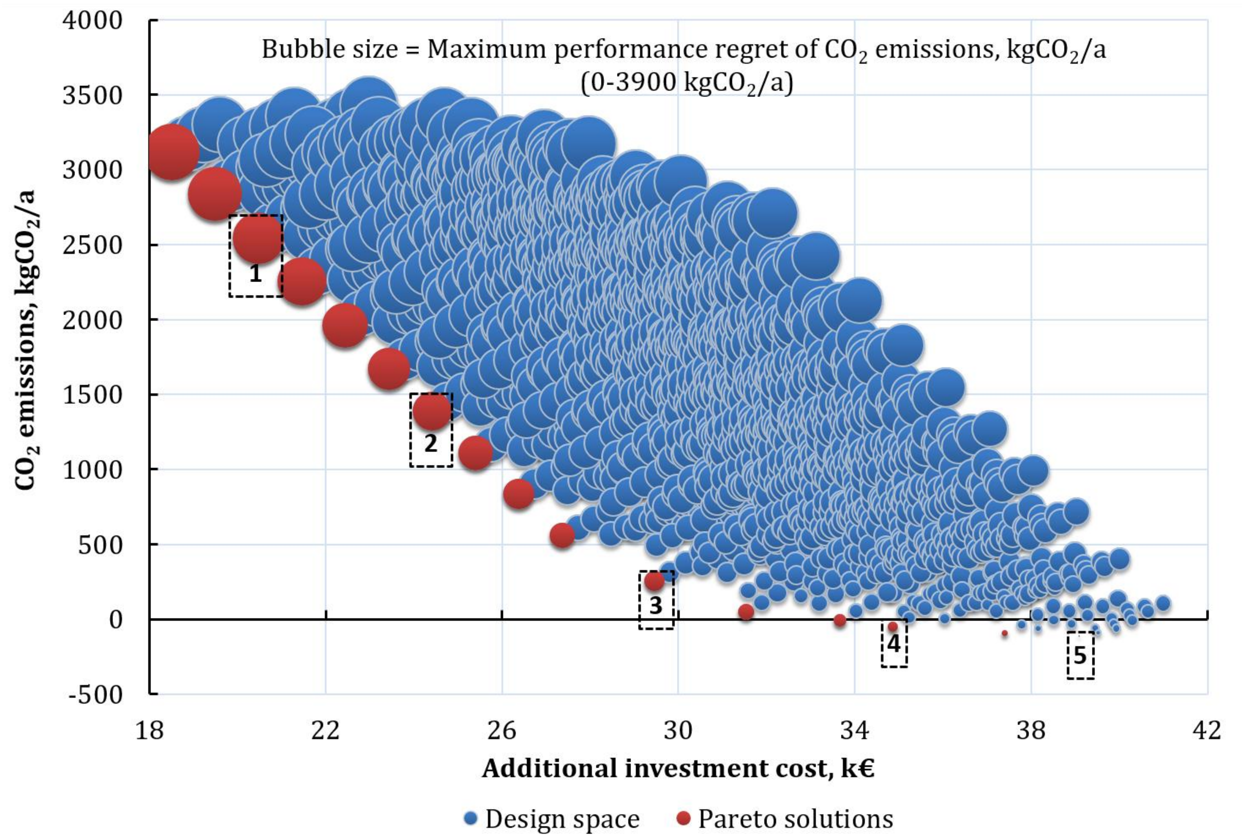

Figure 7 *The design space and Pareto front for the policymaker. Each bubble is a median value across the considered scenarios and bubble size represents maximum performance regret of CO_2 emissions. Pareto solutions are indicated in red. Few Pareto designs that are labelled in box are selected for further analysis.*

It can be inferred from Figure 8 that design-1 and design-2 have very high CO_2 emissions and hence, the policymaker may not prefer these designs despite their low additional investment costs. Moreover, they result in the higher maximum performance regret compared to other three designs and are thus least robust. In contrast, design-5 has very low CO_2 emissions and the lowest maximum performance regret and also zero performance regret for most of the scenarios indicating that design-5 is optimal for all these scenarios. Even though this is the most robust solution, it incurs high additional investment cost, and hence may not be the preferred solution of the policymaker. Comparing design-3 and design-4, the policymaker would prefer design-4 because of the relatively low CO_2 emissions and the lowest maximum performance regret compared to design-3. However, this improvement in predicted performance and performance robustness comes at an extra cost of 5420 € compared to design-3. Hence, to select a preferred robust design, the policymaker should compare predicted performance and performance robustness, and then trade off with required additional investment cost. Applying this procedure to the entire Pareto front of Figure 7 is a time consuming and tedious process.

Therefore, the Pareto solutions are analyzed with an easier and more efficient method in the following section.

Table 4 *Details of selected Pareto designs in different additional investment cost range from the Pareto front of the policymaker for further analysis.*

	Design-1	Design-2	Design-3	Design-4	Design-5
Additional investment cost, k€	20.47	24.41	29.44	34.86	39.08
Building envelope package	P1	P1	P1	P3	P5
WWR	20	20	20	20	20
Infiltration, ach	0.12	0.12	0.12	0.12	0.12
PV system, m^2	9.6	22.4	32	32	32
Solar DHW system, m^2	0	0	2.5	5	5

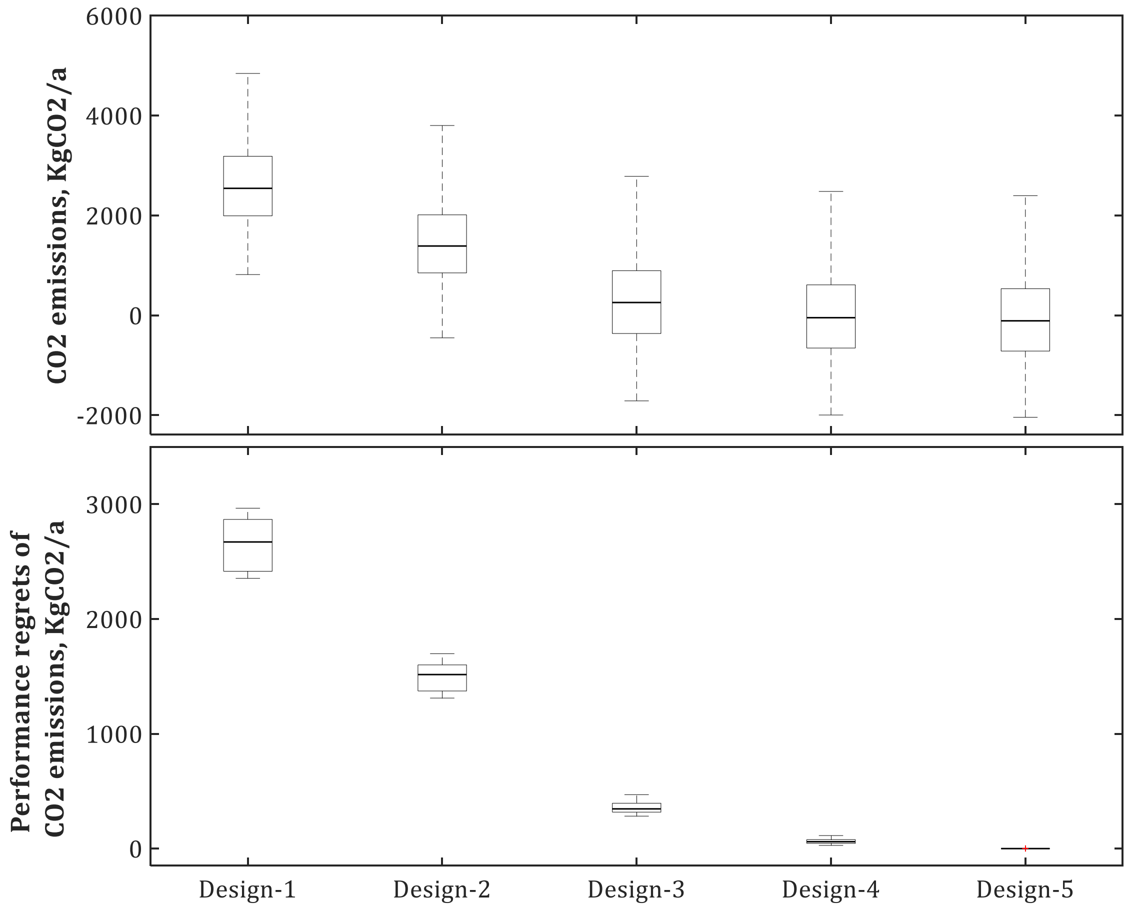

Figure 8 *Variation of CO_2 emissions and corresponding performance regrets of selected Pareto designs for the policymaker. The top graph shows variation of CO_2 emissions and the bottom graph shows variation of performance regrets of CO_2 emissions across considered scenarios.*

It is noteworthy that five designs compared in Figure 8 have similar performance spread and thus, it is hard to distinguish between robustness of these designs using performance spread [23]. However, it is easy to visualize the difference between the maximum performance regrets of these designs and thus, this method can enhance design decision making process. For instance, design-1 and design-5 have similar performance spread, but design-5 has zero regrets as it has optimal performance across all considered scenarios. Similar observations can be made for design-3 and design-4. Furthermore, this method yields a robust design that performs as closely as possible to the optimal performance for every scenario, as it can be observed from Figure 7 and Figure 8 that the maximum performance regret of designs decreases with better predicted performance.

ii. Robust design options

Figure 9 shows the influence of design options on the Pareto solutions. Each box represents a design option; the spread of the box of a design option is due to the scenarios and the remaining design options. For example, box P1 has all PV system and solar DHW system sizes. This figure gives an indication of which design options could lead to optimal performance and a robust design. Note that Pareto solutions differ only in a few design options such as building envelope packages, PV system size and solar DHW system (only these design options are shown in Figure 9). The other design options such as WWR and infiltration are constant at 20 ach and 0.12 ach respectively for all Pareto solutions. This indicates that higher infiltration rates and higher WWR are not robust design options for policy makers. It can be observed from Figure 9 that designs with building envelope package P1 have large variations of CO_2 emissions and corresponding performance regrets across the considered scenarios. However, for the same building envelope package, these variations can be reduced with larger PV and solar DHW systems. For instance, a PV system size of 32 m^2 and solar DHW system of 5 m^2 results in zero performance regret for the building envelope P1. Hence, the policymaker can also opt for building envelope package P1 with large onsite energy generation systems. On the other hand, designs with building envelope packages P2-P5 have low CO_2 emissions and lower corresponding regrets across the considered scenarios.

Designs with building envelope package P5 have zero performance regrets across all considered scenarios, indicating that it is the most robust design option for the policymaker. However, it requires higher additional investment costs compared to other packages. Thus, the policymaker might prefer the building envelope package P2 as it has similar performance compared to packages P3-P5, but requires low additional investment cost. Furthermore, robustness of building envelope package P2 is similar to that of packages P3-P5, indicating that improving insulation levels beyond package P2 does not yield significant benefits compared to the required investment. In contrast, performance regrets gradually decrease with larger PV and solar DHW systems. This is attributed to an increase in renewable energy utilization. It can be observed that that designs with no solar DHW system result in very high CO_2 emissions and corresponding performance regrets across the considered scenarios, which indicates the importance of solar DHW system. Considering variations in CO_2 emissions and corresponding performance regrets, the policymaker would prioritize larger PV system and solar DHW systems. In summary, the policymaker would prefer buildings with moderate insulation levels (P2), a PV system size of 32 m^2, solar DHW system size of 5 m^2, infiltration rate of 0.12 ach and WWR of 20%. However, preferred design options depend on the required additional investment cost. Therefore, using this approach, a decision maker can choose different design options that have low CO_2 emissions and the lowest maximum performance regrets and can trade off with the required additional investment costs.

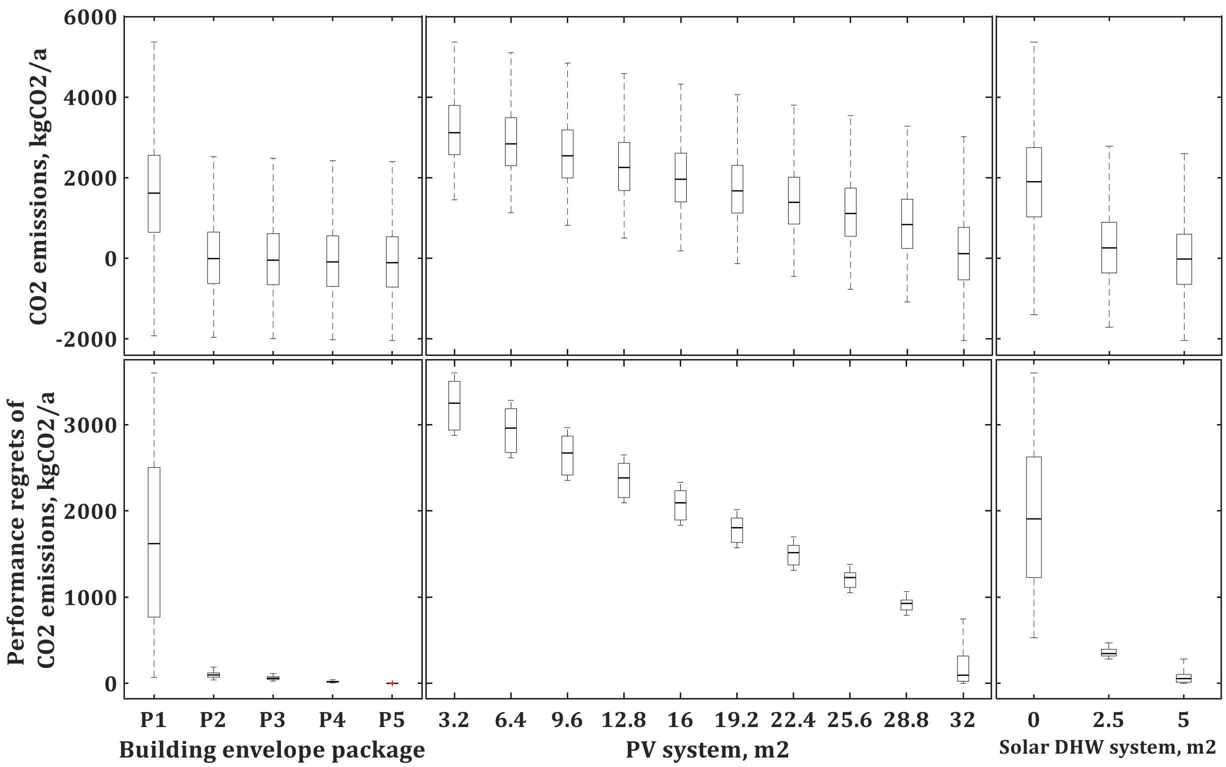

Figure 9 *Variation of CO_2 emissions and corresponding performance regrets for different design options of all Pareto solutions across the considered scenarios for the policymaker.*

iii. The most robust design using the MCDM method

Figure 10 shows the design score of the design space and Pareto solutions for the policymaker. The design score of a design is calculated by normalizing CO_2 emissions, additional investment cost and maximum performance regrets of CO_2 emissions. The design score ranges from 0-1 and the design with the highest score is the robust solution. The Pareto solutions shown in Figure 7 are indicated in red color in Figure 10 . It is worth noting that Pareto solutions have higher design score compared to other designs, but there are many sub-optimal designs as seen in Figure 10.

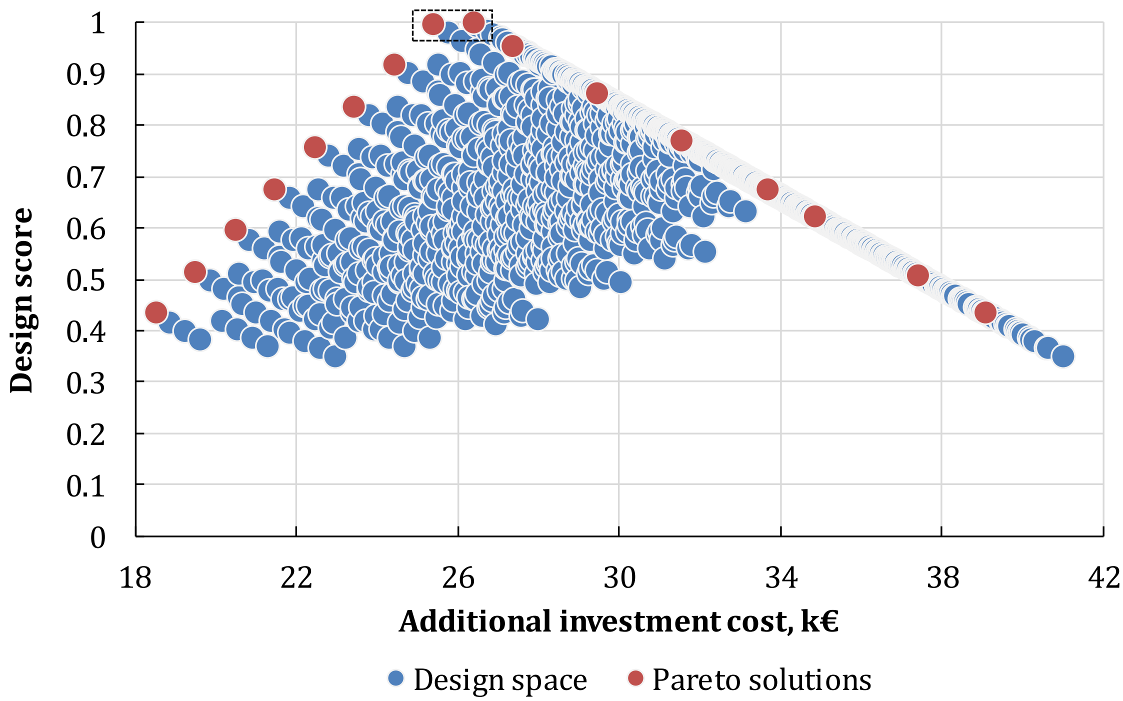

Figure 10 *Design score calculated using the Savage MCDM method for policymaker. Designs with the highest score are the most robust. The Pareto solutions are indicated in red.*

It can be observed that the design score gradually decreases beyond some additional investment cost, for instance beyond 26.3 k€ in Figure 10, indicating that these designs are not cost-optimal robust solutions. The preferred robust designs based on the highest design score are indicated in a box. These designs have building envelope packages of P1 and P2, WWR of 20% and infiltration of 0.12 ach. The PV system size is varying from 25.6-28.8 m^2. The preferred robust design based on trade off (Figure 9) and the MCDM method (Figure 10) has building envelope package P2. This indicates that building envelope packages with insulation levels beyond P2 are not cost-optimal robust design options. The designs with large PV system are found to be more robust solutions for the policymaker. This indicates that installing larger onsite energy generation systems is more robust and cost-optimal compared to improving building insulation levels beyond building envelope package P2. Using this approach, a decision maker can easily select the preferred robust design from the large design space based on design score. This method is more effective if various decision makers with multiple performance requirements are involved in the decision making process.

iv. Sensitivity analysis

The performance variations of these Pareto solutions depend on the considered scenarios and scenarios where 1-p>0.95 are assumed to be sensitive. These values for predicted performance and performance regrets are shown in Figure 11. Scenarios that are sensitive to either predicted performance or performance regrets of CO_2 emissions are shown in Figure 12, which shows variation of CO_2 emissions and corresponding regrets with low and high scenarios. For instance, because occupancy profile has less influence on CO_2 emissions and corresponding regrets (Figure 11, 1-p <0.95) they are not shown in Figure 12. The white box plots represent low values of scenarios and colored box plots represent high values of corresponding scenarios. The variations of CO_2 emissions and corresponding regrets are shown here by pooling all low and high values of each scenario separately. The spread of the box for a low scenario of occupants includes all scenario combinations with low occupant levels.

It can be seen from Figure 12 that both CO_2 emissions and corresponding regrets are sensitive to climate scenarios and heating setpoints. In contrast, low-high scenarios of number of occupants, DHW use, lighting and appliances use and their corresponding IHG only influence the predicted performance i.e. CO_2 emissions; they do not influence performance regrets as the variation in performance regret is the same for both low-high scenarios (Figure 11 and Figure 12). This influence is attributed to the inter-comparison of designs for evaluation of performance regrets. This comparison means that only scenarios that cause variations in either energy consumption or generation for different designs influence the performance regrets of CO_2 emissions, which are calculated based on net-energy consumption. For instance, for an appliance use scenario, energy consumption does not depend on the design options, and, thus it will be the same for all designs. In contrast, energy consumption of different designs varies with reference climate and climate change scenario, because heating demand is reduced for the climate change scenario compared to the reference climate. Similarly, energy consumption due to low and high heating setpoints will be different for different design options. In other words, the influence of low and high heating setpoints is high in low insulated building designs compared to that of highly insulated building designs. This method can be used by decision maker to identify the scenarios with most influence on the preferred performance indicators and can adopt extra measures to reduce their influence.

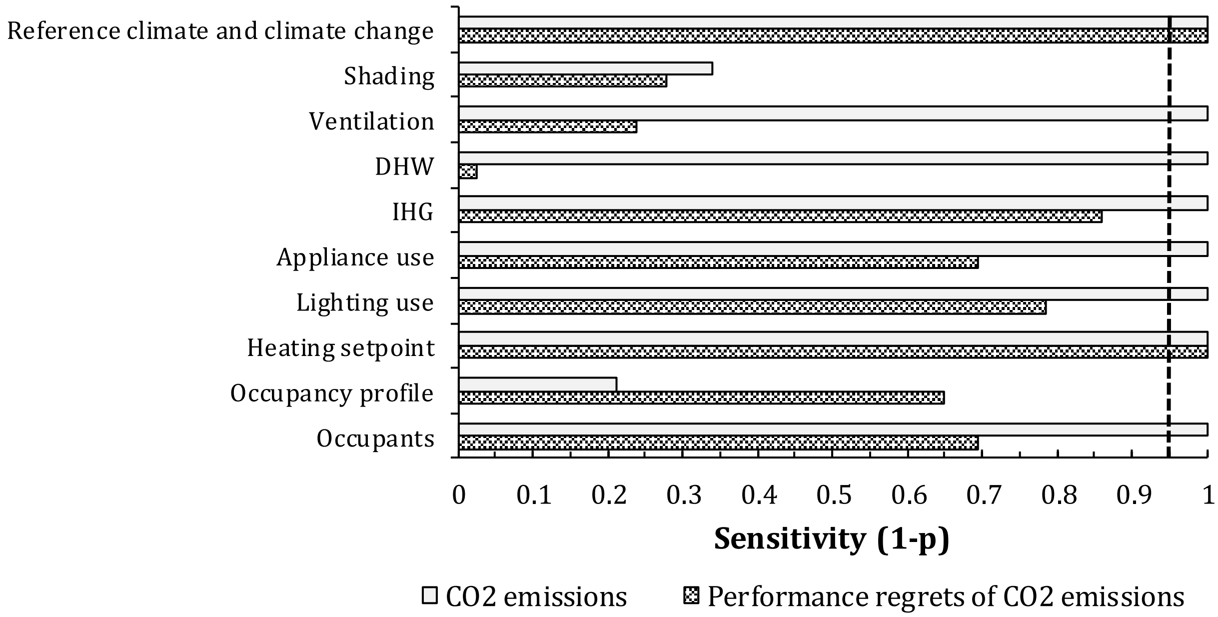

Figure 11 *Sensitivity of various scenarios to the predicted performance and performance regrets of CO_2 emissions calculated using the Mann-Whitney test. Scenarios where 1-p>0.95 (dotted line) are assumed to be sensitive.*

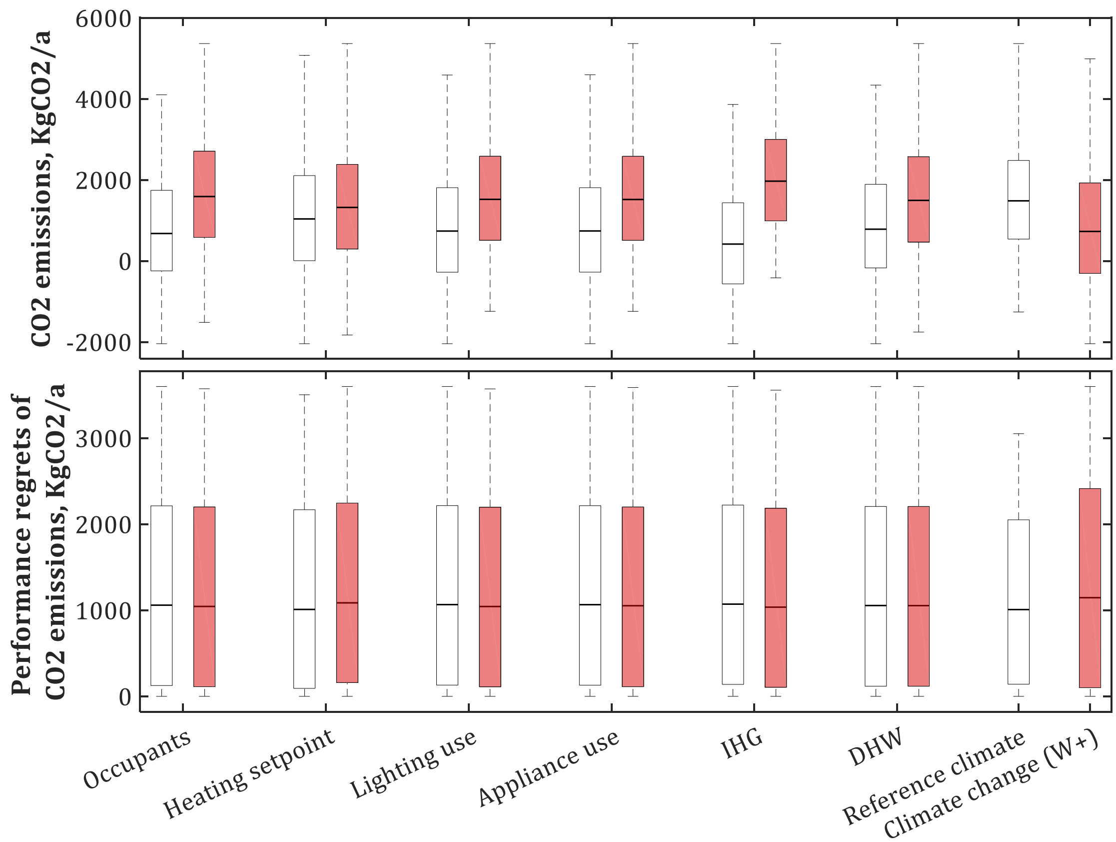

Figure 12 *Variation of CO_2 emissions and corresponding regrets with low and high scenarios for the policymaker. The empty box plots represent low scenarios and filled box plots represent high scenarios. Only scenarios that influence (1-p>0.95) predicted performance and/or performance regrets are shown.*

4 Practical use of the proposed methodology

The proposed methodology can be used by designers and consultants and other decision makers involved in the decision-making process to identify robust designs that deliver the preferred performance in the operation, thus improving end users' satisfaction. In addition, by using this methodology the designers can provide risk-averse solutions i.e. the designs with the least regret. This methodology can be instrumental in reducing performance deviation during operation compared to the predicted performance. For instance, this methodology can be used to find the designs that have the least performance regrets across a wide range of uncertainties. These designs can be used in energy performance contracting options.

As demonstrated through the case study, it is easier to distinguish between the designs based on performance robustness across all considered scenarios (see Figure 8) compared to the predicted performance based on fixed set of assumptions that is typically used in practice. This visualization is instrumental in allowing decision makers to make informed choices, especially when a design has to be selected from a large design space and multiple performance requirements are considered. In addition, using the MCDM approach implemented in this methodology, it is easy to identify robust designs from a large design space, which enhances the design decision-making process.

The selection of robust design options using this methodology can aid decision makers in selecting cost-optimal robust solutions. This methodology also provides information to allow end users to trade-off investment in enhanced insulation levels with energy generation systems. For instance, as shown in Figure 9, upgrading insulation levels beyond P2 (Rc = 5/6/7 for floor/wall/roof) does not yield significant benefits when considering the required additional investment. In contrast, investing in large PV systems can improve a building's robustness to CO_2 emissions to a significant extent.

5 Summary and conclusion

A novel methodology considering future scenarios for performance robustness assessment of low-energy buildings is proposed. This methodology integrates uncertainties in multi-criteria assessment using scenario analysis to quantify robustness and facilitates robust design selection for decision makers. The proposed methodology comprises multi-criteria performance assessment and multi-criteria decision making, taking into account performance robustness among other performance indicators. In this approach, by prioritizing the decision maker's preferences, building design space, future scenarios and performance indicators are defined. The performance of the design space for future scenarios is assessed using building performance simulations with multiple performance indicators and corresponding performance robustness. Maximum performance regret evaluated using the minimax regret method is used as the measure of performance robustness in this study. The Savage multi-criteria decision making method is used to select a robust design among alternatives for all decision makers. This methodology is generic and can be applied to both new buildings and renovations. The proposed methodology is demonstrated using a case study with a policymaker as decision maker.

The proposed methodology is important as it deals with one of the major issues that the building industry is facing in the development of low energy buildings; performance deviation during operation compared to the predicted performance. This methodology can be used by designers and consultants among other actors involved in the decision-making process to identify robust designs that deliver preferred performance in the operation and can thus, improve customer's satisfaction.

The following conclusions can be drawn from this work

- The proposed methodology can be used by a decision maker to select robust designs based on optimal performance and maximum performance regret across all scenarios. In addition, the decision maker can choose a robust design by prioritizing a performance indicator and trading off with the performance and performance robustness of other performance indicators and required additional investment cost.
- The proposed methodology also provides a decision maker with information to trade off investment in improving building insulation levels with that of energy generation systems. In addition, decision makers can choose design options that are more robust to the preferred performance indicators, such as insulation levels or energy generation systems, separately. For instance, policymakers can use this methodology when defining building codes and regulations based on robust design options, such as limiting insulation levels to certain extent (e.g. Rc = 5/6/7 m^2K/W for floor/wall/ roof; U=1.01 W/m^2K) and opting for larger onsite energy generation systems (e.g. PV system of 25.6-32 m^2) as observed from this case study results.
- Low-high scenario combinations are sufficient for performance robustness assessment, which can reduce computational time by about 98% compared to assessment with all scenario combinations in this case study. Using scenario analysis, a decision maker can identify the scenarios with the greatest influence on the preferred performance indicators and can adopt extra measures to reduce this influence. Scenarios that influence predicted performance do not necessarily influence performance robustness because of the inter-comparison of designs in performance robustness calculations (Table 1) implemented in this methodology.
- Robustness assessment used in this methodology is a less conservative approach compared to previous studies [23,29], as it yields a robust design that performs as closely as possible to the optimal performance for every scenario. Furthermore, it is easy to visualize the difference

between the performance robustness of the designs using this method compared to performance spread [23]. This visualization enhances the design decision making process, especially when large design space and multiple performance requirements are considered.

- Using the MCDM method, a decision maker can easily select a cost optimal robust design from the design space based on design score (Figure 10) or can trade off the selected designs based on the design score with required additional investment cost. This method is useful for quicker identification of robust designs form a large design space.

The proposed methodology can be useful when various decision makers are involved in a project with multiple performance requirements, and it is also effective in identifying a robust design from a large design space for various decision makers. This will be presented in our future work.

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Appendix

Figure a *Layout of a typical Dutch terraced house, showing different floors, front and back view of the building. All dimensions are in mm.*

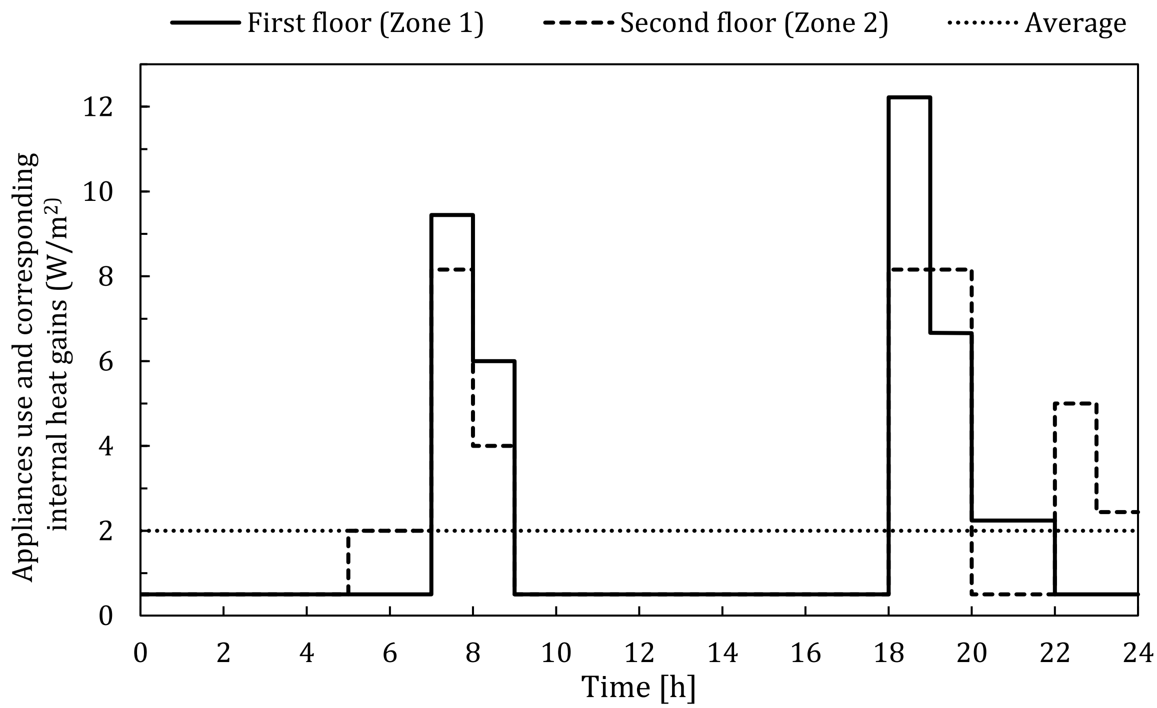

Figure b *Appliance use in the building and the corresponding internal heat gains for an evening occupancy profile in the average usage scenario.*

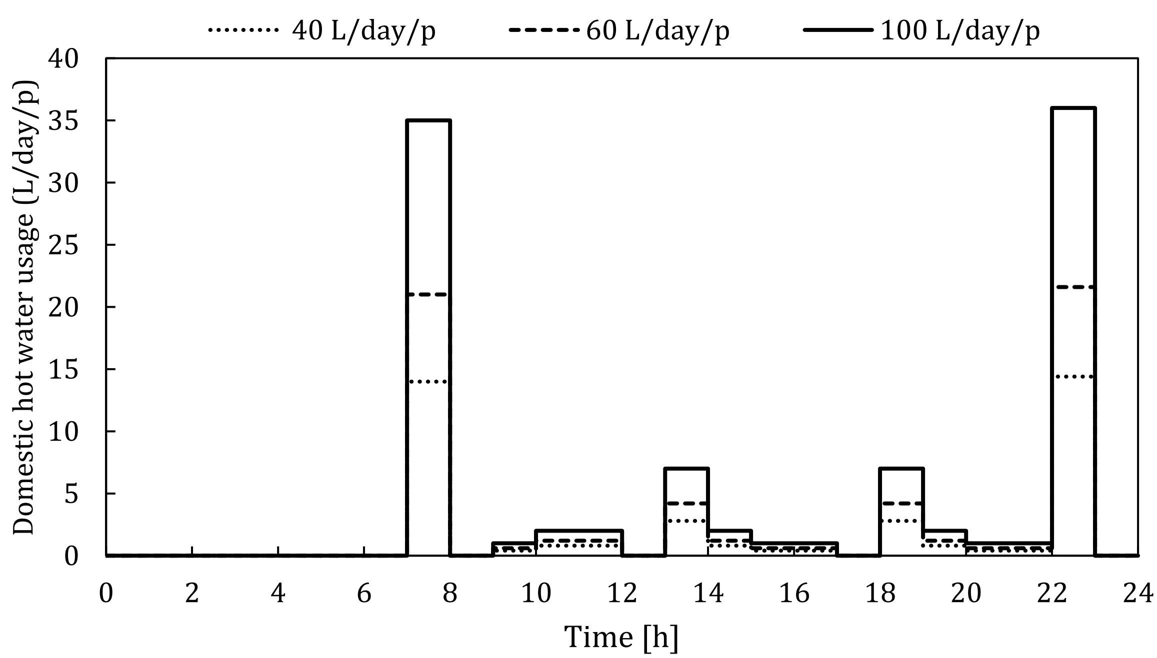

Figure c *Domestic hot water profiles for different usage scenarios.*

Table a *Range of the investment cost of few design options.*

Parameter	Range	Range of investment cost, €	Source
Wall insulation (m^2K/W) per m^2	4.5-10	26.32-55	Prijs- en assortimentslijst Kool therm ® April 2016 Inhoudsopgave https://www.kingspan.com/nl/nl-nl/producten-nl
Roof insulation (m^2K/W) per m^2	3.5-10	20.35-55	
Floor insulation (m^2K/W) per m^2	6-10	33.5-55	
Insulation packages for walls, roof and floor together	P1-P5	8874-18445	
Windows (U, W/m^2K) per m^2	1.43-0.4	75-170	https://www.lente-akkoord.nl/. www.dubbelglasweetjes.nl
Infiltration, ach	0.12-0.48	1500-2000	Email correspondence, Siant Gobian Isover
Heat pump, kWp	2.5-5	4450-9300	http://www.comfortklimaat.nl/
PV system, m^2	3.2-32	983-9838	http://www.eon.nl/thuis/nl/zonnepanelen/onzezonneproducten/premium.html
Solar DHW system, m^2	0-5	0-4165	http://www.iea-shc.org/country-report-netherlands