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Simulation-based comparison of robustness assessment methods to identify robust low-energy building designs

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Abstract

Uncertainties in occupant behaviour and climate change can have a large influence on future building performance, especially in low-energy buildings. These uncertainties cause performance variations resulting in deviations between actual operation compared to the predicted performance in the design phase. Therefore, performance robustness assessment of these buildings should consider uncertainties and should be included in the design phase to ensure the intended performance in the future. The probability of occurrences of these uncertainties are usually unknown and hence, scenarios are essential to assess the performance robustness of buildings. However, studies on robustness assessment using scenarios in the building performance context are limited. Therefore, in this work, scenario analysis is combined with various robustness assessment methods from other fields, and these methods are compared using a case study for different decision makers such as homeowners and policymakers.

The *max-min* and the *best-case and worst-case* methods lead to conservative robust designs and can be used when a risk-free approach is indispensable in decision-making. The *minimax regret* method leads to less conservative robust designs and can be used where a decision maker can accept a certain range of performance variation.

Introduction

In conventional design practice, building performance is predicted, using building performance simulations, considering fixed assumptions about building operation. However, many uncertainties in building operation and external conditions such as occupant behaviour, climate change etc. influence the building performance, which cause variations in energy use, cost and comfort. The impact of these variations is very high in low-energy buildings (De Wilde, 2014; Maier et al., 2009) because of low energy demand and minimally sized energy systems. To reduce the impact of these variations, performance robustness should be considered during the design phase in the design decision-making process. Otherwise, the decision-making process may result in designs that are sensitive to uncertainties (Mavrotas etal., 2015) and might not perform as intended. In general, the decision maker (DM) has little or no information about the probabilities of occurrence of these uncertainties and thus hard to quantify associated risk in decision-making. Therefore, scenarios are essential to assess the future performance and performance robustness of buildings (Hopfe et al., 2013) and to determine both conservative and extreme approaches in decision-making (Kotireddy et al., 2015).

From a broad perspective, the whole of society has a stake in the future performance and performance robustness of buildings, considering the great social and economic efforts required for the implementation of energy reduction and integration of renewable energy technologies in the built environment. More specifically, policymakers can use performance robustness to define energy performance requirements in future building regulations to safeguard intended policy targets. They can also define policies to support adaptations of current buildings to improve their performance and extend their life span. Similarly, performance robustness is a relevant concern for homeowners, to ensure their preferred building performance over the building's life span. 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, contractors and component suppliers can design and deliver more robust buildings, thus guaranteeing the satisfaction of their customers.

Robustness assessment approach is broadly categorized in two types – probabilistic approach, where probabilities of uncertainties are assumed to be known (Gelder et al., 2013) and non-probabilistic approach, where probabilities of uncertainties are unknown. (Hoes et al., 2011; Rysanek and Choudhary, 2013; Gang et al., 2015). Hence, in this work, a non-probabilistic approach is used for performance robustness assessment. Several non-probabilistic robustness assessment methods are used in different fields (Averbakh, 2000; Aissi et al., 2009; Rysanek and Choudhary, 2013) and few selected methods are adopted in the present context. A methodology is presented which compares different robustness methods to aid decision maker in the decision-making process considering future performance and performance robustness.

The objectives of this work are to:

- Identify relevant robustness assessment methods for building performance assessment
- Compare these methods for different decision makers using a case study

Methodology

The methodology to compare various robustness assessment methods follows the steps below, and is depicted in Figure 1.

1. Choose decision makers and define the following parameters based on the decision maker's preference
    a. Building design space
    b. Future scenarios
    c. Performance indicators
2. Assess the performance of designs for future scenarios using multiple performance indicators with building performance simulations
3. Calculate performance robustness of designs using a robustness assessment method (RAM)
4. Compare robustness assessment methods and identify suitable method based on DM's approach towards decision-making.

The building design space comprises current and future Dutch building standards (RVO, 2015) such that the preferred design by a DM will also meet the criteria of building regulations. Future scenarios are formulated based on different household sizes and the wide variety in the possible usage of the building i.e. occupant behaviour, external conditions such as climate change. The performance of the design space is assessed for future scenarios using multiple performance indicators that are relevant to decision makers. In general, the DM will be interested in a trade-off solution. Furthermore, depending on the DM, each performance indicator may have a different weight in the decision-making process. For example, if the DM is a homeowner, then his/her design selection criteria will probably depend heavily on overheating hours and operating costs (global cost). This preference can be contrasted with, for example, a policymaker, who is more focused on CO_2 emissions. In addition to actual performance, performance robustness is also a primary criterion in the decision-making process.

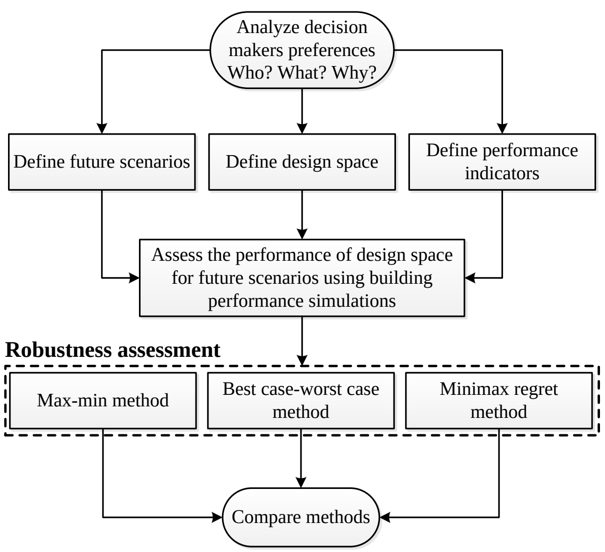


Figure 1: Methodology implemented in this study to compare different robustness assessment methods.

The following methods are used to assess the performance robustness of building designs and each method uses different means to evaluate performance robustness, which are described in the next section.

- *Max-min method* using performance spread as robustness indicator
- *Best-case and worst-case method* using performance deviation as robustness indicator
- *Minimax regret method* using maximum performance regret as robustness indicator

These performance and robustness indicators are compared against additional investment cost (design), which enables DM to select a cost optimal robust design or to carry out trade-offs with respect to the other performance and robustness indicators. This multi-criteria assessment enables different DM to choose robust designs from a large design space based on their preferred performance indicators.

Robustness assessment methods

Max-min method

In this method, the performance spread of a performance indicator is used as a robustness indicator of a design, and is defined as the difference between maximum performance and minimum performance across all scenarios. The preferred robust design is defined as the design with lowest median value and minimum performance spread across all scenarios (Kotireddy et al., 2015). In this method, robustness of a design is calculated without any inter-comparison between designs, and only extreme scenarios causing maximum and minimum performance for a design are considered for robustness assessment. The following steps are implemented based on this method to select the robust design, of a design space, across future scenarios in the present context.

Step-1: Assess the performance of designs (d_m) for all scenarios (S_n) using a performance indicator (PI)

Step-2: Find the maximum and minimum performance of a design across all scenarios, as shown in Table 1.1.

Step-3: Calculate the performance spread of a design across all scenarios. The performance spread is the performance difference between the maximum and minimum performance, as shown in Table 1.3.

Step-4: The performance spread is used as a measure of performance robustness, and the design that has the smallest performance spread is the most robust solution. Ideally, the design having zero performance spread is the most robust solution of a design space.

Best-case *and* worst-case method

In this method, performance deviation between the worst-case performance of a design and the best-case performance of all designs across all scenarios is used as a measure of robustness. This method is adopted from (Hopfe et al., 2013; Hoes et al., 2011) and is improved by considering performance of all designs across all scenarios to find the best-case performance, unlike the predefined best-case performance as in (Hoes et al. 2011). In contrast to the *max-min method*, this method considers all scenarios for performance robustness assessment. The following steps are implemented based on this method to select the robust design, of a design space, across future scenarios in the present context.

Step-1: Assess the performance of designs (d_m) for all scenarios (S_n) using a performance indicator (PI).

Step-2: Find the minimum performance of a design across all scenarios.

Step-3: Compare the minimum performance of all designs and find the best-case performance of the entire design space i.e. minimum performance of all designs across all scenarios as shown in Table 1.1.

Step-4: Find the worst-case (maximum) performance of a design across all scenarios

Step-5: Calculate the performance deviation of a design, as shown in Table 1.3. The performance deviation is the performance difference between the worst-case performance of a design and the best-case performance.

Step-6: The performance deviation is used as a measure of performance robustness, and the design having the smallest performance deviation is the most robust solution. Ideally, the design having zero performance deviation is the most robust solution of a design space.

Minimax regret method

This method is a combination of the minimax (Wald, 1945) and regret methods. In the minimax method, the maximum deviation of a worst-case scenario is minimized. Regret theory models design decision, under uncertainties, considering the effect of anticipated regret. Combining these two methods, in *minimax regret method* (Savage, 1951), the worst-case regret is minimized. In this method, performance regret is the performance difference between the design and the best performance (optimal) for a scenario, and maximum performance regret per design across all scenarios is the measure of robustness. This method has been widely used for robustness assessment in various fields (Chien and Zheng 2012; Ehrgott etal., 2014; Gang et al., 2015). The following steps are implemented based on the *minimax regret method* to select the robust design, of a design space, across future scenarios in the present context.

Table 1.1: Finding the minimum performance for a scenario, minimum and maximum performance across all scenarios and the best-case performance of all designs and scenarios.

Designs	**Scenarios**				Maximum performance across all scenarios (**A**)	Minimum performance across all scenarios (**B**)
	S_1	**S_2**	**…**	**S_n**		
d_1	PI_{11}	PI_{12}	…	PI_{1n}	$A_1 = \max(PI_{11}, PI_{12} \ldots PI_{1n})$	$B_1 = \min(PI_{11}, PI_{12} \ldots PI_{1n})$
d_2	PI_{21}	PI_{22}	…	PI_{2n}	$A_2 = \max(PI_{21}, PI_{22} \ldots PI_{2n})$	$B_2 = \min(PI_{21}, PI_{22} \ldots PI_{2n})$
…	…	…	…	…	……	……
d_m	PI_{m1}	PI_{m2}	…	PI_{mn}	$A_m = \max(PI_{m1}, PI_{m2} \ldots PI_{mn})$	$B_m = \min(PI_{m1}, PI_{m2} \ldots PI_{mn})$
Minimum performance for each scenario (**C**)	$C1 = \min(PI_{11}, PI_{21}, PI_{31} \ldots PI_{m1})$	$C2 = \min(PI_{12}, PI_{22}, PI_{32} \ldots PI_{m2})$	…	$Cn = \min(PI_{1n}, PI_{2n}, PI_{3n} \ldots PI_{mn})$		
		Best-case performance of all designs across all scenarios (**D**) = min(**B**) = min(**C**)				

Table 1.2: Calculation of performance regrets of designs across all scenarios.

	Performance regrets (**R**)			
	S_1	S_2	…	S_n
d_1	$R_{11}=PI_{11}-C_1$	$R_{12}=PI_{12}-C_2$	…	$R_{1n}=PI_{1n}-C_n$
d_2	$R_{21}=PI_{21}-C_1$	$R_{22}=PI_{22}-C_2$	…	$R_{2n}=PI_{2n}-C_n$
…	…	…	…	……
d_m	$R_{m1}=PI_{m1}-C_1$	$R_{m2}=PI_{m2}-C_2$	…	$R_{mn}=PI_{mn}-C_n$

Table 1.3: Performance robustness calculations using three robustness assessment methods.

Performance robustness	Performance spread (**PI_{spread} = A-B**)	Performance deviation (**$PI_{deviation}$=A-D**)	Maximum performance regret (**$PI_{maxregret}$**)
d_1	A_1-B_1	A_1-D	$\max(R_{11},R_{12},..R_{1n})$
d_2	A_2-B_2	A_2-D	$\max(R_{21},R_{22},..R_{2n})$
…	…	…	……
d_m	A_m-B_m	A_m-D	$\max(R_{m1},R_{m2},..R_{mn})$
Robust design	**$\min(PI_{spread})$**	**$\min(PI_{deviation})$**	**$\min(PI_{maxregret})$**

Step-1: Assess the performance of designs (d_m) for all scenarios (S_n) using a performance indicator (PI).

Step-2: Find the best performance for each scenario by comparing the performance of all designs. In this work, the design having minimum performance for a scenario is the best performance.

Step-3: Calculate the regret (R) of a design for each scenario, as shown in Table 1.2. The regret is the performance difference between the design and the best performance for a scenario.

Step-4: Find the maximum performance regret per design across all scenarios.

Step-5: Maximum performance regret is the measure of robustness; the lower the maximum regret, the higher the robustness. To select a robust design, the maximum performance regret of all designs is compared, as shown in Table 1.3, and the design having the smallest maximum performance regret across all scenarios is the most robust design of a design space.

Simulation approach

Genetic algorithm (Deb et al., 2002) based multi-objective optimization is used to optimize the performance and performance robustness of design space across future scenarios. A set of Pareto solutions are obtained using optimization, thus enabling decision makers to trade-off between design alternatives based on their preferred choice of performance indicators and corresponding performance robustness. Multi-objective optimization is carried out using MATLAB in combination with TRNSYS. In this approach, as shown in Figure 2, for every generation, objectives of population (designs) are evaluated. Genetic algorithm (GA) creates population (designs) for the next generation based on the evaluated objectives of previous generation, and this process is repeated until the optimization criterion is met. The optimization process will stop if the average change in the spread of Pareto solutions over 20 generations is less than 0.001.

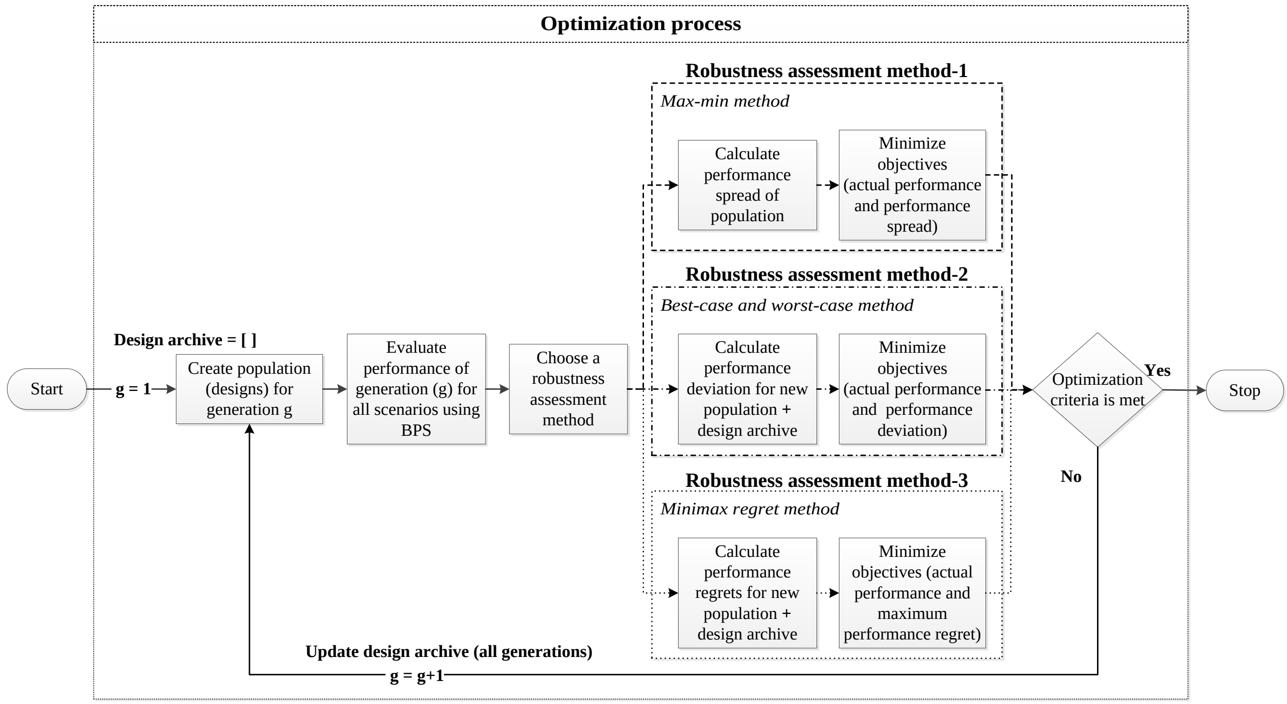


Figure 2: Genetic algorithm (GA) based multi-objective optimization approach considering multiple performance indicators and corresponding performance robustness calculated using three robustness assessment methods.

To compare three robustness assessment methods, the same GA settings, such as the crossover fraction of 0.65, the Pareto fraction of 0.35 and four players for selection tournament that selects parents of crossover and mutation, are used. In addition, a user defined initial population and population size of 30 is used for the three methods. It is worth noting that the optimal settings of GA are different for the three methods (details are not discussed here and will be elaborated in our future publications). Moreover, the method of evaluation of objectives also differs for three methods. For instance, performance spread is evaluated for each design of the population without any inter-comparison of performance of other designs of the population and thus one design at a time is considered for evaluating objectives. On the other hand, maximum performance regret and performance deviation are evaluated with inter-comparison of performance of other designs. Hence, objectives in these two methods are evaluated after calculating the performance of the entire population. Furthermore, for each generation, objectives are evaluated, as shown in Figure 2, considering the current population and design archive of previous generations because of inter-comparison of performance of all designs in these two methods. It is also noteworthy that in the *max-min method*, robustness is optimized with respect to the best performing scenario of a design, whereas in the *best-case and worst-case method* robustness is optimized with respect to the best performing case of all designs and scenarios. In the *minimax regret method*, performance robustness is optimized by minimizing the maximum performance deviation, over all scenarios, between the performance of a design and the best performance of the corresponding scenario (Aissi et al., 2009).

Case study

To assess the suitability and usability of the proposed methodology, this methodology is demonstrated for the following two key decision makers, who represent different interests in the building industry.

- Policymakers – prefer a robust design that has low CO_2 emissions with low investment costs to enable the provision of subsidies in policy
- Homeowners – prefer a robust design that delivers comfortable indoor environment with low operational and investment costs

Case study building

A semi-detached terraced house, a typical Dutch residential house (RVO, 2015), is chosen as the case study building. It is a three-storey building and layout of the building is same as (Kotireddy et al., 2015), which is divided into three thermal zones, in TRNSYS, to calculate 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. The south and north façade has identical sized windows and both windows are shaded by an external shading device to reduce glare and summer overheating in the building.

An air source heat pump supplies heating and the building is ventilated using balanced mechanical ventilation system with a heat recovery unit. Heat recovery is bypassed when the room temperature is greater than the heating set point and when the ambient temperature is greater than room temperature. In addition to mechanical ventilation and infiltration in the building, natural ventilation (free cooling) by opening windows is used, instead of mechanical cooling, to reduce overheating during summer. The domestic hot water needs are met by a standalone solar thermal collector system with an auxiliary heater. It is an all-electric building and the total electricity consumption for heating, ventilation, auxiliary heater and pump for the domestic hot water (DHW) system, lighting and appliances of the building is met by an onsite photovoltaic system. Highly efficient LG photovoltaic panels with an efficiency of 18.3% and an inverter with an efficiency of 97.5% are chosen in this study for onsite-energy generation system (EON, 2016). Solar collectors are placed on the roof, facing south, at a tilt angle of 43°, which is also the slope of roof.

Design variants

Different design variants, as shown in Table 2, are varied in combination to form the design space. The design space comprises designs that meet current and future Dutch building standards and extends to passive house standards (RVO, 2015).

Table 2: Design variants considered in this study.

Design variant	Range
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	[0.4, 0.68, 0.81, 1.01, 1.43]
WWR	[20, 40, 60]
Thermal mass	[Light-weight, Heavy-weight]
Infiltration, ach	[0.12, 0.24, 0.36, 0.48]
PV system, m^2	[5, 10, 15, 20, 25, 30]
Solar DHW system, m^2	[0, 2.5, 5]

Scenarios

The following occupant, usage and climate scenarios are considered in this study.

Occupant scenarios

Four occupant scenarios are formulated based on the Dutch household statistics (CBS, 2016). The first scenario, a single person, represents 37% of the Dutch households and the second scenario, a two-person family, accounts for 33% of the Dutch households (CBS, 2016). 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.

Usage scenarios

For each of the occupant scenarios, usage scenarios are formulated based on energy usage in the building. These various usage scenarios cover very careful energy users to energy wasting users, and cover different types of equipment with low to high efficiencies. Occupancy patterns, heating set point 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 set points are chosen from (VROM, 2009). The evening occupancy profile represents 19% and the all-day occupancy profile accounts for 48% of the Dutch households respectively (VROM, 2009). Three scenarios are considered for average electricity use for lighting and appliances, as shown in Table 3. Each scenario has a similar usage profile for an occupancy pattern, but differs in peak loads resulting in different average electricity consumption. Electricity consumption for lighting (RVO, 2015) and appliances (Papachristos, 2015) for an average user is in line with an average electricity consumption of about 3500kWh for lighting and appliances by Dutch households (CBS, 2016). Internal heat gains due to lighting, appliances etc. is varied, together with appliances and lighting use, from 2 to 6 W/m^2 based on

(NEN7120, 2011). 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 (NEN7120, 2011) and (Guerra-Santin and Silvester, 2016). 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 high usage scenario. Shading control (by occupants) of external shading of windows is implemented based on radiation levels on the façade and indoor temperature (Hoes, 2014).

Climate scenarios

Four climate change scenarios proposed by the Dutch Royal meteorological institute (Van den Hurk et al., 2006) are used in this study. Climate change scenarios are based on global mean temperature rise and changes in atmospheric air circulation patterns. Scenario G represents a moderate increase of the 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. Scenario G and W do not take into account changes in air circulation patterns, whereas scenario 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 5060-2008, is considered as shown in Table 3. It is based on the average months of 20 years of historical data that represents no climate change effect. Hourly weather data generated for all climate scenarios is used in simulations.

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

Parameter	Range
Occupant scenarios	
Household size	[1, 2, 3, 4]
Usage scenarios	
Heating set point (occupied), °C	[18, 20, 22]
Heating set point (un-occupied), °C	[14, 16, 18]
Occupancy profile	Evening, All-day
Average electricity use for lighting, W/m^2	[1,2,3]
Average electricity use for appliances, W/m^2	[1,2,3]
Domestic hot water consumption, l/person per day	[40, 60, 100]
Internal heat gains due to lighting and appliances, W/m2	[2, 3, 4, 5, 6]
Ventilation, ach	[0.9, 1.2, 1.5]
Shading control ON if radiation is above, W/m^2 and if $T_{indoor} > 24$°C	[250, 300, 350]
Shading control OFF if radiation is below, W/m^2 and if $T_{indoor} < 24$°C	[200, 350, 300]
Climate scenarios	
Reference climate and climate change scenarios	NEN5060-2008 G, W, G+, W+

It is worth noting that some of the scenarios are varied together, such as internal heat gains due to lighting and appliances are varied in proportion with electricity use for lighting and appliances. All combinations of occupant, usage and climate scenarios result in 29160 scenario combinations. Performance assessment of the design space with these combinations requires much computational time. To reduce computational time and evaluate the impact of all scenarios with a reasonable sample size, a sampling strategy based on uniform Latin hypercube sampling is carried out. Based on experiments, the smallest sample size that has a similar performance as that of all scenario combinations is 200. The details of sampling strategy are not discussed here, as it is not the focus of this article.

Performance indicators

To assess the building performance for future scenarios, the following performance indicators are used based on the decision maker's preferences,

Additional investment cost

Additional investment cost is the summation of investment cost of design variants such as insulation materials, windows, HVAC system, solar DHW system and PV system (Kingspaninsulation, 2016; EON, 2016). Fixed costs for all designs e.g. land, labour etc. are not considered and only the costs that incur by varying design variants are considered. Hence, investment cost is referred as additional investment in this work.

Table4: Range of investment cost of few design variants.

Parameter	Range	Range of investment cost, €
Insulation (Rc, m^2K/W)	3.5-10	8874-18445
Windows (U, W/m^2K)	1.43-0.4	1651-3048
PV system, m^2	5-30	1537-9233
Solar DHW system, m^2	0-5	0-4165

CO_2 emissions

CO_2 emissions are calculated based on net-energy consumption by the building. An emission factor of 0.5219 $kgCO_2$ per kWh is used to calculate CO_2 emissions (Vreuls, 2005). Embodied emissions are not included in emission calculations.

Global cost

Global cost is evaluated to predict the future financial implications of designs that comprise investment, replacement and operating costs. Global cost is calculated by the following equation (Hamdy et al., 2013):

$$Global\ cost\ = \sum_{j=1}^{n} IC_j + \sum_{j=1}^{n} RC_j + OC + MC + FC$$

Where IC is the investment cost of the different design variants [€], RC is the replacement cost of the building components and energy systems that have a life span less than 30 years [€] and OC is the operating cost [€]. Maintenance costs (MC) and fixed costs (FC) are not considered in this study. The index *j* represents the design variant and n represents total number of design variants. Global cost is calculated for a 30-year period (EPBD, 2010), because interest rates and energy price forecasts are difficult to predict beyond this period (BPIE, 2010). Operating costs are calculated using the current energy prices (CBS, 2016). Replacement and operating costs are discounted, to get net present value, considering real interest rates and energy price escalation rates.

Overheating hours

An adaptive temperature limits based thermal comfort model proposed by (Peeters et al., 2009) is implemented in this work. Thermal comfort is evaluated based on maximum and minimum acceptable indoor temperatures regarding recent outdoor temperatures. Overheating hours are the total number of hours exceeding the allowable maximum indoor temperatures during occupancy in a year. The magnitude of overheating is quantified by taking a weighting factor for every degree above allowable maximum indoor temperatures.

Results and discussion

Policymaker

Figure 3 presents a comparison of Pareto front of designs, for policymakers, obtained by optimization using three robustness indicators. The 3D Pareto front is shown as 2D plot, bubble size being the third dimension. Each bubble represents a median value of CO_2 emissions of a design across all scenarios, and the bubble size depicts robustness of CO_2 emissions. The smaller the bubble size, the more robust is the design. The designs with CO_2 emissions less than or equal to zero are carbon neutral designs and negative emissions are avoided emissions by a design. Policymakers prefer a design with low CO_2 emissions and small bubble size, and can trade-off with additional investment cost.

It can be seen from Figure 3a that performance spread is much lower for designs with high CO_2 emissions (1500-3000 $kgCO_2/a$). In other words, performance robustness is higher if the actual performance of the design is lower. In contrast, performance deviation and maximum performance regret is lower for better performing designs i.e. designs with low CO_2 emissions (0-500 $kgCO_2/a$). The same can be observed from Figure 3b-c that the bubble size is smaller for the designs with low CO_2 emissions. This contrasting trend is attributed to the calculation approach of robustness indicators. For instance, in the *max-min method*, robustness is quantified with respect to the best performing scenario. If the actual performance of a design is bad, then it leads to bad performance even for the best scenario and hence, small difference between maximum and minimum performance across all scenarios. In the other two methods, performance comparison between other designs/scenarios is made to find the best performance to calculate robustness. For instance, in the *best-case and worst-case method*, robustness is quantified with respect to the best performance of entire design space. Moreover, this method results in a robust design that has the best possible performance even in the worst-case scenario. Similarly, the *minimax regret method* yields a robust design that performs as closely as possible to the best performance for every scenario. Thus, performance robustness is proportional to actual performance with these two methods as seen in Figure 3b and 3c (designs with additional investment cost of 24-45K€).

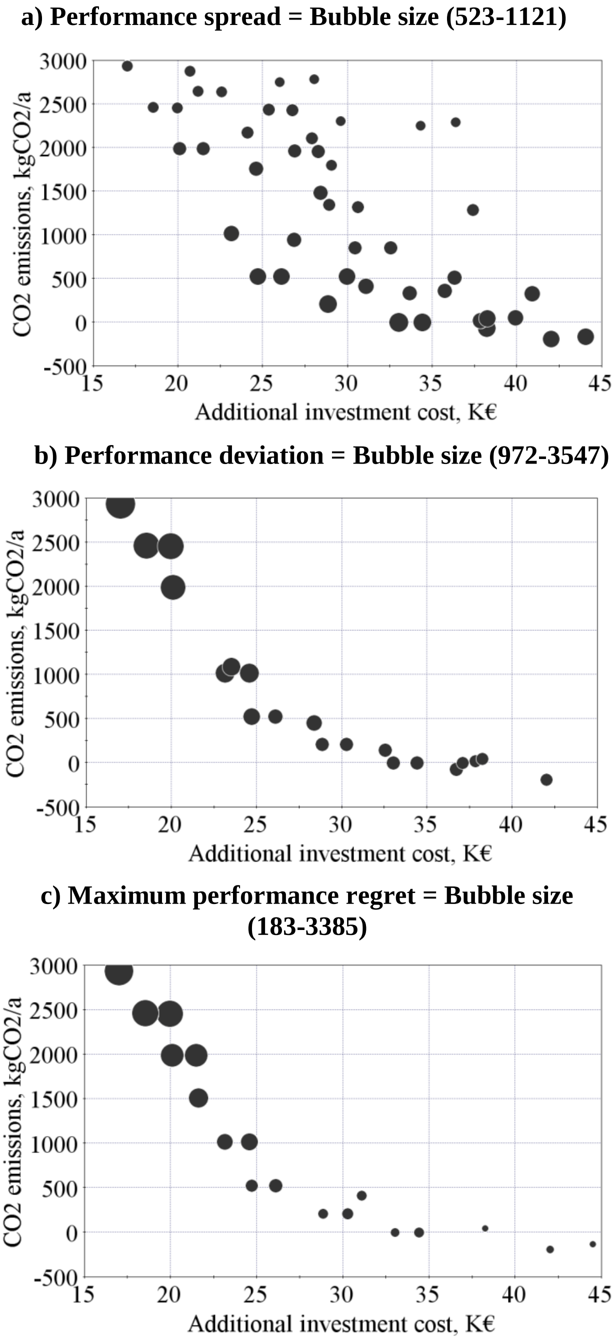


Figure 3: Pareto front of actual performance and performance robustness of CO_2 emissions calculated using three robustness indicators. a) Performance spread, b) Performance deviation, and c) Maximum performance regret.

To give better insights into the comparison of three robustness indicators, a few selected designs that are on three Pareto fronts of Figure 3a-c are analyzed. The median values and performance robustness of CO_2 emissions of selected designs are shown in Figure 4. It can be observed from Figure 4 that the performance spread results in a different robust design (design-1) compared to the other two robustness indicators (design-6). The difference between these two designs is PV system size, among other parameters, which are about 5m^2 and 30m^2 respectively. However, design-1 has very high CO_2 emissions and thus policymaker may not prefer this robust design. Based on actual performance, the policymaker would prefer designs 4-7. However, by considering robustness of these designs, policymaker can trade-off with additional investment cost to select preferred robust design. For instance, comparing design-4 and design-5, policymaker would prefer design-4 because of less investment cost, as the robustness of these designs calculated using performance spread and deviation is very similar. In contrast, maximum performance regret of design-5 is lower than that of design-4. Moreover, it is hard to distinguish between robustness of these two designs using performance spread and deviation, whereas it is easy to visualize the difference between the maximum performance regret of design-4 and design-5. Similar observations can be made for design-6 and design-7. This visualization is crucial in the decision-making process, especially when large design space and multiple performance requirements are considered in decision-making process. It is evident, by comparing robustness of designs 4-7 of Figure 4, that design-6 is more preferred robust design using three methods for policymaker. The design-6 is a light-weight building with very high insulation (Rc =10m^{2}k/W) for building envelope, window U-value of 0.4W/m^{2}K, PV system of 30m^2 and solar DHW system of 2.5m^2 with an additional investment of 38263€.

The preferred robust design by the policymaker depends on the additional investment cost required to further improve robustness and the choice of robustness assessment method depends on the approach by the policymaker in the decision-making process. For instance, if the policymaker adopts a risk-free approach in decision-making, then to improve robustness of design-6 further, the policymaker can use the *max-min method* or *the best-case and worst-case method* as the most robust design using these methods work for all scenarios. The most robust design using the *max-min method* has zero performance spread. However, to achieve zero performance spread of CO_2 emissions of design-6, it requires an additional PV system of 9.8m^2. Similarly, additional size of PV system required to reduce performance deviation to zero is also 9.8m^2. Both these methods are conservative approaches as they result in oversized energy systems requiring high additional investment costs. Conversely, if the policymaker is ready to accept certain risk, then the *minimax regret method* is the preferred robustness assessment method. Using this method, to improve robustness of design-6 further i.e. to reduce maximum performance regret to zero, an additional PV system of 2.6m^2 is sufficient, resulting in cost optimal robust solution.

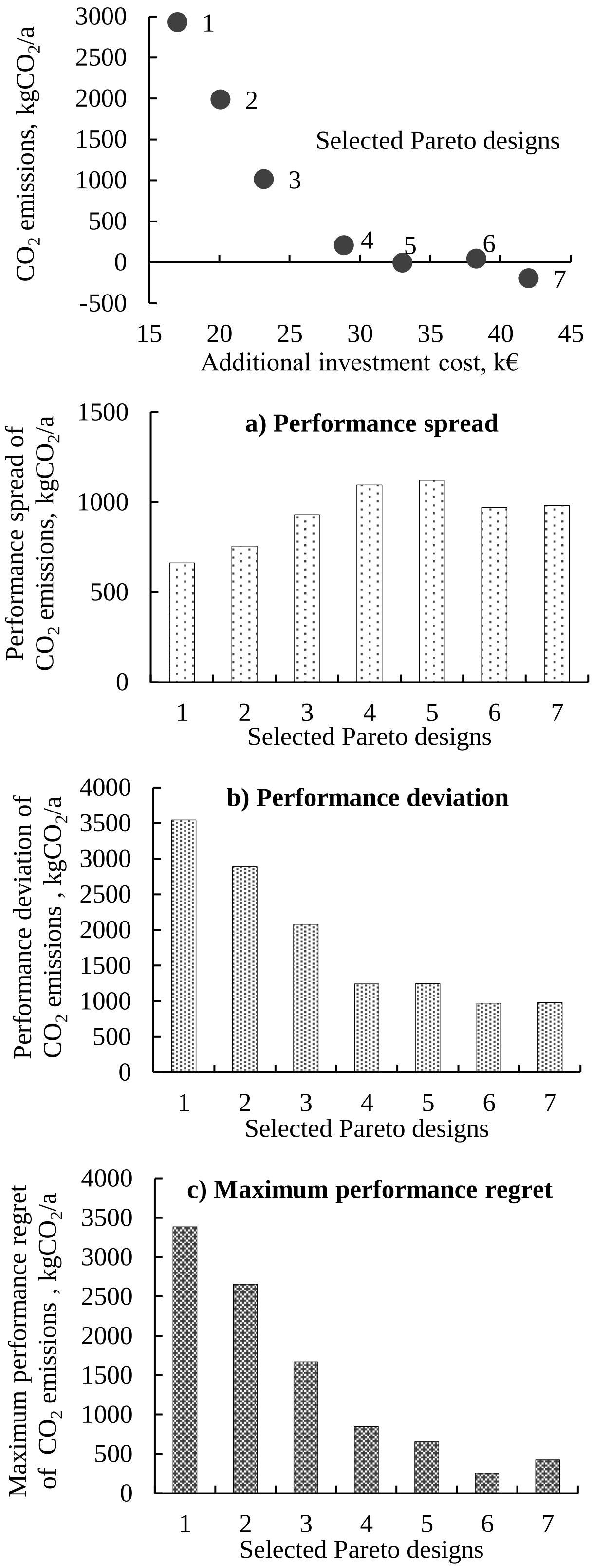
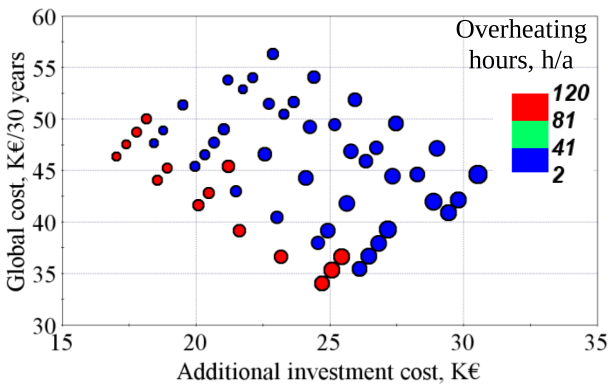


Figure 4: Comparison of actual performance and performance robustness of CO_2 emissions, of selected designs on Pareto front, calculated using three robustness indicators.

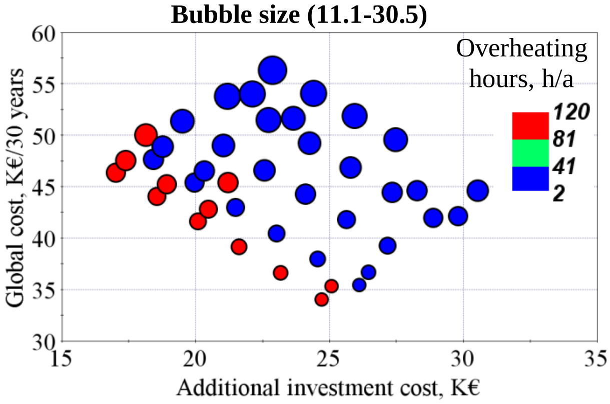
Homeowner

Figure 5 presents a comparison of Pareto front of designs, for the homeowner, obtained by optimization using three robustness indicators. The Pareto front for the homeowner is highly complex, because it is 5D, as there are five objectives in the optimization, which are the preferred performance and corresponding robustness indicators by homeowner. Four of the five objectives are shown in Figure 5 as 2D plot.

a) Performance spread of global cost =Bubble size (6.75-12.9)



b) Performance deviation of global cost = Bubble size (11.1-30.5)



c) Maximum performance regret of global cost = Bubble size (4.2-27.8)

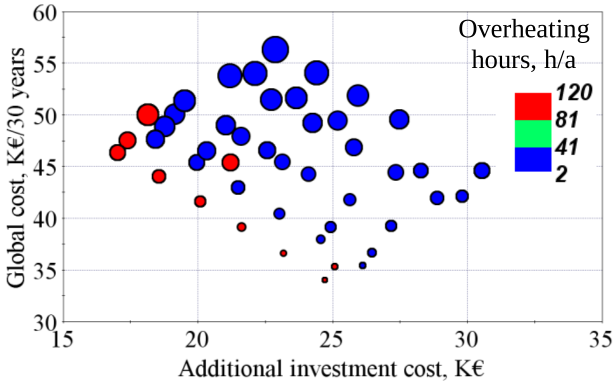


Figure 5: Pareto front of global cost and overheating hours based on actual performance and performance robustness calculated using three robustness indicators.

Each bubble is the median value of global cost of a design across all scenarios and the bubble size depicts robustness of global cost. Bubble colour represents median of overheating hours of a design across all scenarios. It is worth noting that the robustness of overheating hours is not shown in Figure 5. Similar to observations made for the policymaker, performance spread is lower for the design with high global cost (above 40000€), whereas performance deviation and maximum performance regret is lower for the designs with low global cost (below 40000€). In addition, the performance spread results in a different robust design (additional investment cost of 17000€) compared to the other two robustness indicators (additional investment cost of 24692€). The median value of overheating hours for these two designs is about 112h/a, however they differ in performance robustness. For instance, performance spread of overheating is about 304h/a and performance deviation and maximum regret of overheating hours is about 43.5h/a respectively. Thus, to overcome this overheating, the *max-min method* leads to oversized energy systems. However, this method can be applicable for robust designs when homeowner has zero tolerance towards overheating, but prefers to invest more. Conversely, if homeowner accepts certain risk of overheating, but prefer a robust design that has low global cost and additional investment cost, then the *best-case and worst-case* and the *minimax regret* methods are preferred. However, the *best-case and worst-case method* results in performance deviation of global cost of 11169€ compared to *minimax regret method* as the maximum performance regret of global cost is 4192€ for the same design. Thus, homeowner prefer the minimax regret method if he/she accepts certain risk of overheating as a trade-off with global cost.

Conclusions

This work compared different robustness assessment methods, to aid decision makers, for selecting robust designs based on their approach towards decision-making. The following conclusions are drawn from this work:

- In the *max-min method*, the performance robustness of a design is the deviation between maximum and minimum performance across all scenarios, whereas in the *best-case and worst-case method*, performance robustness is the performance deviation between the worst-case performance of a design and the best-case performance of the entire design space across all scenarios. In the *minimax regret method*, performance regret is the performance difference between the design and the best performance for a scenario, and maximum performance regret per design across all scenarios is the measure of robustness.
- Only the scenarios that cause extreme performance are considered for robustness assessment in *max-min method*. The performance of all designs across all scenarios is compared to calculate performance robustness in the *best-case and worst-case method*. The maximum deviation, across all scenarios, between the performance of a design and the best performance of the corresponding scenario is

compared to calculate the robustness using *minimax regret method*.

- The *max-min method* can be used when a design should work for all scenarios including extreme scenarios, whereas the *minimax regret method* can be used when a design should work fairly well for each scenario.
- The *best-case and worst-case method* is a conservative approach, as it yields a robust design that has the best possible performance even in the extreme case, but requires high investment costs. Conversely, the *minimax regret method* is a less conservative approach as it yields a robust design that performs as closely as possible to the optimal performance for every scenario resulting in cost optimal robust solutions.
- The *max-min method* and the *best-case and worst-case method* can be used where the cost/risk associated with failure of design is very high e.g. hospitals, clean rooms etc. *Minimax regret method* can be used where a decision maker can accept certain range of performance variation; for instance, a homeowner can accept designs with certain overheating hours as a trade-off with global costs and required additional investment cost.

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