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A robustness-based decision making approach for multi-target high performance buildings under uncertain scenarios

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HIGHLIGHTS

- A novel approach is introduced for building performance robustness assessment.
- Robustness assessment and decision making are integrated to select robust designs.
- A case study is conducted to demonstrate the value of the approach.
- Impacts of occupancy and weather scenario on building performance are analyzed.
- Robustness of competitive designs with the same performance level are compared.
- The results are compared to the Hurwicz criterion as a decision making method.

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ABSTRACT

Considering the diverse uncertainties in building operations and external factors (i.e., occupancy and weather scenarios that can impact a building's energy and comfort), performance robustness has become as important as the building performance itself. Selecting a robust and high performance building design is challenging, particularly when multiple performance criteria should be fulfilled. It requires performance evaluation, robustness assessment, and multi-criteria decision making in three sequential steps. The current study introduces a new robustness-based decision making approach that integrates the robustness assessment and decision making steps and is more transparent than previously used approaches. The proposed approach normalizes each objective function based on its defined target and combines them into one comprehensive indicator. Moreover, it penalizes solutions that do not meet the targeted margins. The new approach is tested on a case study of a single-family house, where eight competitive designs and 16 occupant and climate scenarios are investigated. Exhaustive searches and sophisticated engineering analysis are applied to validate the logic behind the approach's results. In addition, a test framework is used to validate the reliability of the approach under different combinations of scenarios. The results show that the proposed approach can select a high performance and robust building design simultaneously with less analysis effort (no need for weighting the objectives nor for conducting a robustness analysis for each objective separately) and with much trustworthy rate (selecting solution in comparison to the defined targets and with less dependency on the scenario conditions) compared to one frequently used approach (i.e., the Hurwicz criterion).

1. Introduction

1.1. Background

Improving the energy performance of buildings is an essential goal in environmentally conscious societies. One of the actions that societies take to achieve this is to establish stricter standards and requirements for building components and performance [1]. Although there has been an increase in the construction of environmentally friendly buildings, these buildings do not always perform as expected, e.g., variations in thermal comfort [2], energy, or costs [3]. Designers estimate how a building should perform, but their estimates often deviate from the actual energy consumption when the building is in operation because uncertainties in the design or renovation phase are not adequately considered. The notion of uncertainties in the building context can be related to changes in the building environment, including climate

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Nomenclature

AHP	Analytical Hierarchy Process
ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
ASHP	Air source heat pump
BPS	Building performance simulation
COP	Coefficient of performance
DHW	Domestic hot water
DM	Decision making
EB	Electric boiler
IWEC	International Weather for Energy Calculations
KPI	Key performance indicator(s)
LED	Light emitting diode
MAUT	Multi-Attribute Utility Theory
MCDM	Multi-criteria decision making
PA	Performance assessment
PCM	Phase change material
RA	Robustness assessment
TEK	Norwegian building regulation
WWR	Window to wall ratio
A_m	Maximum performance of design m across all scenarios
B_m	Minimum performance of design m across all scenarios
C_n	Minimum performance of each scenario
D_i	Best performance of all designs across all scenarios
$H(A_i)$	Hurwicz weighted average for alternative A_i
$KPI_{i,rel}$	Relative performance for indicator i
$KPI_{m,n}$	Performance of design m across scenario n
$KPI_{i,m}$	Robustness margin for indicator i
$K\bar{P}I_i$	Mean of performance indicator (i) across scenarios
PD	Performance deviation
PR	Performance regret
PS	Performance spread
T	Test condition
α	Weighting preference
б	Standard deviation

changes [4], variations in occupant behaviour [5], and changes in economic factors [6]. Uncertain environments are rarely considered in the first steps of the design phase, so decisions based on these designs will be sensitive to uncertainties, leading to a gap between the estimated and observed energy performance [7]. Therefore, there is a need to reduce the sensitivity of a building's energy performance to an uncertain environment. Reducing sensitivity to a changing environment can be done by taking robustness assessment into account during the design or renovation phase [8]. In this work, robustness is defined as the ability of a building to perform effectively and remain within the acceptable margins under the majority of possible changes in internal and/or external environments. In the context of building energy performance, robustness can be assessed using probabilistic approaches for cases where the probabilities of uncertainties are known [9] and non-probabilistic approaches where the probabilities of uncertainties are unknown [10]. In the latter approach, the assessment is done based on a scenario analysis, in which scenarios are implemented to formulate alternatives with unknown probabilities [11]. The aim of using scenarios is to better understand the impact of uncertainties and to help decision makers select designs that perform robustly under the uncertainties [12]. There are different robustness assessment methods based on scenario analysis that can aid decision makers in selecting a robust design. Some examples include the max–min, best-case and worst-case, and minimax regret methods [13]. Furthermore, some studies use probabilistic approaches, such as assessing mean and standard deviation across scenarios [14].To select a high performance and robust building design, three main steps should be followed [12]. The first step is to evaluate the performance of the building based on the results obtained from a building performance simulation (BPS). As a building's performance must respond to multiple criteria [15], as the second step robustness is assessed regarding these criteria under various uncertainties. Building performance robustness assessments can be categorized as either single-criterion [16], or multi-criteria [17], where the performance robustness of the building is assessed regarding one or multiple performance criteria, respectively. For instance, energy robustness, comfort robustness, and cost robustness can be assessed for a building. Multi-criteria robustness assessment requires the robustness assessment to be repeated separately for each criterion, and the designs selected as robust based on each criterion may not be the same [17]. In the reported research, a design that is robust for energy consumption is not robust for overheating, and one that is robust for overheating is not robust for cost. Furthermore, it is important to consider the actual performance of selected robust designs and compare them to the performance targets; otherwise, the process can lead to unrealistic designs [16]. Together with both single-criterion and multi-criteria robustness assessments, a multi-criteria decision making (MCDM) step is used as the third step for supporting decision-makers in selecting a robust and high performance building design. The selection of this design in MCDM is based on the trade-off between performance and corresponding robustness. The Hurwicz criterion [17], Minimin, Laplace, Wald [18], and Savage [16] are some examples of decision making strategies that have been implemented to select a robust building design. Based on the preferences of decision-makers, the impacts of different types of performance robustness or actual performance of the building can be prioritized by weighting them in the decision making process. Weights and other preferences data aid decision makers in tuning the selection of the best design (i.e., a high and robust performance design). However, in practice, selecting a robust and high performance design is a complicated and difficult task, particularly when multiple and conflicting performance criteria should be fulfilled. As the number of criteria and/or the conflicts among them increase, the decision making step becomes more difficult and requires more experience in order to set the preference weights for each criterion [19]. Furthermore, in the existing literature, a high performance and robust building design is selected by comparing different alternatives (i.e., building designs) to each other without comparing them with the performance targets set by standards and regulations [17]. In this approach, the best alternative is defined based on the best alternative in the design space (i.e., minimum or maximum of each performance criterion), which may be undesirable in comparison with performance targets. Furthermore, deviations of different alternatives from the performance target can be necessary in some cases. At the same time, repeating robustness assessments focusing on different criteria can be demanding from the computational point of view, especially in cases with a huge number of designs and scenarios that need sampling techniques.

1.2. Contribution of this paper

To bridge the abovementioned gaps, this paper introduces a computational approach, the T-robust approach, that integrates a multi-target robustness assessment into a multi-criteria decision making (MCDM) process and includes performance targets when the decision is being made. There are five main advantages to this approach:

- All assessed alternatives (i.e., building designs) are compared, not only to each other but also to the performance targets set by standards and regulations.
- The performances of alternatives are defined (penalized) based on deviations from the performance targets.

- The performance targets are based on regulations, standards, laws and can be adapted according to specific occupants' needs.
- The robustness assessment is not repeated separately for each performance criterion.
- Criteria preferences are automatically established in the decision making process by including performance targets.

This approach can aid building performance decision makers in selecting robust designs under possible uncertainties (possible scenarios). The integration of robustness assessment into the MCDM is done by introducing a multi-target key performance indicator, which is defined based on the design's performance regarding two different criteria. This indicator penalizes designs that do not meet the robustness margins for different key performance indicators (KPIs). This penalty differentiates between the solutions with performance less than the robustness margin (called feasible solutions in this paper) and solutions with performance greater than the robustness margin (called infeasible solutions). The robustness margins for each KPI are defined based on the requirements specified by regulations for each criterion. The introduced approach is evaluated with four different robustness assessment methods; three of them are non-probabilistic methods, while the last is a probabilistic one. To validate the introduced approach, it was also compared with a commonly used MCDM approach (the Hurwicz criterion) under a test framework. The test framework consists of eight test conditions, which are different combinations of implemented scenarios in the robustness assessment. The present approach can support designers and decision-makers in the design or renovation phase in identifying robust, high performance building designs that meet requirements even under changing conditions.

The paper is organized as follows. Section 2 reviews existing multi-criteria decision making methods in the field of building performance. In addition, different robustness assessment methods that quantify the impact of uncertainties are presented in this section. Section 3 describes the steps toward the multi-target robustness-based decision making approach and the test framework. In Section 4, the introduced approach is demonstrated using a case study. The design options and future scenarios, KPIs, and targets for each indicator are described in this section. Section 5 analyses the results obtained from the introduced approach and compares them with those from the Hurwicz decision making method through the test framework. A summary of the methodology, along with the main conclusions, is presented in Section 6.

2. Literature review

2.1. Review of multi-criteria decision making methods

In the building performance context, the best solution can be selected based on a trade-off between performance and corresponding robustness [17]. When considering multiple criteria, this can be achieved using a framework that makes it possible to compare different designs for various criteria. For such a comparison, the designs and performance criteria are shown in a decision making matrix, and because assessed criteria have different dimensions, a criteria normalization is applied. This allows different criteria to be translated to dimensionless criteria. In the next step, by applying preference weights to each criterion, different alternatives are compared to each other and the best one is selected based on an optimality function. This framework can be obtained through "multi-criteria decision-making" (MCDM) methods. These methods provide a solution to problems that are often associated with a trade-off between the performances of available alternatives under conflicting criteria. In the existing literature, MCDM methods are applied in different fields including energy planning [20], building performance simulation [21], and risk management [22]. Some examples are the Multi-Attribute Utility Theory (MAUT), Analytical Hierarchy Process (AHP), Fuzzy Set Theory, Weighted Sum Method, and Weighted Product Method. In the building performance context, AHP and MAUT are two of the most commonly applied methods in the literature. AHP is a well-known MCDM technique that helps decision makers to integrate different criteria into a single overall score for ranking decision alternatives through a pair-wise comparison [23]. In the building performance context, AHP has been used to develop a comprehensive indicator for indoor environment assessment [24], to select intelligent building systems [25],to develop a housing performance evaluation model that considers different criteria [26], to rank and compare residential energy management control algorithms [27], and to select an optimal phase change material (PCM) for a ground source heat pump integrated with a PCM storage system [28]. The AHP method does not consider uncertainties. For this reason, Hopfe et al. extended the classical AHP for use with uncertain information [15]. The other commonly used MCDM method is "multi-attribute utility theory," which is a more precise methodology for incorporating uncertainty into MCDM [29]. In this method, the overall value of alternatives is defined in the form of a utility function based on a set of attributes. Multi-attribute utility theory has been applied to select cost-effective retrofit measures for existing UK housing stock under uncertainty [30] and to perform a comparative assessment of energy efficiency alternatives with the aim of improving utility savings, and reducing embodied energy and investment cost [31].There are also several other well-known decision making approaches, such as the Laplace [32], Wald [33], Hurwicz criterion [34], and Savage [35] methods. For example, Raysanek et al. [36] used classical decision theories like the Wald, Savage, and Hurwicz criterion approaches to find the optimum building energy retrofits under technical and economic uncertainty. In the context of robust design, Kotireddy et al. implemented Savage [16] that allows decision makers to select a design that has the least risk among alternative that are ranked based on regret. They also used Hurwicz [17] to select a robust design for low-energy buildings and consider decision makers attitudes toward risk. Nikolaidou et al. [18] also used Laplace, Wald, and Savage to find robust optimal Pareto solutions under uncertainty. The weaknesses of most of the methods that have been previously used to find high performance and robust designs under uncertainty are as follows. First, one of the criteria for finding a high performance robust design is the performance (with respect to energy consumption, comfort, cost, etc.) of each design across the assessed scenarios, which can be expressed by different indicators such as, mean, median, standard deviation. This can be confusing for a decision maker who wants to find the best indicator to reflect the design performance across all scenarios. Moreover, the concept of performance targets that are based on standards and regulations have not been used in previous studies, and the ideal alternative is determined based on the best performance (i.e., maximum and minimum value among all alternatives). This is in contrast with reality, in which the ideal alternative of some criteria does not have the minimum or maximum value. Furthermore, finding the optimal preference criteria can be a difficult task, particularly when multiple conflicting criteria should be fulfilled. In order to show the differences between the proposed approach and previously used methods, the results of the proposed approach are compared with the results of robustness assessment and decision making based on the Hurwicz criterion. This criterion states that the best alternative is the one located in a middle ground between the extremes posed by the optimist and pessimist criteria. The first step for the Hurwicz criterion is to calculate a weighted-average return for each alternative. This calculation averages the minimum and maximum of each alternative using α and 1-α as weights; α (0 ≤ α ≤ 1) is the Hurwicz index and reflects the decision-makers' personal attitude toward risk taking. A Hurwicz weighted average can be calculated as below for each alternative (A_i):

For positive − flow payoffs:

$$H(A_i) = \alpha(\text{maximum of row}) + (1-\alpha)(\text{minimum of row}) \tag{1}$$

For negative − flow payoffs:

$$H(A_i) = \alpha(\text{minimum of row}) + (1-\alpha)(\text{maximum of row}) \quad (2)$$

The best Hurwicz score is the one with the maximum H for positive-flow payoffs and minimum H for negative-flow payoffs.

2.2. Introducing robustness assessment methods

The selection of robustness assessment methods is related to the purpose of the study, the decision-makers, and their preferences [37]. In the building performance context, robustness assessment is done with both probabilistic and non-probabilistic approaches. Hoes et al. [38] were the first to investigate the Taguchi method, which uses the signal-to-noise ratio value for decreasing variation in the signal (performance) due to the noise (uncertainty) in the building performance context. The robustness indicator implemented by Hoes et al. [38] is the relative standard deviation, which is similar to the signal-to-noise ratio. This indicator leads to designs that are robust for one performance indicator and sensitive for others (e.g., overheating hours). The conclusion of that study highlights the importance of considering the actual performance in addition to the relative robustness. Different robustness assessment methods have been implemented in the literature, such as Chinazzo et al. [39], Buso et al. [40], Karjalainen [41] and Gang et al. [42] implemented the spread of box plot (max–min), relative standard deviation referred to the basic model, best-case and worst-case, and minimax regret methods as robustness assessment methods respectively. Scenario analysis is one of the most widely used methods for robustness assessment. Some studies use probabilistic approaches such as comparison of mean and standard deviation across scenarios [14]. Nik et al. [43]used the mean across scenarios as a robustness indicator for robustness assessment of energy retrofits when considering climate scenarios as a source of uncertainty. Hoes et al. [10] also used relative standard deviation in the optimization of design robustness. This approach is questionable because the likelihood of occurrence of different scenarios is unknown. Thus, considering the mean and standard deviation across all scenarios does not represent the impact of each scenario, and the fluctuation between different scenarios will not be depicted. Furthermore, Li et al. [44] found that it is not suitable to adopt the standard deviation of building annual or hourly energy demand as an optimization objective function to select a robust optimal design of zero/low energy buildings. Another option is implementing a non-probabilistic approach with scenario analysis; for example, Kotireddy [13] implemented three robustness assessment methods—max–min, best-case and worst-case and minimax regret—with scenario analysis. In the present paper, the same three non-probabilistic robustness assessment methods (max–min method, best-case and worst-case method, and minimax regret method) are implemented. These methods are compared with one probabilistic method (mean and standard deviation based on the Taguchi method) as a frequently used method. The implemented robustness assessment methods are described below.

2.2.1. The Max-Min method

This method is based on the difference between the maximum performance for each design (A_m) and the minimum performance for each design across all scenarios (B_m), as shown in Appendix I. The design with the smallest difference is the most robust one. In this method, the performance of a single design is only compared between different scenarios, without comparison between different designs. This indicator is calculated as in Eq. (3), in which PS is an abbreviation of performance spread.

$$PS = A_m - B_m \quad (3)$$

2.2.2. The best-case and worst-case method

This method is based on the difference between the maximum performance of each design (A_m) and the minimum performance of all designs across all scenarios (D), as shown in Appendix I. The design that has the smallest difference between these two factors is the most robust. This indicator is calculated as below, in which PD is an abbreviation of performance deviation.

$$PD = A_m - D \quad (4)$$

2.2.3. The minimax regret method

This method is based on the difference between the key performance indicator (KPI) value for each design and the minimum performance of each scenario across all designs (C_n). This indicator is calculated as below, in which PR is an abbreviation of performance regret and KPI_{mn} represents the performance of design m under scenario n.

$$PR = KPI_{mn} - C_n \quad (5)$$

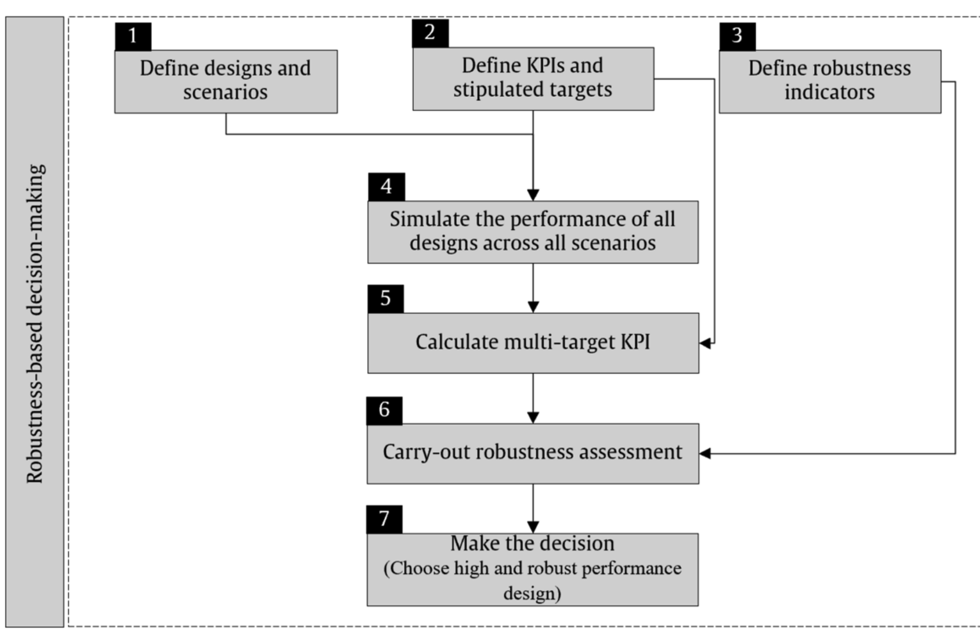

Fig. 1. Diagram flow of the multi-target robustness-based decision making approach.

The maximum performance regret represents the highest deviation in each design, i.e., the largest difference between the worst performance and the best performance. The most robust design is then the one with the smallest maximum performance regret across all designs. Appendix I shows the calculation of performance regret for designs across all scenarios.

2.2.4. The mean and standard deviation based on the Taguchi method

In this method, mean and standard deviation are considered as robustness indicators. The most robust design is the design that has the smallest variation (standard deviation) around the target performance (mean) based on the Taguchi method, which is also called the Robust Design Method. This method was used for the first time in product development [45]. The calculation of this indicator is shown in Appendix I.

3. Methodology

This section is divided into two major parts. The first section will focus on introducing the multi-target robustness-based decision making approach, and the second section will focus on validating of this approach under different test conditions (various sets of scenarios) in a test framework. Steps toward developing the approach are shown in Fig. 1 and in more detail in the following subsections.

3.1. Multi-target robustness-based decision making approach (T-robust)

In this section, the robustness-based decision making approach, which is called the T-robust approach in this paper, is introduced. This approach integrates robustness assessment into the decision making process. It considers multiple criteria for building performance and applies penalties if the robustness margins for them are not met. There are seven steps to this approach (Fig. 1), which are described below.

Step 1: Define designs and scenarios

Different possible designs for a building should be defined based on the preferences of the stakeholders who are involved in the project. Furthermore, designs are defined based on the building regulations and requirements of each country [46]. Designers also need to define scenarios for formulating alternative future conditions, considering the effects of various uncertainties in a building's energy performance during its lifespan. For instance, changes in occupant behaviour are one of the significant factors that impact a building's energy consumption [47]. Other external factors can also have effects on building performance, e.g., changes in climate conditions [48] and changes in economic factors [36]. Robustness assessment should be evaluated across the combination of all considered scenarios because the probability of occurrence of any combination is unknown. This can lead to high computational cost. The literature shows that different sampling strategies can be implemented in order to find samples that are representative of all scenario combinations [49].

Step 2: Define key performance indicators and stipulated targets

The performance of a building can be measured based on different indicators. These indicators can be related to objectives that originated from demands, such as energy consumption, thermal comfort, and cost. Indicators can be defined based on the preferences of the decision-makers involved in the building project or by considering the existing risks and technical problems in the building. Furthermore, buildings must meet specific requirements according to regulations [50], building codes, and standards [51]. In this paper, requirements are called performance targets, and the performance of the building under the design conditions (reference scenario) should not exceed the performance target. However, as stated before, the performance of buildings deviates from the performance target during operation, and this is where the robustness is needed. In order to evaluate robustness in this paper, another concept is defined, which is called the robustness margin. Fig. 2 shows the difference between "the performance target" and "the robustness margin" for energy consumption. According to this figure, the building will be robust from an energy perspective if its energy consumption does not exceed the robustness margin. The arrows in Fig. 2 represent the changes that can occur during the building's operation and lead to an increase or decrease in its energy consumption.

Step 3. Define robustness assessment methods

The performance robustness of a building can be assessed by various methods. These methods are introduced in Section 2.

Step 4. Simulate the performance of designs across all scenarios

In this step, the performance of each design across the formulated scenarios is simulated in simulation software, and based on the defined performance indicators, the results are extracted from the software.

Step 5. Calculate Multi-target KPI

In order to integrate the robustness assessment into the decision making process, a new KPI is developed called a multi-target KPI (MT-KPI). This KPI reflects the performance of the building regarding multiple criteria and penalizes the solutions that do not meet the robustness margin. In this way, it can differentiate between feasible and infeasible solutions. In the current paper, the development of the MT-KPI focuses on only two performance indicators (energy and comfort), but it can also be extended for more than two criteria. The vital point in the definition of this KPI is considering the robustness margin ($KPI_{i,m}$) for each primary KPI for penalizing infeasible solutions. Considering $KPI_{i,m}$, two parameters can be defined as below, which represent the relative performance of each indicator.

$$KPI_{1,rel} = \frac{KPI_1}{KPI_{1,m}} \times 100 \qquad KPI_{2,rel} = \frac{KPI_2}{KPI_{2,m}} \times 100 \tag{6}$$

Implementing the robustness margin leads to differentiating between the feasible solutions (KPIi < KPIi,m) and infeasible solutions (KPIi > KPIi,m). Fig. 3 shows an example of the performance of a building under 16 scenarios. Point (100,100) in Fig. 3 shows the relative margin point, at which the performance of the building regarding both indicators is equal to the robustness margin. Around the relative margin point, four different performance zones are created, of which two (i.e., zones 2 and 4) are feasible regarding one KPI and infeasible regarding the other, one (zone 3) is feasible for both KPIs, and the last

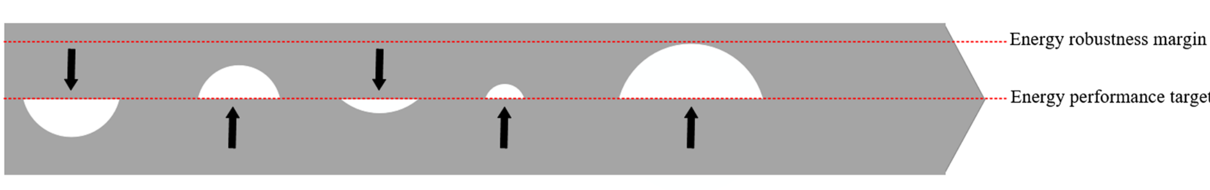

Fig. 2. Conceptual illustration of performance target and robustness margin for energy consumption.

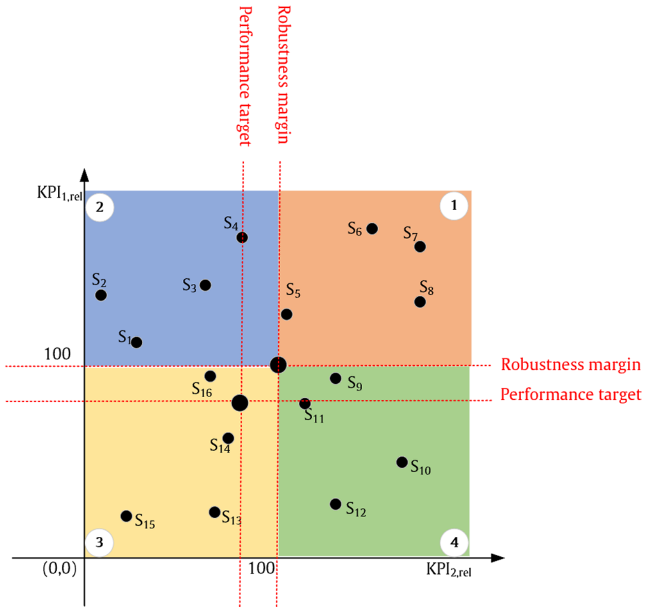

Fig. 3. Illustration of the performance zones of one design under 16 possible scenarios.

zone (zone 1) is completely infeasible.

The calculation of the MT-KPI depends on the performance zones, and is defined in Table 1. As can be seen from Fig. 3 and Table 1, in the completely infeasible zone (zone 1), the MT-KPI is the sum of the KPIs' difference with their corresponding robustness margins. This is applied as a penalty for the infeasibility of both indicators. In the completely feasible zone (zone 3), the MT-KPI is the sum of the inverted difference between indicators and their corresponding robustness margins. Inverting the differences is used in order to differentiate the feasible designs. For the other two zones, which are feasible for one KPI and infeasible for the other (zones 2 and 4), a penalty is applied only for the infeasible solutions, and the MT-KPI is defined based on Table 1.

Step 6. Carry out robustness assessment

In this step, the performance robustness of buildings is assessed with the mentioned robustness indicators for the MT-KPI. Assessing robustness using this KPI reflects not only robustness for multiple criteria but also the actual performance of the building because of the incorporation of the robustness margins in the definition of the MT-KPI.

Step 7. Make the decision

In this step, the best solution (i.e., high and robust performance design) is chosen based on the results of the robustness assessment with the MT-KPI.

3.2. *The test framework*

The combination of scenarios for a robustness assessment can vary based on the knowledge of the designers. A combination of a huge number of scenarios can lead to high computational costs. On the other hand, decreasing the number of scenarios will remove some useful information, and this can affect the selection of a robust design. The literature shows that considering extreme scenarios (low–high scenarios) can be sufficient for performance robustness assessment [49]. In order to test the validation of the T-robust approach, a test framework was developed. For this purpose, the robustness assessment in the previous section was considered as input data, and the designs selected as robust under different scenario combinations (test conditions) were compared, as shown in Fig. 4. The steps of developing the test framework are described below.

Step 1: Develop test conditions

To test the performance of the robustness assessment methods, test conditions are needed. The original set of scenarios suggested for robustness assessment is called a reference test condition. This condition is the most informative condition, and other test conditions have fewer scenarios than the reference one. In the limited number of scenarios, extreme scenarios (low–high scenarios) can be identified based on the comparison of performance across scenarios. For cases with a high number of scenarios, extreme scenarios can be found using special sampling techniques [16]. In this study, test conditions were created based on a random combination of extreme and non-extreme scenarios. Notably, each test condition must have some extreme scenarios in order to sufficiently assess robustness.

Step2: Repeat robustness-based decision making for each test condition

In this step, the robustness assessment is repeated for the created test conditions in order to determine how different robustness assessment methods behave when the combination of scenarios is changed from the reference condition to other test conditions.

4. Demonstration of the T-robust approach using a case study

A representative model of Norwegian single-family houses [52] was chosen as the case study building. This model is based on representative models in the IEEE project TABULA (Typology Approach for Building Stock Energy Assessment) [53], which aimed to develop building typologies for 13 European counties. A synthetic average building is defined for each building type, whose characteristics are representative of the most common features found in that building type based on the best available knowledge. This building is a two-story building located in Oslo with a floor area of 162.40 m^2, and is divided into three zones in a detailed model in IDA Indoor Climate and Energy software (IDA-ICE) [54] which is validated using the BESTEST: Test Procedures [55]. The zones consist of a representative day room (i.e., a combined zone for living room, kitchen, and entrance), bedroom, and bathroom. Occupancy schedules, domestic hot water distribution, and internal gains are derived from Nord et al. [56]. The building envelopes, window to wall ratio, and building energy systems (heating system, ventilation system, and DHW generation system) are considered as design options and will vary between eight competitive designs. Heating set-points, window opening, and shading strategies are considered as scenario parameters

Table 1
Calculation of MT-KPI in different performance zones.

Num	Performance zone	Feasibility	Mt-KPI
1	$KPI_{1,rel} > 100$ and $KPI_{2,rel} > 100$	Completely infeasible	$(KPI_{1,rel}\text{-}100) + (KPI_{2,rel}\text{-}100)$
2	$KPI_{1,rel} > 100$ and $KPI_{2,rel} \leq 100$	Feasible for KPI_2	$(KPI_{1,rel}\text{-}100) + (1/(100\text{-}KPI_{2,rel}))$
3	$KPI_{1,rel} \leq 100$ and $KPI_{2,rel} \leq 100$	Completely feasible	$(1/(100\text{-}KPI_{1,rel})) + (1/(100\text{-}KPI_{2,rel}))$
4	$KPI_{1,rel} \leq 100$ and $KPI_{2,rel} > 100$	Feasible for KPI_1	$(1/(100\text{-}KPI_{1,rel})) + (KPI_{2,rel}\text{-}100)$

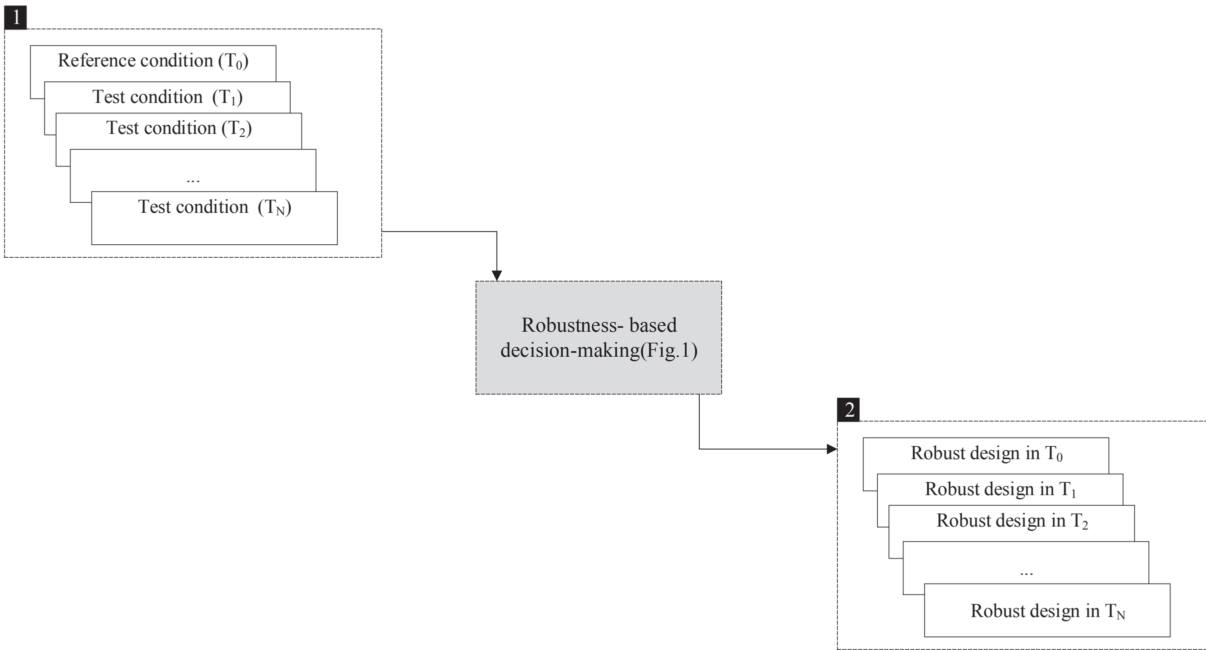

Fig. 4. Flow diagram of the test framework.

and 16 scenarios are created, which will be explained in the upcoming sections. Fig. 5 shows a screenshot of the IDA-ICE model and the building layout, which has a window to wall ratio of 30%. Steps toward the T-robust approach and test framework are described below for the considered case study.

4.1. Description of case study

4.1.1. Design variants and scenarios

4.1.1.1. Competitive designs. In this study, eight design configurations are considered for the case study building. The same energy and thermal comfort targets are set for all of the design configurations under the reference scenario (S_1). This creates the opportunity to compare the robustness of designs with the same performance targets across the considered scenarios. The target set for annual energy consumption is 110 KWh/m^2 based on the TEK17 standard [50]. For thermal comfort, the number of unacceptable hours (including underheating and overheating hours based on the TEK17 standard) should not exceed 5% of occupied hours. To achieve these energy and thermal comfort targets, the building envelope, window to wall ratio,

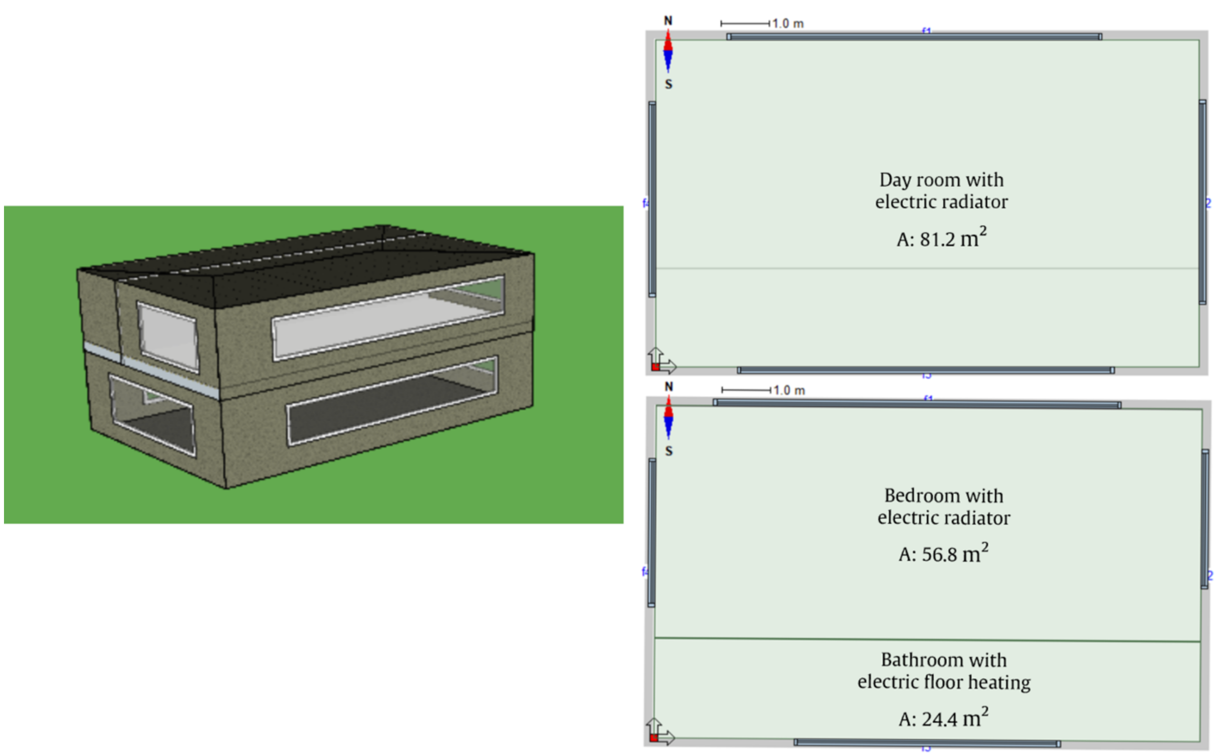

Fig. 5. Layout and appearance of a representative single-family house with a floor area of ca. 162 m^2.

and energy systems are considered as design options for the competitive designs. For example, the targets can be achieved by combining the envelope with low insulation and very efficient energy and ventilation systems. In contrast, another design can achieve the targets via a highly insulated envelope and less efficient ventilation and energy systems. However, targets are met only in the reference scenario, and when uncertainties arise, designs can have different magnitudes of performance deviations from the energy and comfort targets. Hence, the robustness margin is considered in the definition of the MT-KPI in order to select a design based on both its actual performance and performance robustness. Table2 shows the details of the designs and the assessed KPIs under the reference scenario (S_1). The building envelope of D_1 is based on the TEK17 standard, the current minimum requirement in Norway [50]. In the building envelope, the U-values of the floor, walls, and roof, infiltration, and thermal bridges are variable, and the overall U-value shows the effect of these changes. Two WWR values are considered in the design options. The heating system options are an electric boiler and an air source heat pump with a COP (coefficient of performance) of 3.2 under the rating condition. The heat emitter are electric radiators in the living room and bedroom and electric floor heating in the bathroom. It should be noted that in the designs with the air source heat pump, the heat pump is used in combination with an electric boiler, which is used to generate heat for the electric floor heating in the bathroom. Options for the ventilation system are balanced mechanical ventilation with a heat recovery unit that has an efficiency of 80% and mechanical exhaust ventilation without a heat recovery unit. Domestic hot water in the building is generated with the electric boiler, but in some of the designs (i.e., D_2 and D_6), in order to compensate for the high energy consumption due to other design options, an auxiliary solar thermal collector is added. For lighting, in most of the designs, typical lighting (luminous efficacy of 12 W/m) is implemented, but in the designs with high energy demand (i.e., D_2 and D_6), LED light (luminous efficacy of 60 W/m) is used in order to keep the total energy demand lower.

4.1.1.2. Scenarios. The scenarios that are considered in this paper include two groups of parameters: occupant behaviour and climate scenarios. The eight occupant behaviours consist of eight possible combinations of two heating setpoints, two window opening strategies, and two window shading strategies. In the climate group, two climate scenarios are considered, which leads to a total of 16 scenarios. Table 3 summarizes the scenario parameters and combinations of them across the 16 scenarios.

i. Heating setpoints

The first option for heating setpoint is taken from [52]. In order to create an option with more heating use, heating setpoints are increased in the second scenario based on the survey data taken from [57].

ii. Window shading strategies

The first window shading strategy, taken from [52], is based only on temperature control. This strategy creates a moderate usage of lighting and moderate solar gain. The second scenario increases the shaded time during the day, leading to more lighting use and less solar gains from the window.

iii. Window opening strategies

The first window opening strategy is based on [58], and is adapted with the Norwegian scale. The second option is a hybrid option that uses the first option for window opening in the day room and bathroom. In contrast, in the bedroom, which faces more overheating, it uses the upper limits of the adaptive temperature limits proposed by [59] and is developed by a macro control in IDA ICE. This reflects a group of occupants who prefer a lower inside temperature.

iv. Climate scenarios

To consider the effect of climate uncertainties, two climate files from The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), IWEC and IWEC2, are used from the library of IDA ICE [54]. The IWEC file is derived from up to 18 years of DATSAV3 hourly weather data from 227 locations, originally archived at the National Climatic Data Center (NCDC), and the IWEC2 file is derived from Integrated Surface Hourly (ISH) weather data for 3012 locations, also originally archived at the NCDC. Direct radiation parameters in the IWEC weather file have a strong negative bias of approx. 20 to 40% for Northern Europe [60]. The difference between dry-bulb temperature and direct normal radiation in the IWEC and IWEC2 weather files is shown in Fig. 6. These are the parameters with the strongest effects on the simulation results regarding energy consumption and thermal comfort, and for this reason, other parameters (e.g., relative humidity, etc.) are not compared in this paper.

4.1.2. Simulation model validation

The simulated model is validated using two different approaches. The first approach is to compare the amount of annual energy consumption to the calculated value based on the TEK 17 standard [50]. The comparison shows that if the model implements all of the requirements of TEK 17 standard (D_1 in the considered case study), it can meet the targeted value for annual energy consumption based on that standard, which is 110 KWh/m^2 for the considered case study. Furthermore, the annual energy consumption is compared with that of a similar building from [61]. Karlsen et al. [61] evaluated the annual energy consumption of a Norwegian single family house with two different envelope levels: typical ’60 s buildings and TEK 17 standards. Their results show that the range of energy consumption for the Norwegian single-family house based on the TEK 17 standard and without electric vehicles is varing from 100 to 200 KWh/m^2. This is in line with the estimated energy consumption for the current case study, which is 110 KWh/m^2. The second approach focuses on the energy use of

Table 2
Details of the eight competitive designs considered in the case study demonstration.

Design parameters	Designs							
	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
Overall U-value (W/m^2. k)	0.31	0.25	0.43	0.36	0.33	0.29	0.51	0.44
WWR (%)	30	30	30	30	40	40	40	40
Heating system	EB	EB	ASHP + EB	ASHP + EB	EB	EB	ASHP + EB	ASHP + EB
Ventilation system	Balanced	Exhausted	Balanced	Exhausted	Balanced	Exhausted	Balanced	Exhausted
Solar domestic hot water system size (m^2)	0	5	0		0	5	0	0
Lighting	Typical	LED	Typical	Typical	Typical	LED	Typical	Typical
KPIs	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
Total energy consumption (KWh/m^2)	110	110	110	110	110	110	110	110
Unacceptable hours (hr)	18	15	12	188	18	3	75	334

ASHP: Air source heat pump, EB: Electric boiler.

Table 3
Summary of the considered occupant behaviour and climate parameters and their combinations in the 16 considered scenarios.

Parameter	Options	Scenarios															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Heating setpoint	1) Bedroom, Living room, bathroom 18 ,21.5 ,23 °C (291.15, 294.65, 296.15 K)	×	×	×	×					×	×	×	×				
	2) Bedroom, Living room, bathroom 20 ,23 ,23 °C (293.15, 296.15, 296.16 K)					×	×	×	×					×	×	×	×
Window shading	1) Shading control On if $T_{indoor} > 23$ °C (296.15 K)	×	×			×	×			×	×			×	×		
	2) Shading control On if radiation above 100 W/m^2			×	×			×	×			×	×			×	×
Window opening	1) Open if $T_{indoor} > T_{out}$ and $T_{indoor} > 23$ °C (296.15 K) for windows in all zones	×		×		×		×		×		×		×		×	
	2) Open if $T_{indoor} > T_{out}$ and $T_{indoor} > 23$ °C (296.15 K) for day room and bathroomOpen based on adaptive thermal model limits for bedroom		×		×		×		×		×		×		×		×
Climate	1) IWEC	×	×	×	×	×	×	×	×								
	2) IWEC2									×	×	×	×	×	×	×	×

internal gains. Norwegian standard SN/TS 30301:2016 [46], which was developed for the calculation of the energy performance of buildings with standardized requirements, considers internal gains as fixed average values per square meter of the building which is shown in Appendix II. In the considered simulation model, these values are based on realistic values for each zone in order to increase the reliability of the energy demand profile in the model. In this validation approach, the energy consumption caused by realistic schedules is compared with the fixed values from the standard. The comparison shows that the range of simulation results is close to the reference values (Appendix II).

4.1.3. Performance indicators and stipulated targets

A building's performance robustness may be evaluated in terms of different key performance indicators. In this paper, it is evaluated for two KPIs, annual energy consumption and thermal comfort, the latter of which is evaluated in terms of unacceptable comfort level hours.

i. Total energy consumption

Total net specific energy use, which includes space heating, heating for ventilation air, space cooling, domestic hot water, ventilation, lighting systems, and appliances, is considered as the first performance indicator. TEK17 (the current minimum energy requirements in Norway) states that the total net specific energy use for a single-family house is derived from the following equation [50]:

$$\text{Total net specific energy use} = 100 + \frac{1600}{\text{heated gross internal area}} (\text{KWh/m}^2) \tag{7}$$

Considering this equation, total energy use for the case study building shall not exceed 110 KWh/m^2. This target is the one that all eight designs should not exceed under the reference scenario. As stated before, infeasible solutions are penalized based on the robustness margin in the definition of the multi- target KPI. In this paper, the robustness margin allows 5% tolerance from the energy consumption target (110 KWh/m^2), which sets115 KWh/m^2 as the robustness margin.

ii. Thermal comfort (unacceptable hours)

Energy-robust buildings are only effective when the users of the building feel comfortable. This leads us to adopt thermal comfort as the second performance indicator in this paper, which is only evaluated for the bedroom zone. TEK17 recommends an operative temperature between 16 and 26 °C (289.15 and 299.15 K) for bedrooms in Norway [50]. Unacceptable hours include both overheating hours ($T_{indoor} > 26$ °C, 299.15 K) and underheating hours ($T_{indoor} < 26$ °C, 299.15 K). In this paper, the indoor temperature should not fall outside of TEK17′s comfort range for more than 5% of occupied hours. Furthermore, the robustness margin allows 5% tolerance from this limit for a solution to be considered feasible.

4.2. Validation under the test framework

Since excluding extreme scenarios may lead to designs that are more sensitive to change, all of the created test conditions should include some extreme scenarios. For this reason, test conditions are a combination of random extreme and random non-extreme scenarios. Because there are limited numbers of scenarios in this paper, extreme scenarios were identified by observing and comparing the performance across scenarios, as can be seen in Fig. 7. Extreme scenarios that lead to the same robust design as all scenarios are S_6, S_9, and S_{11} for energy consumption and S_1, S_8, S_{12}, S_{13}, and S_{16} for thermal comfort. Since the case study for this paper is a heating-dominated building, a large portion of the unacceptable hours is related to underheating hours. The combination of underheating and overheating hours makes the identification of extreme scenarios more complex. Fig. 8 represents the

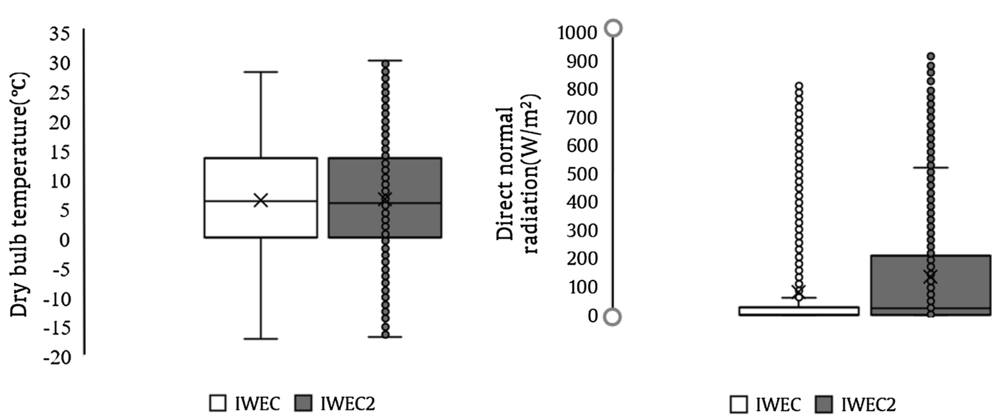

Fig. 6. Temperature and radiation differences in the IWEC and IWEC2 weather files.

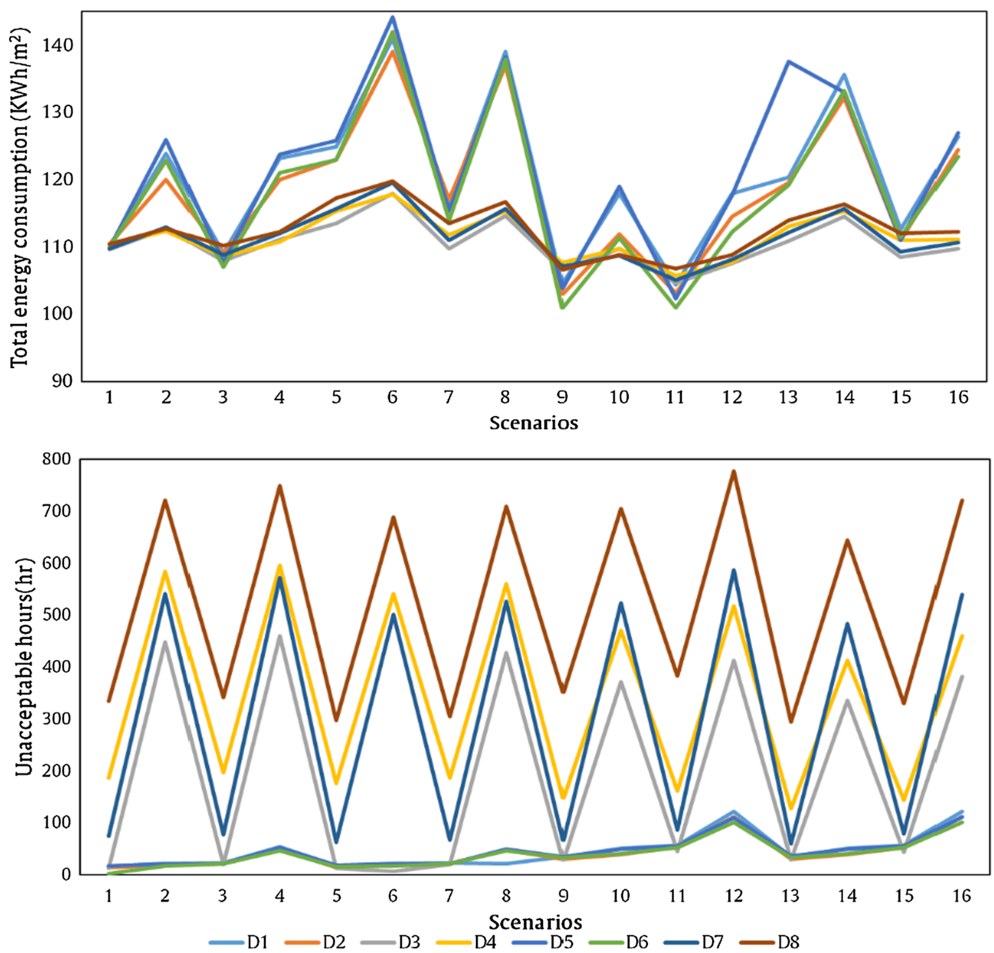

Fig. 7. Predicted performance (total energy consumption and unacceptable hours) of eight competitive designs across all scenarios.

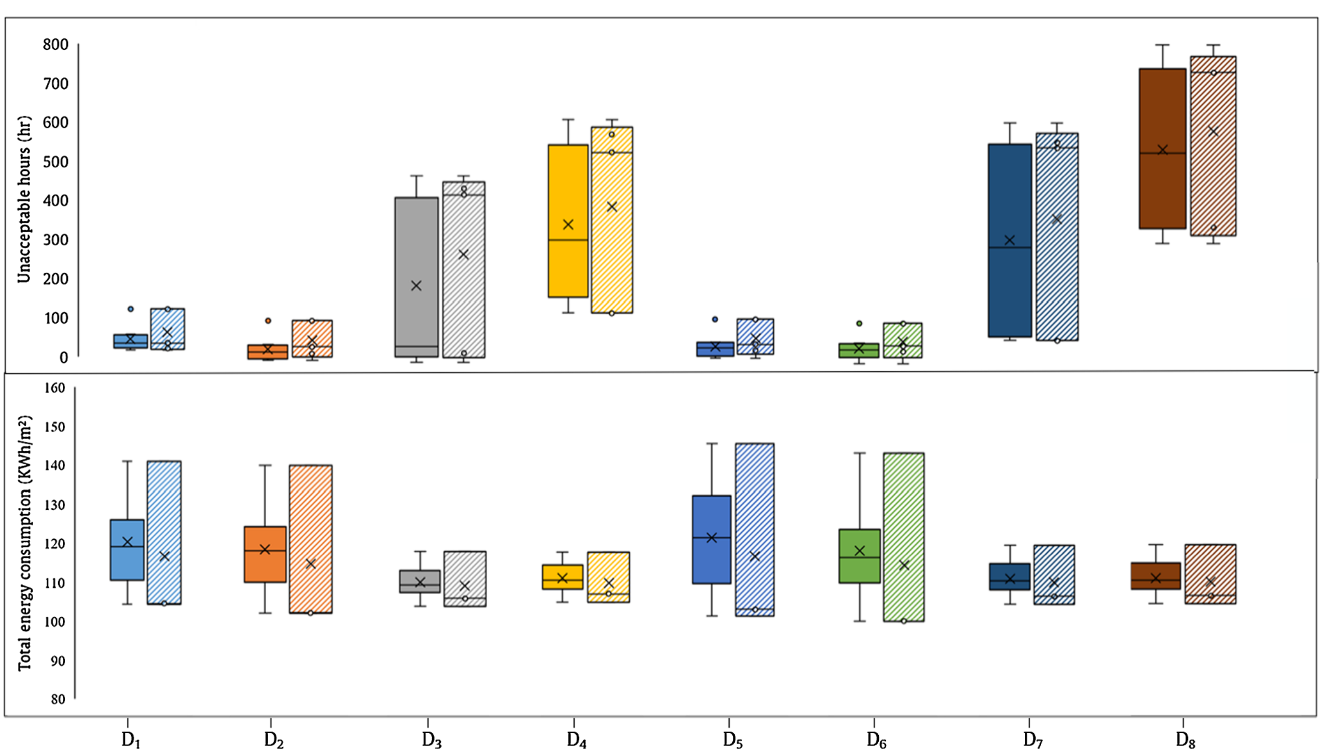

Fig. 8. Comparison of performance of eight competitive designs for combinations of all scenarios and extreme scenarios. The solid box represents all scenarios, and the hatched box represents extreme scenarios (S_6, S_9, and S_{11} for total energy consumption and S_1, S_8, S_{12}, S_{13}, and S_{16} for unacceptable hours).

comparison of building design performances from the energy and comfort perspectives for all scenarios and for extreme scenarios. As can be seen, the range of predicted performance with extreme scenarios is the same as the predicted performance across all scenarios. This shows that a test condition without any extreme scenarios cannot be sufficient for testing the performance of robustness assessment methods. So, in addition to the reference test condition (16 scenarios), eight test conditions are developed in this paper. The first test condition consists of all extreme scenarios, and the other test conditions consist of four random extreme scenarios and four random non-extreme scenarios. These combinations are shown in Table 4. Finally, robustness-based decision making was assessed for all developed test conditions with four proposed robustness assessment methods.

5. Results and discussion

5.1. Performance assessment for considered scenarios

Fig. 9 represents the variations in total energy consumption and unacceptable hours for the eight designs across the considered scenarios. The ranges of the boxes indicate the distribution of performance indicators. It can be inferred from Fig. 9 that the performance range of the designs with the electric boiler (D_1, D_2, D_5, D_6) is entirely different from that of the designs with the air source heat pump (D_3, D_4, D_7, D_8). D_3 has better predicted energy performance, and D_4 has the least variation in total energy consumption. So, it is not easy to determine which of them is the best design if total energy consumption is prioritized. If unacceptable hours are prioritized, it can be noted that D_1 has better performance and D_6 has the least variation. Fig. 9 shows that the designs with the air source heat pump (D_3, D_4, D_7, D_8) exhibit significant variation in the number of unacceptable hours. This is because the decrease in heat pump's COP (coefficient of performance) on cold winter days leads to more underheating hours during winter operation. So, if uncertainties are not considered in the performance prediction, the decision making process can select designs that lead to more underheating hours during winter operation. It can be concluded that selecting the best design based on performance cannot be achieved easily because some designs perform well but with significant variation across scenarios. So, robustness assessment is needed to facilitate the selection of designs that are robust under uncertainties and also have optimal actual performance.

5.2. Robustness assessment and robust design selection

In this section, the robust designs selected for the case study are compared based on four robustness assessment methods using two approaches:

- Choosing the best design based on robustness assessment and the decision making steps (Hurwicz criterion approach is used for the decision making step here.)
- Multi-target robustness-based decision making approach (T-robust approach)

5.2.1. Decision making based on the Hurwicz criterion

In this approach, first, robustness assessments are performed separately for total energy consumption and for unacceptable hours. Then, the design that is robust regarding both criteria is selected in a decision making step based on the Hurwicz criterion, with equal prioritization of energy and comfort. The robustness of the eight designs is calculated using the four robustness assessment methods in Fig. 10. It can be seen that for both KPIs, there are two trends among the robustness assessment methods. First, the spreads using the max–min method and standard deviation follow the same trend. This is because both of these robustness indicators are calculated based on the variation. Second, the maximum regret using the minimax regret method, the deviation using the best-case worst-case method and the mean follow the same trend because all define robustness with respect to the optimal performance. Furthermore, it should be noted that considering the mean by itself cannot be a good indicator for selecting the robust design because that does not reflect the fluctuation across different scenarios. For this reason, the mean and standard deviation in the Taguchi method is considered as a robustness indicator in this paper. It can be inferred from Fig. 10 that D_4 is the most robust design regarding total energy consumption for the max–min, best-case and worst-case, and Taguchi methods, but the minimax regret method selects D_3 as the robust design. This is in line with what the literature states about the max–min and best-case worst-case methods as conservative approaches and the minimax regret method as a less conservative approach [13]. In this case, D_4 is a design that can exhibit the best performance even in extreme cases, and for this reason, it is selected by the conservative approaches. Similarly, comparing the robustness of unacceptable hours, it can be found that the max–min, best-case and worst-case, and Taguchi methods select designs D_5 and D_6, which have better performance even in extreme cases, and the minimax regret method selects D_1, which is less conservative. In order to select a robust and high performance design regarding both criteria, a decision making approach using a neutral Hurwicz criterion ($\alpha = 0.5$) is implemented. For this decision making, the actual performances regarding both KPIs and their corresponding robustness values are normalized, and a design score is calculated based on the following equation:

$$H(A_i) = \alpha(\text{maximum of row}) + (1 - \alpha)(\text{minimum of row}) \tag{8}$$

It should be noted that in this paper, all actual performance and corresponding robustness values are prioritized equally to simplify the demonstration. The design scores for all robustness assessment methods are calculated and presented in Fig. 11. The most robust design is the design with the highest score. It can be observed from Fig. 11.a that D_1 is the most robust design using the max–min method and D_3 is the most robust design using the best-case and worst-case, minimax regret, and Taguchi methods. It can also be seen that without prioritizing the performance criteria, the max–min method selects a design that performs better for unacceptable hours (D_1), and the other methods select a design (D_3) that performs better from the energy consumption perspective.

5.2.2. Multi-target robustness-based decision making

In this section, the results of the T-robust approach are presented. In this approach, based on the definition, MT-KPI differentiates between feasible and infeasible designs by considering the robustness margin. The results of the robustness assessment with MT-KPI are shown in Fig. 11.b, which indicates that the most robust designs regarding MT-KPI are D_1 for the max–min method and D_2 for the best-case worst-case, minimax regret and Taguchi methods. D_1 is a design that has better performance for MT-KPI even in extreme scenarios, and the selected designs show that regarding the MT-KPI, the max–min method selects the most robust design using a conservative approach. The max–min method selects D_1 in both the Hurwicz decision making and the T-

Table 4
Details of scenario combinations of the eight considered test conditions.

Test condition	Number of scenarios	Extreme scenarios	Non-extreme scenarios
1	8	S_1, S_6, S_8, S_9, S_{11}, S_{12}, S_{13}, S_{16}	–
2	8	S_1, S_6, S_{13}, S_{16}	S_2, S_3, S_{14}, S_{15}
3	8	S_8, S_9, S_{11}, S_{12}	S_2, S_5, S_7, S_{10}
4	8	S_1, S_6, S_8, S_9	S_2, S_3, S_4, S_7
5	8	S_{11}, S_{12}, S_{13}, S_{16}	S_2, S_3, S_{10}, S_{14}
6	8	S_1, S_6, S_{11}, S_{12}	S_5, S_7, S_{10}, S_{15}
7	8	S_6, S_9, S_{13}, S_{16}	S_4, S_5, S_{14}, S_{15}
8	8	S_1, S_8, S_9, S_{12}	S_2, S_3, S_7, S_{10}

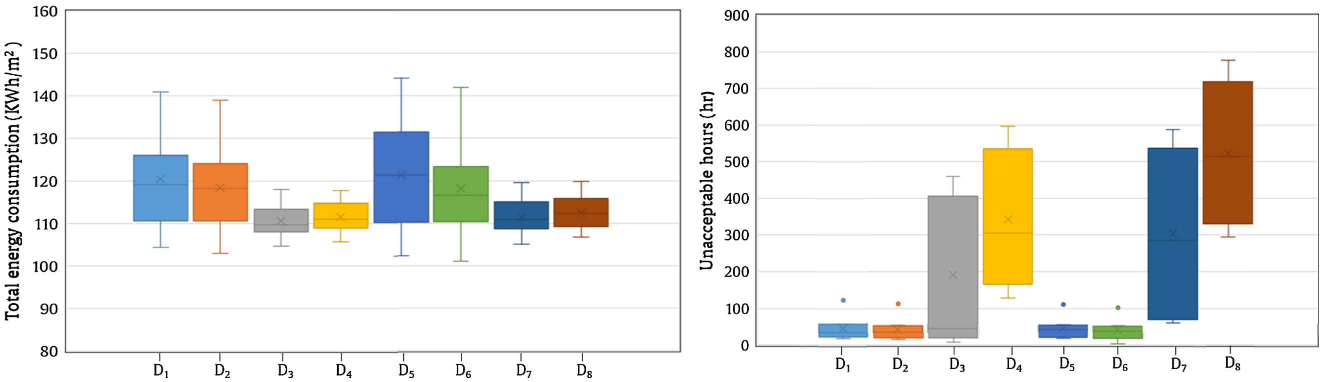

Fig. 9. Variation of total energy consumption and unacceptable hours for eight competitive designs across considered scenarios.

robust approaches; however, for the other indicators, the design selected using the Hurwicz method is D_3, but the one selected using the T-robust approach is D_2. In the T-robust approach, the preferences are automatically incorporated into the MT-KPI by using a robustness margin. Selecting designs D_1 and D_2 in the T-robust approach shows that the comfort criterion is prioritized in the robust design selection. This is in contrast with the designs selected using the Hurwicz criterion, in which all performance indicators are equally prioritized. In order to test the validity of the designs selected in the implemented approaches using different robustness assessment methods, the test framework was developed. The results for this test are represented in the next section.

5.3. Test results

As stated earlier, eight test conditions were generated in addition to the reference condition (T_0). The robustness assessment was repeated under the test conditions, and the results are shown in Table 5 for total energy consumption and unacceptable hours, respectively. It can be observed from this table that the design selected as most robust by all robustness assessment methods is repeated in conditions T_1, T_2 T_4, T_6, and T_7 for total energy consumption. In contrast, the designs selected as robust by the best-case worst-case method and the Taguchi method vary under conditions T_3, T_5, and T_8. So, for total energy consumption, the max–min and the minimax regret robustness indicators selected the same robust design across all generated test conditions. For the unacceptable hours, the T_1 and T_8 test conditions resulted in the selection of the same robust design as the reference condition for all robustness indictors. It can be inferred from Table 5 that the best-case worst-case and Taguchi methods selected the same robust design across all test conditions for unacceptable hours. A comparison of the robustness assessments for total energy consumption and unacceptable hours shows that one robustness assessment method can select the same design across all test conditions for one KPI but select different designs for the second KPI. For example, in this case study, the max–min method selects the same design across all test conditions for total energy consumption but different designs for unacceptable hours. Furthermore,

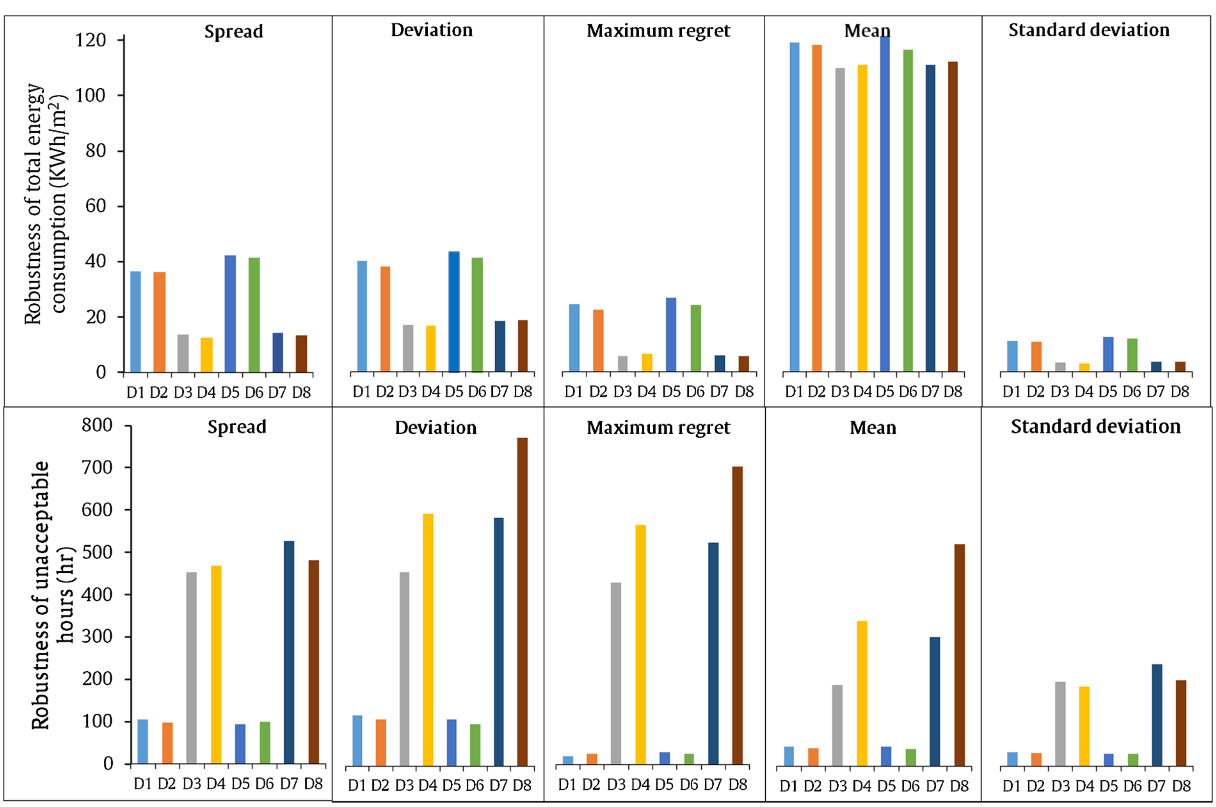

Fig. 10. Robustness of total energy consumption and unacceptable hours using different robustness assessment methods for eight designs across considered scenarios.

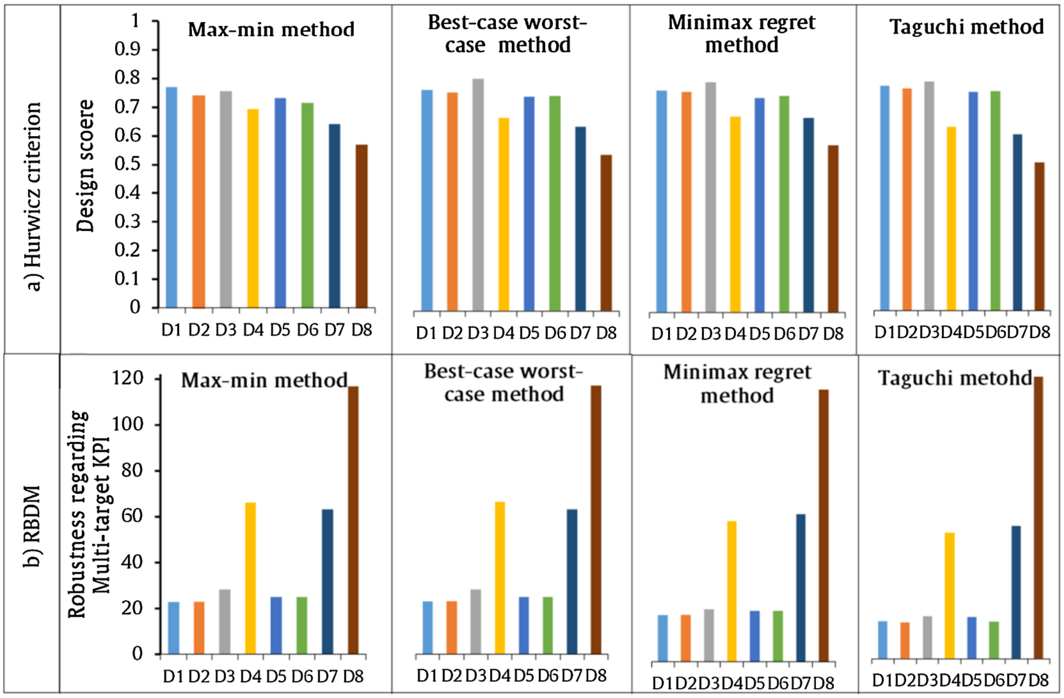

Fig. 11. (a) Design scores calculated using the Hurwicz criterion considering both performance indicators and corresponding robustness with different robustness assessment methods; (b) robustness calculated using the T-robust approach with different assessment methods.

between the implemented robustness methods, the Taguchi method selects different designs across test conditions regarding both total energy consumption and unacceptable hours. This shows that the Taguchi method is the most sensitive one regarding test conditions.

Table 6 shows the robust designs selected by the Hurwicz criterion and the T-robust approach across test conditions. The same designs that are selected as most robust by each robustness assessment methods under the Hurwicz criterion are also selected for conditions T_1, T_4, and T_7. No robustness assessment method generates the same result across every test condition in the Hurwicz decision making process, highlighting the complexity of the decision making process, which takes both indicators and their corresponding robustness into account. Even though there are some robustness assessment methods that perform consistently under different test conditions for individual KPIs, the design selected in the different test conditions is not the same when it comes to the decision making step. In the Hurwicz decision making process, D_1 is the most-selected design by the max–min method, and D_3 is the most-selected design by the other three methods. This is in line with the designs selected in the reference condition. Furthermore, the two designs selected most often by all methods across all test conditions, which are called the first and second dominant designs, are D_3 and D_1 for decision making based on the Hurwicz criterion. Regarding the T-robust approach, it can be observed that in this approach, as in the previous one, no assessment method selects the same design across all test conditions. In test conditions T_3 and T_4, all robustness assessment methods select the same design that they do in the reference test condition. The most-selected designs are D_1 for the max–min method and D_2 for the other three methods. In this approach, the designs selected most often by each robustness assessment method are again in line with the designs selected in the reference condition. In the T-robust approach, the first and second dominant designs are D_2 and D_3, respectively.

The differences between the two decision making approaches that can lead to diversity between the selected robust designs are summarized in Table 7. As can be seen from this table, the T-robust approach decreases the number of steps needed to find the best design from three to two steps by integrating the robustness assessment and decision making steps. Furthermore, the T-robust approach only assesses robustness for MT-KPI, instead of assessing it separately for energy and comfort. Performance and corresponding robustness in the Hurwicz criterion are normalized regarding the maximum performance among the alternatives. This makes the Hurwicz criterion dependent on the

Table 5
Designs selected as robust regarding total energy consumption and unacceptable hours under test conditions.

	Total energy consumption				Unacceptable hours			
Test conditions	Max-min	Best-case worst-case	Minimax regret	Taguchi	Max-min	Best-case worst-case	Minimax regret	Taguchi
T_0	D_4	D_4	D_3	D_4	D_5	D_6	D_1	D_6
T_1	D_4	D_4	D_3	D_4	D_5	D_6	D_6	D_6
T_2	D_4	D_4	D_3	D_4	D_6	D_6	D_1	D_6
T_3	D_4	D_3	D_3	D_3	D_5	D_6	D_1	D_1
T_4	D_4	D_4	D_3	D_4	D_6	D_6	D_6	D_6
T_5	D_4	D_3	D_3	D_3	D_6	D_6	D_6	D_6
T_6	D_4	D_4	D_3	D_4	D_5	D_6	D_6	D_6
T_7	D_4	D_4	D_3	D_4	D_6	D_6	D_6	D_6
T_8	D_4	D_3	D_3	D_3	D_5	D_6	D_1	D_6
Most selected	D_4	D_4	D_3	D_4	D_5	D_6	D_1	D_6
Dominant design		D_4				D_6		

Table 6
Selected robust design using the Hurwicz criterion and T-robust approach under test conditions.

	Hurwicz criterion				T-robust approach			
Test conditions	Max-min	Best-case worst-case	Minimax regret	Taguchi	Max-min	Best-case worst-case	Minimax regret	Taguchi
T_0	D_1	D_3	D_3	D_3	D_1	D_2	D_2	D_2
T_1	D_1	D_3	D_3	D_3	D_3	D_3	D_3	D_3
T_2	D_2	D_3	D_3	D_3	D_6	D_6	D_1	D_6
T_3	D_1	D_6	D_6	D_1	D_1	D_2	D_2	D_2
T_4	D_1	D_3	D_3	D_3	D_1	D_2	D_2	D_2
T_5	D_2	D_2	D_2	D_2	D_2	D_2	D_2	D_2
T_6	D_3	D_3	D_3	D_3	D_3	D_3	D_3	D_3
T_7	D_1	D_3	D_3	D_3	D_1	D_2	D_2	D_3
T_8	D_1	D_6	D_6	D_1	D_6	D_6	D_6	D_6
Most selected	D_1	D_3	D_3	D_3	D_1	D_2	D_2	D_2
First dominant	D_3				D_2			
Second dominant	D_1				D_3			

combination of performances in the solution space, and if the performance in the solution space change, the normalization process will be changed, which will affect the selected designs. In the T-robust approach, the normalization process is based on the performance targets and it does not vary with the changes in the combination of performances in the solution space. The last difference is related to the selection basis. In T-robust approach, the best design is selected by the integration of performance targets in the robustness assessment and there is no need for preferences in order to weight various criteria. This is exactly in contrast with the Hurwicz approach, where preference weights are needed for selecting the best design. For example, in the current case study, the energy and comfort criteria are weighted equally, and this can be one reason for differences between the designs selected by the two approaches. In order to validate the logic behind the selected designs and compare the dominant designs identified by the two approaches, the designs were ranked in an exhaustive search based on their physical meaning, as described in the next section.

5.4. Selection of the best design with an exhaustive search

In this section, the designs selected as robust using the Hurwicz criterion and T-robust approaches were compared via an exhaustive search. A limited number of designs was considered for the case study building in order to be able to analyse them with the exhaustive search and engineering knowledge. It is remarkable that in both approaches, designs D_1, D_2, D_3, and D_6 are selected by robustness assessment methods under different test conditions, but the dominant design in the Hurwicz criterion is not the same as in the T-robust approach. This difference can be attributed to the approach of quantifying the MT-KPI, which takes a robustness margin into account and differentiates between feasible and infeasible solutions. This differentiation is done by penalizing infeasible solutions in the definition of the MT-KPI. To make the penalizing process more understandable, an exhaustive search was implemented for the proposed designs based on two performance criteria.

It should be noted that the exhaustive search could be done for this case study because it has a limited number of designs, but in cases with a large number of designs, it would be a tedious task to make a ranking based on design physical meaning and trade-off between different performance perspectives. This can lead to computational and practical difficulties. Furthermore, this search requires a deep understanding of the physical meaning of each design and expert knowledge. First, the most influential design options that can affect total energy consumption and thermal comfort were identified based on the physical meanings of designs. Then, the designs were ranked based on those options. The ranking is summarized in Table 8. Based on the evaluation of the simulation results (Figs. 8 and 9), the most influential design option for total energy consumption is implementing the electric boiler (D_1, D_2, D_5, D_6), and its effect is stronger when there is no solar thermal collector for generating hot water, which occurs in designs D_1 and D_5. On the other hand, designs with a higher U-value and larger WWR lead to higher energy consumption. So, of the two designs, D_5 consumes higher energy than D_1, because it has higher U-value and larger WWR. After D_5 and D_1, the next highest energy consumption is related to D_2 and D_6, but they consume less electricity because they have solar thermal collectors for generating hot water. The other designs consume less energy and are not considered in detail in the ranking for total energy consumption because they do not include the most influential options.

Table 7
Summary of differences between the Hurwicz and T-robust approaches.

Num	Criteria	Approaches: Hurwicz criterion	Approaches: T-robust
1	No. of needed steps	3 steps (PA, RA, and DM)	2 steps (PA, integrated RA and DM)
2	No. of needed RAs	Dependent on the number of performance criteria (here 2)	1
3	Normalization basis	Maximum performance in the solution space	Performance targets
4	Selection basis	Weights of criteria are necessary(Equally prioritized for the current case study)	Weights are based on the required targets

No.: Number, PA: performance assessment, RA: Robustness assessment, DM: Decision making

Table 8
Design ranking based on total energy consumption and unacceptable hours.

Performance indicator	Most influential design options	Design ranking
Total energy consumption	1) Electric Boiler without solar thermal collectors 2) Higher U-value 3) Larger WWR	Bad → Good $D_5 > D_1 \gg D_6 > D_2 >$ other designs
Underheating hours	1) ASHP 2) Exhausted ventilation 3) Higher U-value 4) Larger WWR	Bad → Good $D_8 > D_4 > D_7 > D_3 >$ other designs
Overheating hours	1) Air balanced ventilation 2) Lower U-value	Bad → Good $D_1 > D_5 >$ other designs

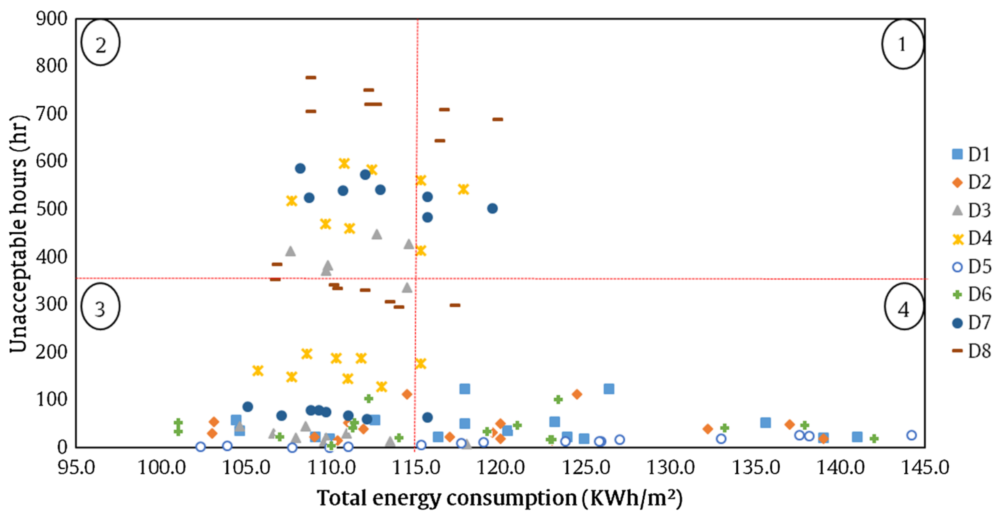

Fig. 12. Unacceptable hours vs. total energy consumption of the eight addressed designs under the 16 considered scenarios (the red lines show the robustness margin for each indicator). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Regarding underheating hours, the air source heat pump, which occurs in designs D_3, D_4, D_7, and D_8 is the most influential option for increasing underheating hours. The second influential parameter is exhaust ventilation, which can be found in D_8 and D_4, and the last options are higher U-value and larger WWR. So, the four designs with the most underheating hours are, in order, D_8, D_4, D_7, and D_3. Other designs have fewer underheating hours and are not considered in the ranking. Air balanced ventilation is the most influential parameter that increases overheating hours, and the second influential parameter is a lower U-value. This makes D_1 the design with the most overheating hours, followed by D_5. Fig. 12 summarises the results for all designs and scenarios using the same four performance zones defined previously in Fig. 3. Designs D_4, D_7, and D_8 are placed in zone 4 (infeasible for both criteria) for some scenarios, and for this reason, they are not preferable designs. D_1 is a design with high energy consumption and the highest overheating, so it cannot be selected as the best design, either. This is completely proven by both the T-robust and the Hurwicz approach, neither of which selected D_4, D_7, D_8, or D_1. The next design that cannot be selected as the best design is D_5, because it has the highest energy consumption and is ranked in the high overheating category. D_6 also cannot be selected as the best design because it has more energy consumption than D_2. The remaining candidates for selection as the best design are D_2 and D_3. The energy ranking shows that D_2 is the best design among the four designs considered from an energy perspective (D_5, D_1, D_6, D_2). On the other hand, based on the unacceptable hours ranking, D_3 is the best design among the four considered designs (D_8, D_4, D_7, D_3). This shows that there is a trade-off between the selection of D_2 or D_3 as the best design. The results show that the effect of unacceptable hours ($\frac{\text{Maximum unacceptable hours}}{\text{Unacceptable hours margin}} = \frac{460}{330} = 1.40$) for D_3 is more severe than the effect of energy consumption ($\frac{\text{Maximum energy consumption}}{\text{Energy margin}} = \frac{139}{115} = 1.2$) for D_2. Furthermore, D_3 violates both the energy and comfort criteria (under different scenarios) because its performance is placed in zones 2 and 4. In contrast, D_2 only violates the energy criterion. The selection of D_2 by the T-robust approach proves that this approach can completely reflects the effects that can occur due to the sever deviations from target and the violation from two perspective. Nevertheless, selecting the best design between these two designs by ranking their performance regarding both criteria is not so easy, and this shows that D_2 and D_3 are the best two designs that can be selected by exhaustive search. This is also in line with the results of the designs selected by the Hurwicz and T-robust approaches. As stated before, the first dominant designs selected by the Hurwicz and the T-robust approaches are D_3 and D_2, respectively, which are also selected as the best design in the exhaustive search. Furthermore, the T-robust approach selects D_3 as the second dominant design. In contrast, the second dominant design selected by the Hurwicz approach is D_1, which is not a preferable design based on the results of the exhaustive search and the physical meaning of the designs because it results in high energy consumption and high overheating hours. One of the reasons for the selection of different designs by two approaches is that in the T-robust approach, preferences regarding energy and comfort are automatically included in the robustness assessment by using robustness margins in the definition of the MT-KPI. This is in contrast with the decision that is made by the Hurwicz approach with equally prioritized energy and comfort. This can be solved by prioritizing energy and comfort criteria using commonly agreed upon weights and preferences. However, in practice, identifying those preferences and tuning the decision making can be dependent on the project and vary for different objectives. Furthermore, finding the optimum weights that lead to the best design selection becomes more difficult when it comes to real-world problems that face a high number of conflicting criteria. Implementing the T-robust approach reflects the decision-makers' preferences in a transparent way to ease the decision making process to select the best design without any guiding and tuning steps, at the same time reducing the computational cost.

The main contributions of this research are dual. First, it has proposed the T-robust approach, which allows a robust high performance building design to be selected by comparing assessed designs with performance targets. Second, the proposed approach was applied to a case study with eight competitive designs that all have the same energy and target requirement.

5.5. Practical use of the proposed approach

The proposed approach can be used by building designers, architects, engineers and other decision makers such as grid suppliers to find high performance and robust building designs. These designs can perform based on targeted requirements during operation while exhibiting minimal sensitivity to future uncertainties. Robust buildings can assure homeowners and building designers that the building will perform as expected against uncertainties, which can include changes in occupant behaviour, climate conditions, etc. As an example, it is documented that in identically constructed buildings, energy use can vary up to 17 fold due to the influence of occupants [62]. These fluctuations can be decreased by appropriately selecting robust designs. From broader perspective such as demand-side management, the energy consumption fluctuations created by uncertainties in the building sector can lead to issues such as grid failure and can increase grid stress. Thus, these fluctuations are not desirable for companies such as grid suppliers that are planning for current and future energy use in the building sector as the major energy consumer worldwide [63]. As an example, electricity demand can increase significantly during extreme weather conditions, which can be caused by buildings that are not designed for such conditions. This can leave thousands of buildings out of the comfort range and threaten the lives of vulnerable people. Furthermore, as demonstrated for the case study building, it is easier to compare designs based on the performance robustness of MT-KPI under uncertainty (Fig. 11.b), instead of comparing them regarding two different performance indicators (i.e. energy and comfort) across scenarios (Fig. 9). This comparison can be instrumental in decision making, especially when designs are going to be selected from a large design space. This approach also provides designers with information on which designs deviate more from the performance targets. This is done by penalizing the designs that do not meet the required targets.

6. Conclusion

This paper focuses on the selection of high performance and robust building designs under climate and occupant uncertainties. It introduces a new approach that integrates robustness assessment and decision making steps and selects the best design by not only comparing different designs to each other but also comparing them to performance targets that can be set by building regulations, standards or the desires of homeowners. The proposed approach comprises building performance simulation, scenario analysis, and different robustness assessment methods and then describes the robustness-based decision making approach based on the combination of these steps in a transparent and easy to understand way. This approach can be effectively used by building designers, architects, engineers, and decision-makers to select high performance and robust designs that can meet the established requirements even when considering possible changes in the internal and external environments.

The integration of robustness assessment into the decision making process is achieved using a multi-target key performance indicator, which takes multiple performances into account and differentiates between feasible and infeasible solutions using robustness margins. Using this approach also removes the need for repeated robustness assessments regarding multiple criteria. The introduced approach was assessed using four robustness assessment methods (i.e., max–min, best-case and worst-case, minmax regret and Taguchi methods) for a representative model of Norwegian single-family houses as a case study under occupant behaviour and climate scenarios in order to identify the best design. The designs of the case study building are competitive designs and all of them met the same requirements for energy and comfort based on Norwegian standards under the reference scenario. In the demonstration example, performance robustness was assessed in terms of energy and thermal comfort. Furthermore, the introduced approach was compared to one of the frequently used methods for selecting robust designs (i.e., the Hurwicz criterion) in a test framework that consisted of different sets of scenarios (test conditions).

The following conclusions can be drawn based on this comparative study:

- The proposed approach can be used by designers and decision makers to select a robust and high performance building design by comparing designs not only to each other but also to performance targets based on standards, regulations or the desire of homeowners.
- The inclusion of the performance targets in the proposed approach can automatically establish the criteria preferences. This removes the need for a weighting process which requires high levels of experience and knowledge in real-world projects that face many conflicting criteria.
- Regardless of how many performance criteria are going to be evaluated, the proposed approach needs only one robustness assessment for the multi-target key performance indicator. This can reduce the demand for the computational cost.
- Implementation of the performance targets in the proposed approach can lead to the selection of different designs in comparison with the Hurwicz approach (D_2 in contrast with D_3 for the considered case study). This can be related to the differences in the selection basis; in the proposed approach, the designs are selected based on the performance targets, whereas the Hurwicz approach requires the weighting preferences in order to select the best design.
- Robustness assessment methods can exhibit different behaviours under test conditions when they are evaluating different key performance indicators. For example, in this case study, the max–min and minimax regret methods repeatedly selected the same design under all test conditions regarding total energy consumption. In contrast, they selected different designs under different test conditions when they were evaluating unacceptable hours. This also led to different designs being selected designs in the decision making process, which shows the complexity of multi-criteria decision making under uncertainty.
- In the introduced approach, the max–min method selected a design that can work for all scenarios, including extreme scenarios, and can thus be considered as a conservative method for this approach. Other methods (the best-case worst-case, minimax regret, and Taguchi methods) selected less conservative designs.

The proposed approach is a generic approach that can be implemented for case studies with different backgrounds. In this paper, it was assessed for a two-criteria (energy and comfort) robust design problem. In future works, this can be extended to address other criteria such as cost, which is an important perspective in high performance building design. Furthermore, in this paper, the context of the proposed approach is considered for a single building. In the real world, buildings interact with each other and with the connected grids. It is, therefore, an interesting option to consider this approach for larger scales, such as a neighbourhood scale.

CRediT authorship contribution statement

Shabnam Homaei: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Mohamed Hamdy:** Conceptualization, Methodology, Resources, Data curation, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I. Calculation of implemented robustness indicators are shown in the following tables.

See Tables A1.1–A1.4.

Table A1.1
Finding the maximum and minimum performance of a design across scenarios and best performance for designs and scenarios [17].

Design	**Scenarios**					**Max and Min performance across scenarios**	
	S_1	S_2	…	S_i	S_n	Maximum performance (A)	Minimum performance (B)
D_1	KPI_{11}	KPI_{21}	…	KPI_{i1}	KPI_{n1}	A_1 = max (KPI_{11},…, KPI_{n1})	B_1 = min (KPI_{11},…, KPIn1)
D_2	KPI_{12}	KPI_{22}	…	KPI_{i2}	KPI_{n2}	A_2	B_2
…			…				
D_i	KPI_{1i}	KPI_{2i}	…	KPI_{i2}	KPI_{ni}	A_i	B_i
D_m	KPI_{1m}	KPI_{2m}	…	KPI_{3i}	KPI_{nm}	A_m	B_m
Minimum performance for each scenario (C)	C_1 = min (KPI_{11},…, KPI_{1m})	C_2	…	C_i	C_n		
Best performance of all designs across all scenarios						D = min(B) = min(C)	

Table A1.2
Robustness calculation using max–min, best-case and worst-case, and minimax regret methods [17].

Design	**Performance spread (PI)**	**Performance deviation (PD)**	**Performance regret (PR)**
D_1	A_1- B_1	A_1- D	max (R_{11},… , R_{n1})
D_2	A_2- B_2	A_2- D	max (R_{12},… , R_{n2})
…			
D_i	A_i- B_i	A_i- D	max (R_{1i},… , R_{ni})
D_m	A_m- B_m	A_m-D	max (R_{1m},… , R_{nm})
Robust design	min (PS)	min (PD)	min (PR)

Table A1.3
Calculation of performance regret of designs across all scenarios [17].

Designs	**Performance regret(R)** **Scenarios**			
	S_1	S_2	…	S_n
D_1	R_{11} = KPI_{11}- C_1	R_{21} = KPI_{21}- C_2	…	R_{n1} = KPI_{n1}- C_n
D_2	R_{12} = KPI_{12}- C_1	R_{22} = KPI_{22}- C_2	…	R_{n2} = KPI_{n2}- C_n
…			…	
D_i	R_{1i} = KPI_{1i}- C_1	R_{2i} = KPI_{2i}- C_2	…	R_{ni} = KPI_{ni}- C_n
D_m	R_{1m} = KPI_{1m}- C_1	R_{2m} = KPI_{2m}- C_2	…	R_{nm} = KPI_{nm}- C_n

Table A1.4
Robustness calculation using the Taguchi method [17].

Design	**Scenarios**						
	S_1	S_2	…	S_i	S_n	**Mean**	**Standard deviation**
D_1	KPI_{11}	KPI_{21}	…	KPI_{i1}	KPI_{n1}	$K\bar{P}I_1 = \frac{KPI_{11} + KPI_{12} + \cdots + KPI_{1n}}{n}$	$\text{б}_1 = \sqrt{\sum_{i=1}^{n} \frac{(KPI1i - K\bar{P}I_1)^2}{n}}$
D_2	KPI_{12}	KPI_{22}	…	KPI_{i2}	KPI_{n2}	$K\bar{P}I_2 = \frac{KPI_{21} + KPI_{22} + \cdots + KPI_{2n}}{n}$	$\text{б}_2 = \sqrt{\sum_{i=1}^{n} \frac{(KP21i - K\bar{P}I_2)^2}{n}}$
D_m	KPI_{1m}	KPI_{2m}	…	KPI_{3i}	KPI_{nm}	$K\bar{P}I_m = \frac{KPI_{m1} + KPI_{m2} + \cdots + KPI_{mn}}{n}$	$\text{б}_{\mathrm{m}} = \sqrt{\sum_{i=1}^{n} \frac{(KPImi - K\bar{P}I_m)^2}{n}}$
Robust design						$\min(\bar{P}I \cap \sigma)$	

Appendix II

See Table A2.1.

Table A2.1
Comparison of load schedules based on SN/TS 3031:2016 (2016) [46] to simulated results for the case study building. For lighting only, the daily amount is used.

Hour	Equipment (Wh/m^2)	DHW (Wh/m^2)	Lighting (Wh/m^2)
1	0.96	0.00	0.3
2	0.96	0.00	0.3
3	0.96	0.00	0.3
4	0.96	0.00	0.3
5	0.96	0.00	0.3
6	0.96	0.96	0.3
7	0.96	6.87	1.7
8	1.92	0.96	1.7
9	1.92	0.96	1.7
10	0.96	0.96	1.7
11	0.96	0.96	1.7
12	0.96	0.96	1.7
13	0.96	0.96	1.7
14	0.96	0.96	1.7
15	0.96	0.96	1.7
16	2.88	0.96	1.7
17	4.81	0.96	1.7
18	4.81	13.74	1.7
19	4.81	13.74	1.7
20	4.33	1.37	1.7
21	4.33	1.37	1.7
22	2.40	1.37	1.7
23	2.40	0.96	1.7
24	0.96	0	0.3
Total daily operation (Wh/m^2)	48.05	68.67	31
Annual operation (KWh/m^2)	17.53	25.06	11.35
Annual operation based on simulationmodel (KWh/m^2)	17.56	26.56	11.29

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