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EFFECTIVE AND ROBUST MEASURES FOR ENERGY EFFICIENT DWELLINGS: PROBABILISTIC DETERMINATION

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ABSTRACT

Deterministic simulations are commonly used to calculate the energy use and indoor climate of a single dwelling in the design stage. Many of the influencing parameters are however inherently uncertain. As a result, deterministic calculations are not able to reliably predict the impact of design measures. In order to improve this determination, this paper suggest a robust design method based on a probabilistic approach. Major advantage is that by uncertainty and sensitivity analysis of the heat demand and indoor temperatures the most effective and robust energy efficiency measures can be determined. Two very different dwellings are analysed, which exemplifies the possibilities of such a robustness approach.

INTRODUCTION

The energy efficiency of dwellings is becoming increasingly important with regard to climate change and fossil fuel depletion challenges. Consequently all new dwellings should be low-energy, while passive and zero-energy buildings will become the standard in the near future. Deterministic simulations are commonly used to calculate the energy use and comfort of such a dwelling. Many of the influencing parameters are however inherently uncertain, e.g. user behaviour. As a result, deterministic calculations are not able to reliably determine the impact of several design measures on heat demand and indoor climate. This determination is however increasingly important to investigate the most effective measures. In order to reduce the lifecycle cost, for example, one can wonder if it makes sense to decrease the U-value of the outer wall. Moreover, neglecting uncertainties may result in large deviations between the deterministic design value and the actual building performance. Both from the point of view of the occupant in particular as well as society in general, excessive deviations between design and reality are undesirable: dwelling owners need confidence in the return on their investments in energy efficiency and indoor climate, while governments want to ensure that their subsidy programs have the desired impact. The development and promotion of effective and robust building envelopes and service solutions is thus an important step to avoid large deviations between design and actual performances, and thus to reduce the influence of uncertain conditions. To support the development of such robust buildings, this paper uses a probabilistic approach based on an uncertainty and sensitivity analysis to calculate the building performances (Lomas and Eppel, 1992; MacDonald and Strachan, 2001; de Wit and Augenbroe, 2002; Haarhof and Mathews, 2006; Hopfe and Hensen, 2011).

Using such a probabilistic analysis, this paper introduces a robust design method for building physics based on effectiveness and robustness. Effectiveness is defined as the ability to accomplish a desired result. Robustness is generallly defined as the ability of a system to resist the influence of uncontrollable factors (Sanchez, 2000). The objective of robust design, which has its origin in manufactured products, is more specifically to optimise the average performance (effectiveness) and to minimize the variability due to uncertainty (robustness) (Zang et al., 2005). These ideas were already implemented in building mechanics and physics (van den Berg, 2005; Hoes et al., 2011). Effective solutions were however selected using optimization, whereafter the robustness of these solutions was studied. For the purpose of this study, effectiveness and robustness of design options is evaluated at the same time for all performance criteria and for the entire range of uncertain conditions and design options. The effectiveness ε and robustness R_P of a design option x_n for performance y (greater than or equal to zero and to minimise) are defined as (Figure 1):

$$\varepsilon(x_n) = 1 - \frac{y_{50}(x_n) - y_{min}}{y_{50} - y_{min}} \tag{1}$$

$$R_P(x_n) = 1 - \frac{y_{50+P/2}(x_n) - y_{50-P/2}(x_n)}{y_{50+P/2} - y_{50-P/2}} \tag{2}$$

with P the user specified percentage of included sample points, y_k the kth percentile under full uncertainty and $y_k(x_n)$ the kth percentile after selecting design option x_n. y_{min} is the minimal value which is not an outlier, whereby an outlier is defined as a sample point smaller than y_{25}-1.5(y_{75}-y_{25}). Effectiveness is thus determined as the improvement the median performance of a design option makes in proportion to the best possible improvement. The

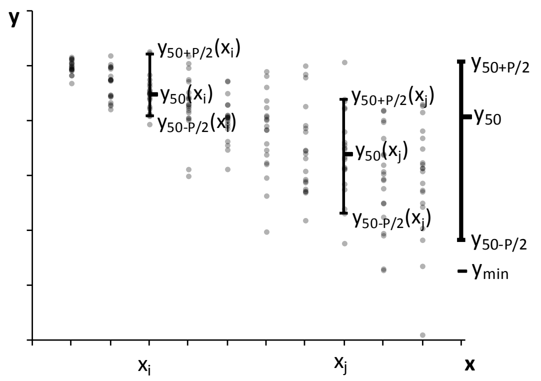


Figure 1: Effectiveness and robustness definition

robustness is analogous determined as the improvement the spread of the performance of a design option makes in proportion to the spread under full uncertainty. Both effectiveness and robustness can be used in optimization problems. According to this definition a measure with an effectiveness and robustness of one is the best possible, while negative values are to be avoided. Figure 1 shows as an example that design option x_j is more effective, while x_i is more robust.

To exemplify the possibilities of such a robustness approach, this paper presents simulations of heat demand and indoor temperatures under uncertain conditions for two very different dwelling models, taking into account several design options without touching the overall design. Major advantage is that by this approach the most effective and robust measures can be determined. The first section (simulation) describes the case study and the model used for the probabilistic analyses. The second section (discussion and result analysis) handles the results of the uncertainty analyses. The most influencing parameters are selected because these will be important in the robust design method. The final section deals with the next research steps to investigate the development of robust dwellings.

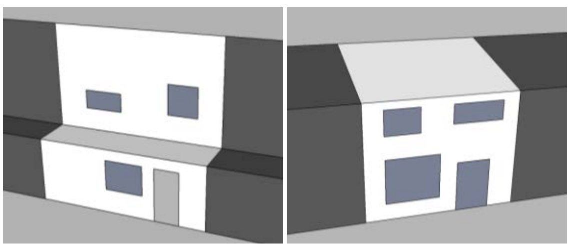


Figure 2: North and south facade dwelling 1

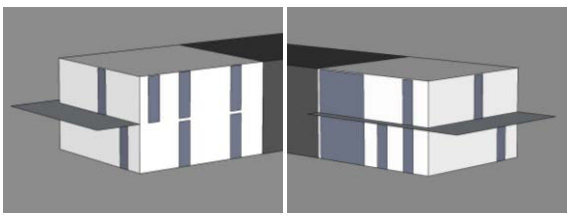


Figure 3: North and south facade dwelling 2

SIMULATION

Case study

We consider two different dwellings, representative for newly built dwellings in Belgium. Figures 2 and 3 show the building models used. Dwelling 1 is a small terraced house with a volume of 275 m³ and a north/south orientation. Dwelling 2 is a semi-detached house with a volume of 450 m³ and a north/east/south orientation. This dwelling also has an uninsulated basement and sheds for sun shading.

Dynamic model

Heat demand and indoor temperature were calculated for a reference year in Uccle, Belgium, with the use of a transient simulation tool developed in Modelica, which is explained in more detail in (Baetens et al., 2012). To model the differences in use of day and night zones of the dwellings, a two-zone model has been used. The indoor temperature of the adjacent dwellings is kept at 19 °C.

To calculate the heat demand of each zone, an ideal heating system is assumed. A ventilation system is incorporated in the model both for natural and mechanical ventilation, the latter with or without heat recovery. In summer, the heating system and heat recovery are switched off. To optimize the summer comfort, additional summer ventilation is taken into account: when occupants are present and the indoor temperature of the day zone exceeds the user dependent comfort temperature, the air change rate is doubled for the next six hours or until the occupants leave the dwelling. This algorithm simulates the user behaviour to manipulate a comfortable indoor climate.

Probabilistic approach

A Monte Carlo simulation was implemented in Matlab, which was coupled to the dynamic simulation tool, to take into account all uncertain and design variables.

A Monte Carlo analysis aims to quantify the probability distributions of the preferred outputs by repeating the simulation several times while varying the values of the stochastic input parameters according to their probability. To reduce calculation time of the Monte Carlo simulation, an advanced sampling technique was applied (Janssen 2013). For each dwelling 10 sets of 60 samples were created with a space-filling, non-collapsing sampling scheme – maximin Latin Hypercube – (Husslage et al., 2008) in order to control the convergence of the outputs.

Input parameters

Most influencing parameters for heat demand and indoor temperature are inherently uncertain, e.g. user behaviour and workmanship of implementation into practice, or are design parameters, such as U-values and glazing type. All parameters are considered stochastic. For the uncertain parameters, we assumed a probability distribution inspired by a measurement

Table 1
Distributions of stochastic input parameters

PARAMETER	DISTRIBUTION*
Occupancy profile day zone	D(1,2,3,4) (*see Table 2)*
Occupancy profile night zone	D(5,6,7) (*see Table 2)*
Set temperature occupancy day zone (°C)	N(21,1.35)
Set temperature absence day zone (°C)	D(15,no reduction)
Set temperature occupancy night zone (°C)	N(19,2)
Type of ventilation system Recovery efficiency	D(A+,C,C+,D,D+) U(0.7,0.95)
Air change rate (1/h) zone 1 Ventilation system A+ Other Air change rate (1/h) zone 2 Ventilation system A+ Other	 Dwelling 1: L(-0.3,0.53) Dwelling 2: L(-0.8,0.528) Dwelling 1: L(-0.3,0.23) Dwelling 2: L(-0.8,0.235) Dwelling 1: L(-0.8,0.515) Dwelling 2: L(0,0.39) Dwelling 1: L(-0.8,0.21) Dwelling 2: L(0,0.115)
Infiltration rate (m³/m²h)	U(0.45,12.5)
Construction type	D(massive,wood)
U-value roof (W/m²K)	U(0.1,0.3)
U-value floor (W/m²K)	U(0.1,0.3)
U-value door (W/m²K)	U(0.8,2)
U-value wall (W/m²K)	U(0.1,0.3)
Type of window	D(1,2,3,4,5) *(see Table 3)*
Type of sunscreen	D(1,2,3,4,5)
Type of sunscreen control	D(1,2,3,4)
Internal gains persons (W)	U(35,175)
Basis internal gains appliances (W)	U(20,180)
Summer internal gains appliances (W) Winter internal gains appliances (W) Spring and autumn internal gains appliances (W)	U(130,1000) U(180,1300) U(140,1150)
* Explanation of the symbols used: N(μ,σ): normal distribution with mean value μ and standard deviation σ D(a,b): discrete uniform distribution between a and b U(a,b): uniform distribution between a and b L(μ,σ): lognormal distribution with mean value μ and standard deviation σ	

campaign of 70 new dwellings in Flanders (Belgium) (Staepels et al., 2013). The design parameters, on the other hand, are chosen with equal probability.

As seen in Table 1, 19 stochastic inputs are considered in the models. The other model parameters, such as boundary conditions, are deterministic and not described in this paper because the focus lies on the probabilistic approach.

The heating system is controlled with occupancy profiles for the day and night zone, as shown in Table 2, and corresponding set temperatures of Table 1.

Table 2
Occupancy profiles

	1	2	3	4	5	6	7
00:00-06:00					X	X	X
06:00-09:00	X	X	X	X			X
09:00-12:30		X		X			
12:30-17:00			X	X			
17:00-22:30	X	X	X	X		X	
22:30-00:00					X	X	X

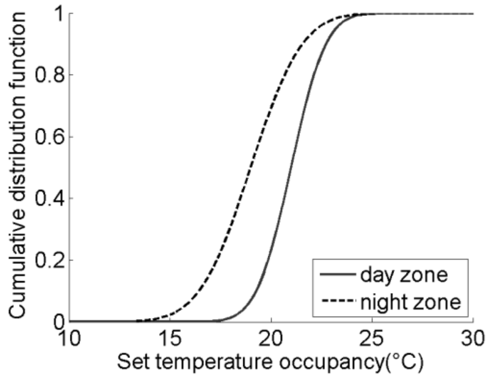


Figure 4: Cumulative distribution functions of set temperatures

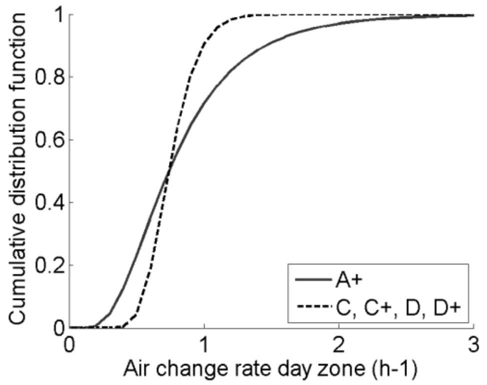


Figure 5: Cumulative distribution functions of air change rates dwelling 1

Profiles 1 to 4 are for the day zones, 5 to 7 for night zones. We assume that all profiles are equally probable. During weekends, profile 4 is taken for all day zones. The distributions for the set temperatures (Figure 4) are based on the measurement campaign (Staepels et al., 2013). Half of the households lower the set temperature of the day zone to 15 °C and all households switch off the heating of the night zone when absent.

Five types of ventilation systems are implemented and equally sampled: A+, C, C+, D and D+. The numbering corresponds to Belgian standard NBN D 50-001 (1991), where natural ventilation is indicated with A+, mechanical exhaust ventilation with C and mechanical balanced ventilation with D. Type D and D+ are equipped with heat recovery, of which the efficiency is normally distributed due to workmanship. The air change rate of system C+ and D+ is lowered when the occupants are absent. As

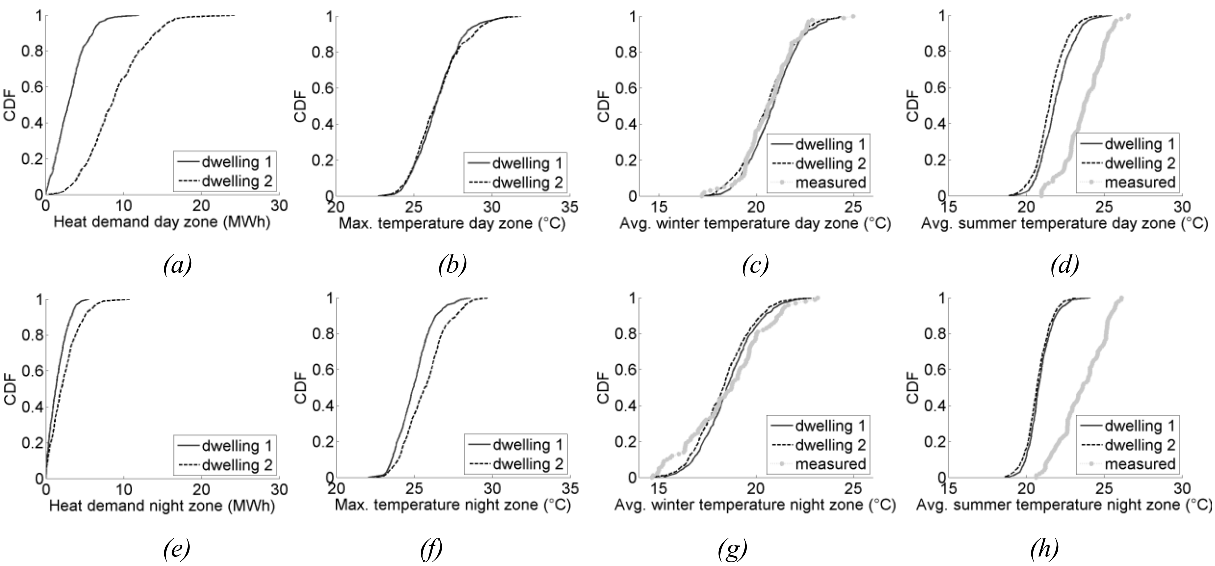


Figure 6: Cumulative output distributions for both dwellings

Table 3
Window types

	U-VALUE (W/M²K)	G-VALUE (-)
1	2.07	0.631
2	2.07	0.521
3	1.29	0.631
4	1.31	0.551
5	0.7	0.407

type A+ indicates natural ventilation, the occupants and climate conditions have more impact on the air change rate, which is lognormally distributed for both zones with a chance of 68% to have a value between -50% and +50% of the design value. For the mechanical systems, there is a chance of 95% to have a value in this range and thus, the spread is lower. Lower values are physically more probable. As an example, Figure 5 shows the distribution of the air change rate for day zone 1.

Another design parameter is the construction type. Traditionally massive, but nowadays also wooden constructions are common in Belgium. The construction type (massive or wood) of common walls, outer walls, flat roofs, internal walls and internal floors are changeable in the model.

For all dwellings, the infiltration rate per loss area can be seen as a combination of a design parameter (air tightness) and an uncertain variable (workmanship). The U-values are combinations of design and uncertain parameters as well. Note that all U-values for roofs, floors, doors and walls correspond to well insulated components.

Based on commercially available glazing types, five types of windows are considered, with different U- and g-values to vary heat losses and solar gains through the windows (see Table 3).

Sunscreens are implemented in the model. There are five equally probable possibilities: no sunscreens, sunscreens on the south facade with a transmission of 0.1 or 0.3 or sunscreens on all facades with a transmission of 0.1 or 0.3. The sunscreens are controlled automatically or manually. Four options are possible: control on solar irradiance (down above 250 W/m² and up below 145 W/m²), control on solar irradiance and indoor temperature (down above 23°C and up below 20 °C), control on indoor temperature in summer or manually controlled in summer (indoor temperature and presence).

Finally, the internal heat gains are modelled as uncertain parameters. The heat gains contain gains by persons present, standby appliances and lighting, and appliances and lighting in use. All heat gains are considered constant over the seasons and over the time that someone is present in the zone, and are thus averaged values coupled to the occupancy profiles. The averaged heat production by individuals is assumed to vary uniformly between 35 and 175 W. This assumes an averaged presence of 0.5 to 2.5 adult persons (when someone is present according to the occupancy profile). In the day zone, the standby heat production is assumed uniformly distributed and present during the whole year. When someone is present in the day zone, a season dependent heat gain by appliances and lighting is added. The three values for those seasonal heat gains are fully correlated to each other.

DISCUSSION AND RESULT ANALYSIS

Uncertainty analysis

Based on the described input distributions, the probability distribution of several outputs is created with a Monte Carlo analysis for both dwelling models. For both day and night zone, we consider the total heat demand, the maximal temperature and the average temperature in winter and summer, as shown in Figure 6. A large spread can be observed. Both heat demand and temperatures are higher in the day zones. Dwelling 2 has a higher heat demand, which is obvious given its bigger volume. The maximum and average temperatures are very similar for both dwellings. If one compares the simulated temperatures with the measured ones (Staepels et al., 2013), one can see a good agreement for the winter temperatures. This is logical as the set temperatures are chosen based on these measurements. For the summer period however, the simulations underestimate the measured indoor temperatures. This can be ascribed to the absence of sunscreens and to the ventilation habits of the occupants in the real dwellings.

Sensitivity analysis

In order to investigate the robustness of energetic measures for dwellings, the most influencing uncertain and design parameters are selected based on scatter plots and Pearson's correlation coefficients (Hamby, 1994). For the current case, both sensitivity methods come to the same important parameters.

As an example, Figure 7 shows the scatter plot to investigate the impact of the set temperature on the heat demand for dwelling 1. The dots represent the median value for each parameter value. The set temperature of the day zone when people are present appears to highly influence the heat demand of dwelling 1. Figure 8 shows the scatter plot of an important design option. The maximal temperature in a wooden construction seems to be higher than the temperature in a massive one. On the other hand, Figure 9 shows the scatter plot of an apparentely insignificant design parameter, the U-value of the outer walls.

Table 4 gives an overview of the Pearson's correlation coefficients of the most important parameters for heat demand and maximal temperature for both dwellings and zones. One can see that for both dwellings the same parameters are important. For the heat demand, the ventilation system (with or without recovery) and infiltration rate are the most influencing design parameters. The user behaviour, and more specific the set temperature, shows to be the most important uncertain parameters. For the maximal temperature, on the other hand, the type of construction, type of sunscreen, and g-value of the window are the most important design parameters. The internal heat gains, and thus again user behaviour, are the significant uncertain parameters. For dwelling 1 the heat gains are even more important then for dwelling 2, because of the relative higher impact due to its smaller volume. Note that the insulation is found to be not important at all. Of course, one has to remind that the considered U-values correspond to well insulated components, but even then this result is striking.

Based on the assumed input distributions, we selected the influencing design and uncertain parameters. Those can be used to examine robust and user indepentent dwellings in the next section.

Effectiveness and robustness

Based on the outcomes of the sensitivity analysis, we investigated the effectiveness and robustness of the most influencing design options for dwelling 1 as an introduction to a robust design method as governments need confidence on the impact of these measures. Figure 10 shows the cumulative distribution functions for the measures concerning construction, sunscreen and ventilation type. In order to facilitate the comparison of these subsamples, Table 5 demonstrates the effectiveness and robustness of these measures as defined in Equation (1) and (2).

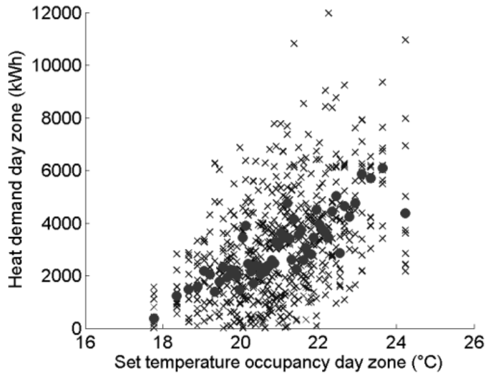


Figure 7: Scatter plot dwelling 1 – influence of set temperature on heat demand, whereby dots indicate median values

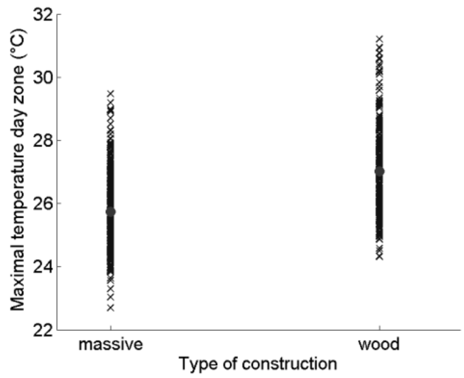


Figure 8: Scatter plot dwelling 1 – influence of construction type on maximal temperature, whereby dots indicate median values

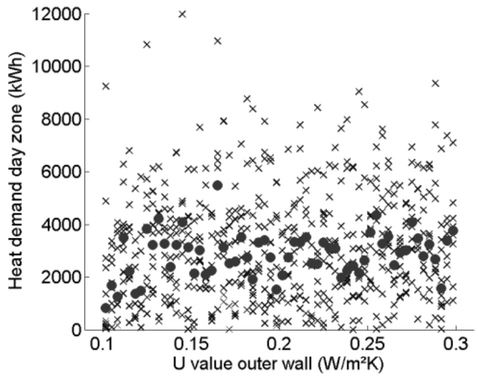
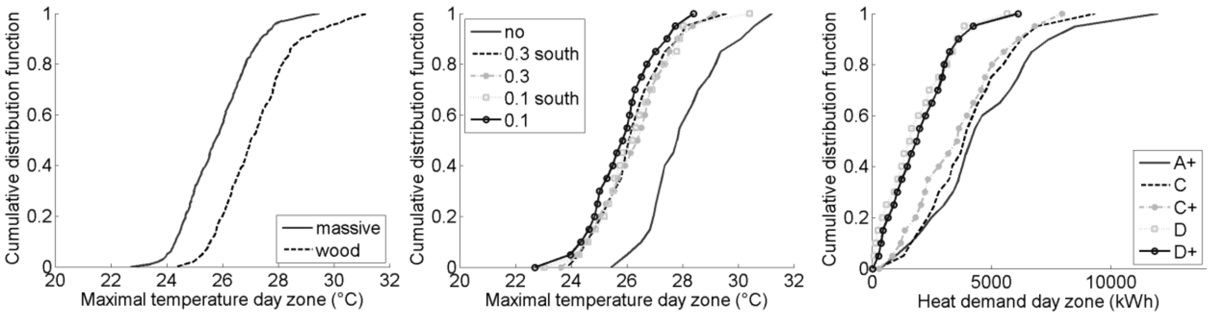


Figure 9: Scatter plot dwelling 1 – influence of U-value outer wall on heat demand, whereby dots indicate median values



(a) *(b)* *(c)*

Figure 10: Cumulative output distributions for design options for dwelling 1

Table 4
Pearson's correlation coefficients dwelling 1 and 2

DESIGN PARAMETER		UNCERTAIN PARAMETER	
Heat demand day zone			
Recovery efficiency	-0.51 / -0.46	Set temperature occupancy day zone	0.49 / 0.55
Type of ventilation	-0.50 / -0.39	Air change rate	0.40 / 0.30
Infiltration rate	0.19 / 0.41	Internal gains appliances	-0.35 / -0.23
		Set temperature absence day zone	0.31 / 0.28
		Set temperature occupancy night zone	-0.21 / -0.20
Heat demand night zone			
Recovery efficiency	-0.29 / -0.39	Set temperature occupancy night zone	0.80 / 0.75
Type of ventilation	-0.28 / -0.39	Set temperature occupancy day zone	-0.26 / -0.29
Infiltration rate	0.17 / 0.15	Air change rate	0.22 / 0.21
Maximal temperature day zone			
Type of construction	0.47 / 0.53	Internal gains appliances	0.61 / 0.33
Type of sunscreen	-0.42 / -0.58	Basis Internal gains	0.16 / -
g-value window	0.12 / 0.22	Internal gains persons	0.14 / -
Type of sunscreen control	- / 0.15		
Maximal temperature night zone			
Type of construction	0.61 / 0.71	Internal gains appliances	0.38 / 0.21
Type of sunscreen	-0.42 / -0.50	Internal gains persons	0.15 / -
g-value window	0.14 / 0.20	Basis Internal gains	0.11 / -
Type of sunscreen control	0.11 / 0.12		

Table 5
Effectiveness and robustness of measures

			ε	$R_{50\%}$
Maximal temp. day zone	Construction type	Massive	0.18	0.05
		Wood	-0.17	0.06
	Sunscreen type	No	-0.38	0.01
		0.3 south	0.08	0.16
		0.3	0.00	0.03
		0.1 south	0.05	0.12
		0.1	0.15	0.17
Heat demand day zone	Ventilation type	A+	-0.41	-0.13
		C	-0.32	0.14
		C+	-0.21	0.02
		D	0.46	0.20
		D+	0.36	0.26

Comparing the different measures concludes that a massive construction ensures overall lower maximal temperatures in the day zone of dwelling 1. Note that massive dwellings has a larger effectiveness with respect to the indoor comfort, while the robustness for massive and wooden constructions is similar. Adding sunscreens seems to have the same effect on the maximal temperature, but the type of sunscreen has only little influence. Balanced ventilation (system D and D+) appears an effective and robust measure to lower the heat demand of the day zone. In fact, this can be ascribed to the influence of heat recovery.

Besides the influence of single measures on the average performance criteria and robustness, examining coupled measures is also interesting in the development of robust designs. Figure 11 shows that in a massive dwelling adding sunscreens, which is the next effective parameter after construction type, is still an effective measure.

Analogous to this example, one can add design options (and thus lower the number of stochastic design parameters) in order of effectiveness and robustness, until no significant difference between two designs appears. In that case, we converged to the most effective and robust design. When comparing several options, this can become very time consuming and an optimisation method will be more appropriate. Because most effective measures are not always most robust and because design

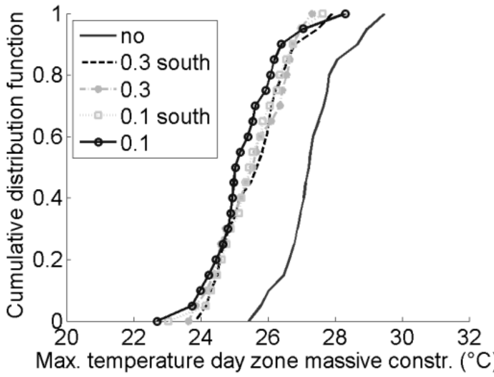


Figure 11: Cumulative distribution function dwelling 1 for sunscreen types in a massive construction

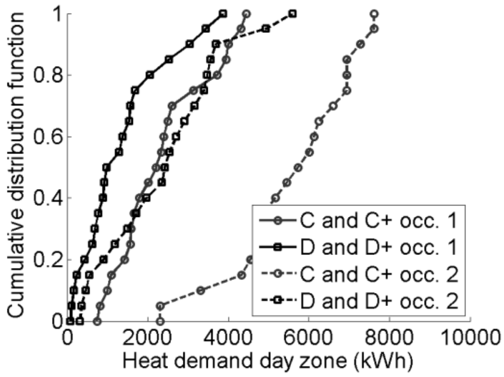


Figure 12: Cumulative distribution function dwelling 1 for ventilation types and different occupants

options can oppositely influence several performance criteria, weight factors need to be introduced as well.

As caution is needed when making subsamples of a maximin design (Van Gelder et al., 2012), the reliability of the robustness of the design options is doubtful. Because 25th and 75th percentiles are more reliable for small subsets than 5% and 95%, $R_{50\%}$ is chosen in this paper, however one would prefer to take 90% of the outputs into account.

Occupant independence

In the previous section, the robustness and effectiveness of design options was investigated, as this is interesting for governments. In addition, occupant behaviour is an essential part in the development of robust dwelling designs. It is obvious that some occupants use more energy than others do; however, occupants want to ensure that overall effective and robust measures are effective and robust for him as well. It is therefore interesting to investigate if those measures are occupant independent to a certain extent.

This section exemplifies how to control the efficiency of measures for different occupant types. We consider two subsets of two occupants: occupant 1 is not much at home (profile 1 cfr. Table 2), has a set temperature for the day zone below 21°C and lowers the temperature when absent; occupant 2 is always at home (profile 4), has a set temperature for the day zone above 21°C and does not lower the temperature at night. As one can imagine, occupant 1 will have a lower heat demand then occupant 2. This can be seen in Figure 12 for dwelling 1. Additionally, this figure shows the cumulative distribution functions for mechanical ventilation systems with and without heat recovery. Heat recovery (or ventilation type), which seemed to be an effective measure in Figures 10(c), contributes to the heat demand reduction for both occupant types.

CONCLUSION

This paper focussed on a probabilistic analysis in order to reliably calculate the building performances of a dwelling in the development of robust buildings to avoid large deviations between design and actual performances. This approach was applied on two very different dwellings, for which the most effective and robust measures on heat demand and indoor climate could be determined. Therefore, the transient simulations took the uncertain conditions and design options, which were described in this paper, into account without touching the overall design. Those uncertainties could be considered using a Monte Carlo analysis with a space-filling sampling scheme.

The uncertainty analysis showed a large spread on the heat demand and indoor temperatures. In order to investigate this spread, a sensitivity analysis based on scatter plots and Pearson's correlations showed the most influencing uncertain and design parameters. For both dwellings, the same parameters appeared important. For the heat demand, the ventilation system (and heat recovery) was the most significant design parameter, whereas the set temperature was the most important uncertain parameter. For the maximal temperature, on the other hand, the construction and sunscreen type were the most influencing design parameters and internal heat gains most influencing uncertain parameters. The most striking result was the unimportance of the U-values, corresponding to well insulated components.

The robust design method, as introduced in this paper, defined and investigated the effectiveness and robustness of the most influencing design options for dwelling 1. These measures appeared to have a large influence on both the average performance and the spread. To ensure that selected measures are optimal for all types of occupants, the influence of the user on the optimal ventilation measure was also investigated as an example. For both considered occupants, heat recovery seemed to be an effective measure.

FURTHER RESEARCH

The uncertainty analysis will be extended in some ways. The current research describes only two, but very different, dwelling types. To ensure that the robustness results can be generalized, some more types have to be investigated. It would be good to examine also the impact of the choice of some of the input parameters, as this can has an impact on the results. Only limited correlations are taken into account so far. One can imagine that correlations between U-value or construction type and air tightness are possible, and therefore may have a significant influence on the robustness as well.

The sensitivity analysis as described in this paper is currently state of the art. More advanced techniques should make it possible to investigate coupled sensitivities and to split sensitivities to means and standard deviations, which is very interesting in view of a robust design method.

Moreover, the robustness and occupant analysis needs improvement. To investigate all design parameters and combinations, current approach is very time consuming and not accurate enough. As taking too many subsamples makes the results unreliable, an adapted more-layered sampling scheme (Dehlendorff et al., 2011) should be implemented. This will ensure that all uncertain parameters are equally sampled for all design options. A coupling with metamodelling and optimization methods will be very interesting as this can reduce calculation time.

As the most effective and robust design may be not very cost efficient, a cost analysis can be included in the research. The overall life cycle cost can be added as an output parameter next to the heat demand and the maximal temperature.

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