Predicting energy savings at district level: representative vs. individual dwelling approach

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SUMMARY:
When predicting energy savings at aggregated level, a common simplification is the representation of a large group of similar houses by one single representative dwelling, occupied by one specific inhabitant. The calculated energy savings for this representative dwelling are then multiplied with the number of houses to obtain the expected aggregated energy savings. In this paper, this representative dwelling approach is compared with the individual dwelling approach where multiple different dwellings are modelled separately and their energy savings are added. When combined with probabilistic user behaviour, it is found that the representative dwelling approach predicts similar mean aggregated savings, but underestimates the actual spread due to the lack of variety in building characteristics.

1. Introduction

Policy makers often rely on aggregated building stock models to estimate the energy saving potential of future policy measures. Due to the aggregated scale, assumptions and simplifications have to be made to keep the building stock models manageable. A simplification often used is the representation of similar housing groups by a single dwelling model with most probable characteristics like size, orientation, insulation level, equipment etc. This is called the ‘representative dwelling’ approach (Cyx 2011). A single user behaviour profile which best reflects the ‘average’ user is then chosen and the calculated energy savings for this single dwelling are multiplied with the number of houses to obtain the expected aggregated energy savings. The main advantage of this approach is the limited modelling work and reduced calculation time. However, there are some important disadvantages. The existing variability in building use and characteristics, even for houses belonging to the same district, cannot be reflected by one single building model and a single user, which limits its applicability for policy makers. Also, the specific choice and combination of both the representative dwelling and average inhabitant have an important impact on the predicted energy savings. If one would select another dwelling and /or user, the aggregated outcome could be heavily influenced.

In this paper, two different approaches in modelling energy savings at district level will be compared: (i) the *representative dwelling* approach where a fictitious dwelling is modelled, based on average characteristics from the district, and where its energy savings are scaled up to district level and (ii) the *individual dwelling* approach where 10 individual dwellings, sampled from the district, are modelled in detail and where their individual energy savings are added up to compose the district savings. In both approaches, the user behaviour will be implemented in a probabilistic way, meaning that heating patterns and temperature setpoints are given by probability distributions instead of fixed values. A Monte Carlo analysis based on the maximin Latin-hypercube sampling is performed to obtain the overall spread on the energy savings due to this user behaviour.

In the next section, the case district and the generic building model are described and the composition of the representative dwelling is discussed. The third section shows how the probabilistic user behaviour is modelled and how the Monte Carlo analysis is performed. The final section discusses the results of the simulations.

2. Case study

2.1 Description

The case study in this paper is a small district in Leuven, Belgium, consisting of 52 identical dwellings built by the same building company around 1970. They are relatively large 2-storey dwellings with uninhabited attic, both in detached and in semi-detached typology. Some pictures and the original floor plan of the dwellings are given in Figure 1. The total volume V is 432 m³ and gross floor area (including garage) is 162 m². Due to the limited floor area of the ground floor, many owners have enlarged the dwellings by adding a ground floor extension at the backside. Outer walls are cavity walls in brick. Both slab-on-ground and internal floors are concrete structures, while the pitched and flat roofs are wooden structures.

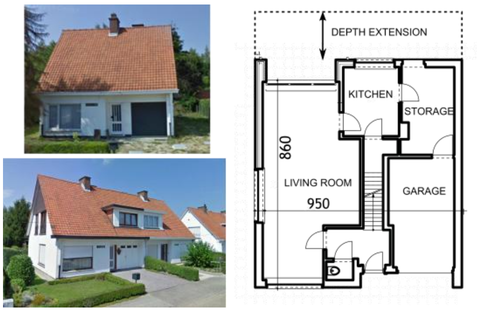

FIG 1. Casestudy dwelling (open and semi-terraced) and floor plan of ground floor (dimensions in mm).

The detailed survey information of 10 randomly sampled dwellings can be found in Table 1. Although all dwellings were originally uninsulated, roof insulation (mineral wool) and cavity wall insulation (blown-in foam) is recently installed in most of them and original windows sometimes have been replaced by better performing ones. The overall mean U-value, U_m [W/(m²K)], varies between 0.76 and 1.34.

TABLE 1. Survey data of 10 individual dwellings

Dwelling		1	2	3	4	5	6	7	8	9	10
Typology	(Semi)-Detached	D	D	D	D	D	S-D	S-D	S-D	S-D	S-D
orientation front facade		NW	SE	SE	SE	NE	SE	SE	SE	SE	SW
$depth_{extension}$	[m]	3.3	0	3.6	2.8	1.8	2. 6	2.7	0	0	3.9
$d_{wall,PUR}$	[m]	0.06	0	0	0.06	0	0	0	0.06	0	0
$d_{roof,MW}$	[m]	0	0	0.05	0	0	0.13	0	0.08	0	0.12
$d_{floor,PUR}$	[m]	0	0	0.03	0.06	0	0	0.10	0	0	0.10
U_{window}	[W/(m²K)]	1.1	1.1	2.83	2.83	2.83	1.4	1.1	2.83	1.4	1.4
v_{50}	[m³/(h.m²)]	7.3	7.0	17.5	4.6	12.3	4.8	3.8	7.0	15.9	13.2
Condensing boiler?	[Yes/No]	Y	Y	Y	N	Y	Y	Y	N	N	N
U_m	[W/(m²K)]	0.85	1.26	0.89	0.76	1.34	1.13	1.04	1.04	1.31	1.03

2.2 BES-model

A generic building model, easy adaptable to simulate the different building variants, is developed in TRNSYS, a dynamic building energy simulation (BES) software package. The dwelling is divided in 2 zones: a dayzone at the ground floor (V_{day} = 243 m³, $A_{fl,day}$ = 80 m²) and a nightzone at the second floor (V_{night} = 189 m³, $A_{fl,night}$ = 82 m²). The depth of the extension (if present - see Figure 1 and Table 1) is treated as a parameter in the BES-model, leading to an enlarged volume and heat loss area of the dayzone. Different temperature settings are applied in both zones. Each zone is considered as one node for which heat balances are solved every time step. The time step is set at 30 minutes. Heat transfer between the different zones is assumed to occur only by heat conduction through the internal walls and floors, thereby neglecting possible heat transfer via interzonal air flows. Hourly outside conditions are taken from the Meteonorm weather data file of Ukkel, Belgium.

Air infiltration rates are expressed as a function of the heat loss surface area A_i and the measured air permeability at 50 Pa, v_{50} [m³/(h.m²)], given in Table 1: $\dot{V}_{inf} = 0.04\ v_{50}\ A_i$ [m³/h]. Since none of the dwellings are equipped with a ventilation system, no additional ventilation rates are incorporated in the BES-model. Hence, the heat loss due to the occasional air flows from opening windows and doors is not included in the calculated heat loss, leading to a slight underestimation of total energy use. Internal gains are assumed only function of the heated volume and set constant throughout the year ($\Phi_{int} = (220 + 0.67/V)*V\ [W]$), which is consistent with the Flemish implementation of the EPBD. 70% of this value is attributed to the dayzone, the remaining part to the nightzone.

To reduce the calculation time, the heating system is not explicitly modelled in TRNSYS. Instead, a monthly overall efficiency of the heating system $\eta_{TOT,m}$ [-] is used to obtain the monthly total energy use $E_{use,m}$ [kWh] = $E_{net,m}$ / $\eta_{TOT,m}$ with $E_{net,m}$ [kWh] the monthly net energy demand. $E_{net,m}$ is obtained by using an ideal heater (no production, distribution or emission losses and no thermal inertia) in the TRNSYS model and is defined as the energy the ideal heater would need to deliver to reach the zone set point temperatures at any time. 30% of the heat is emitted by radiation and the remaining part by convection, which corresponds with convecto-radiators, an emission system commonly used in Flanders. The heating power for each zone is limited by the maximum heating power as determined by the European standard EN 12831. The monthly overall heating efficiency $\eta_{TOT,m}$ for different systems and control parameters is obtained from Peeters et al. (2008) in function of the monthly heat balance ratio, being the ratio of the occurring heat gains (internal and solar gains) and the occurring heat losses (ventilation, infiltration and transmissions losses). Here, two systems are chosen: (i) an on/off non-condensing high efficiency boiler and (ii) a modulating condensing boiler, both with central room thermostat and no thermostatic valves on the convecto-radiators.

2.3 Composition of the representative dwelling

Given the survey information in Table 1, a representative dwelling could be composed in different ways. One could choose to search for a dwelling likely to occur in reality and as close to the average values as possible, or one could choose to compose a fictive dwelling that equals the average values, even if these values do not occur in reality.

In this paper, the last approach is chosen: a fictive dwelling is made by averaging all dwelling parameters (see Table 2). This is also done for the typology and geometry, resulting in a semi-terraced typology with a common wall area half the common wall area of the semi-terraced typology and an extra outer wall area equal to half the outer wall area of the open typology. For the ‘averaged’ heating system, the weighted average efficiency of both monthly system efficiencies is applied. Yet, the modelling software imposes an important limitation in averaging the U-value of the window, since a predefined window has to be chosen in the simulation software. The mean U-value of the representative dwelling should equal 1.88 W/(m²K), a U-value which is not commercially available and thus, not readily available in the software. Therefore, the representative dwelling model is duplicated: once with a window type with U=1.4 W/(m²K) and once with a window type with U=2.83 W/(m²K). The energy uses of both dwelling models are then weighted averaged with weighing factor $f_{2.83}$ = (1.88-1.4)/(2.83-1.4) and $f_{1.4}$=1-$f_{2.83}$ to obtain the final energy use of the representative dwelling. Yet, one has to be aware of the limitations of the latter procedure. The window type does not only influence the transmission losses by its U-value, but also influences the amount of solar gains by its solar transmission factor (*g*-value). Or thus, the representative dwelling should in fact also have the average *g*-value of all 10 dwellings. Since the predefined window types come with a fixed combination of U-value and *g*-value, a choice has to be made which of both values will be averaged in the representative dwelling. For moderately insulated dwellings as in this paper, the heating season energy use is proven to be more sensitive to the exact U-value than to the solar gains (see Brohus et al. 2009, Firth et al. 2010), so the U-value is chosen here.

TABLE 2. Composition of the representative dwelling

		Representative dwelling
Typology	Free/Semi-Terraced	S-T
orientation front facade		216° (S=0°/W =90°)
$depth_{extension}$	[m]	2.1
$d_{wall,PUR}$	[m]	0.018
$d_{roof,MW}$	[m]	0.038
$d_{floor,PUR}$	[m]	0.029
U_{window}	[W/(m²K)]	(1.88) →(1-*f*)*1.4 + *f**2.83
v_{50}	[m³/(h.m²)]	9.33
Heating system		60% eff condensing + 40 % eff non-cond

3. Incorporating probabilistic user behaviour

Instead of using a fixed heating schedule and/or temperature setpoints, all dwelling models are subjected to different possible combinations of heating schedules and setpoints. As such, the expected energy consumption of every dwelling will be formulated as a probability distribution rather than a fixed deterministic value. The possible heating patterns and temperature setpoints and their respective probability distributions are defined in 3.1. The procedure to compose stochastic user behaviour from these distributions is explained in 3.2.

3.1 Heating patterns and setpoints

By lack of reliable and extended datasets, realistic user behaviour is defined based on the approach of Deurinck et al. (2012). Based on mainstream employment status (full-time out to work, halftime out to work, continuously home), the different time schedules from Table 3 are imposed in both day- and nightzone.

TABLE 3 - Overview of the different deterministic time schedules in the dayzone and nightzone. All 7 days of the week are identical, except for the dayzone where during the weekend dayzone pattern 4 is always used. 'X' = set temperature presence, '--' = set temperature absence, ' ' = no heating.

	dayzone				nightzone		
	1	2	3	4	1	2	3
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 – 22:00	X	X	X	X		X	
22:00 – 00:00	--	--	--	--	X	X	X
PROBABILITY	0.5	0.125	0.125	0.25	0.33	0.33	0.33

Table 4 summarizes the probability distributions used. In total, 11 parameters are to be altered per simulation run. The set temperature in the dayzone during presence is picked from a uniform distribution between [19-21] °C. During absence and during night, the set temperature in the dayzone is picked from [15-18] °C. The nightzone is never heated during the day. During the night, a probability of 0.3 is attributed to the chance that the nightzone is heated to a temperature of

[13-18] °C; the remaining 0.7 probability is attributed to the nightzone being unheated. Probabilities of occurrence are arbitrary attributed to each of the time schedules. After a time schedule is chosen, each of the start and end times of every heating period is altered with a random value picked from a uniform distribution between [+0.5h,-0.5h]. Finally, the internal gains are uniformly changed by [-20%; +20%] of their initial value of section 2.2. Remark how all parameters are assumed to be uncorrelated, which is unlike reality. For example, elderly persons are likely to be at home all day (see schedule 4) and tend to choose higher temperature settings. However, for the pragmatic modelling of user behaviour in this paper, correlations are not considered.

TABLE 4 – Probability distributions for the 11 user behaviour parameters (p = probability; U(a,b) = uniform continuous distribution between a and b; Bern(p) = Bernoulli distribution with p = chance at success)

nr	parameter	distribution
1	$T_{day,presence}$	U(19 °C , 22 °C)
2	$T_{day,absence}$	U (15 °C , 18 °C)
3 – 4	$T_{night,presence}$	U(13 °C , 18 °C) * Bern(0.3)
5 – 8	start and end times (max #4)	initial start/end time + U(-0.5 h,+0.5 h)
9	Heating pattern dayzone	p(1)=0.5 ; p(2) = p(3) = 0.125 ; p(4) = 0.25
10	Heating pattern nightzone	p(1) = p(2) = p(3) = 1/3
11	Internal Gains	initial value * U(0.8,1.2)

3.2 Monte-Carlo analysis using maximin Latin-Hypercube sampling scheme

The Monte Carlo technique is used to vary all 11 user behaviour parameters simultaneously in multiple simulation runs, leading to a large range of possible output values per dwelling. The parameter sampling is done with a distance-based space-filling maximin sampling scheme that maximizes the minimal distance between Latin Hypercube sampling points and that proves to be more efficient than a random or Latin Hypercube sampling (Janssen 2013). Due to this efficient sampling scheme the number of simulation runs per dwelling can be limited to 100 runs. Note that only one single sampling scheme (with 100 user profiles) is generated and re-used for all dwellings, since this is the only way one can be assured that the observed differences in output are to be attributed to the different user characteristics and not to different sampling schemes. Or, this means that the same set of 100 stochastically defined inhabitants is used for all dwelling simulations.

For the calculated energy savings in this paper, this also implies that the user and its heating habits remain the same before and after retrofit. However, it is generally known that inhabitants tend to take back part of the potential energy savings in enhanced indoor comfort by increasing the set temperature, heating more rooms more often etc. This effect, known as the *rebound* or *temperature takeback* effect, is not incorporated here.

4. Predicting energy savings

To illustrate the methodology, only one retrofit measure is discussed here: all pitched (MW) and flat roofs (PUR) and the ceiling (MW) between nightzone and unheated attic are insulated to reach a total insulation thickness of 0.2 m. Note that this might not be an economically viable retrofit measure for every single dwelling, since some cases already have (partly) insulated roofs. However, for this study the economical viability of a retrofit measure is not assessed, but the applicability of aggregated models evaluated. To calculate the energy savings, the BES-model of every dwelling with every sampled user profile thus needs to be simulated twice, both for the original and retrofitted situation. Per dwelling, this leads to 100 calculated energy use values before and after retrofit and thus, to 100 values of net energy savings.

4.1 At dwelling level

In this section, the simulation results of the 11 separate dwelling models (10 individual dwellings and 1 representative dwelling) are discussed. Figure 2 shows the empirical cumulative distributions of the total heating season energy use, both before and after retrofit. These cumulative curves show both the influence of the insulation levels on the energy use (compare the lateral position along the x-axis between left and right curves) and the impact of user behaviour on the calculated energy use (the steeper the cumulative curves, the lower the impact of the user behaviour on the energy use). The mean energy use can differ by a factor two, with the representative dwelling situated in the middle of all curves. The curves before retrofit are slightly flatter than the ones after retrofits. This indicates that the energy use in pre-retrofit dwellings is more sensitive to inhabitants than post-retrofit dwellings.

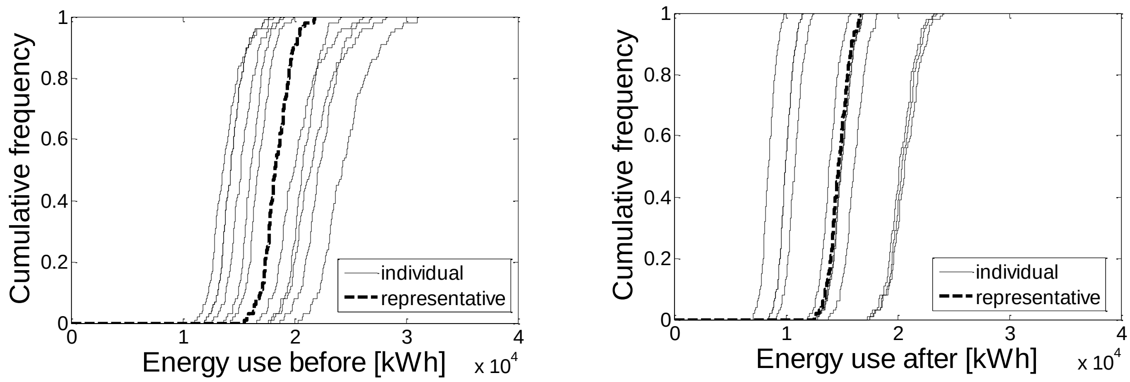

FIG 2. Cumulative plots of total heating season energy use for every individual and the representative dwelling model, both before (left) and after (right) retrofit.

Figure 3 shows the empirical cumulative distributions of the resulting energy savings at dwelling level. Here, user behaviour heavily impacts the distributions. Around the cumulative frequency of 0.7, a clear shift in distribution is seen. This shift divides the users who do not heat the nightzone (70% of them, see Table 4) and those who do heat the nightzone. Although it is an artificial division due to the rigid application of the proposed user behaviour in section 3.1 and thus, unlikely to occur in reality in this extent, it does show how heating patterns can have a great impact on calculated energy savings. If only part of the dwelling is heated, the energy savings will be lower and less influenced by temperature setpoints and time schedules (see first steep part of curves). If one chooses to heat the nightzone during the night, the energy savings will be higher and a larger spread is found around the mean value (see flatter second part of curves). Since the representative dwelling already has some roof insulation before renovation, as is the case for the 4 dwellings at the left of it, the impact on the energy savings of heating the nightzone is less pronounced.

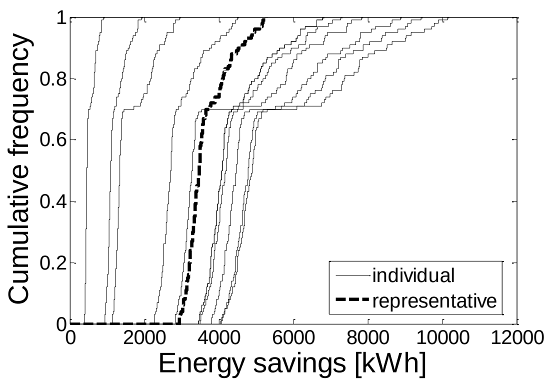

FIG 3. Cumulative plot of total heating season energy savings of every dwelling model.

4.2 At district level

4.2.1 Composing the district data

The district level is defined here on a small scale, the sum of 10 dwellings. To compose the data at this level, single datapoints are randomly picked from every dwelling and added up. Due to the small calculation time of this procedure, this can easily be repeated 10000 times, resulting in 10000 aggregated values for each approach. For the representative dwelling approach, 10 values are picked only from the representative dwelling values. For the individual dwelling approach, one value is picked from each of the 10 dwellings, so every dwelling is always represented once in the aggregated sample.

Note that the composition of the district data by (randomly) sampling 10 values, adding them and repeating this multiple times, is the appropriate procedure to obtain a reliable distribution of the aggregated outcome. Another procedure would be to obtain 100 aggregated energy values by multiplying the 100 representative dwelling values by 10 (representative dwelling approach) or by adding all 10 energy uses under the first user to obtain a first aggregated energy use value, adding all energy uses under the second user for a second value etc. (individual dwelling approach). However, a housing group is then composed in which all 10 dwellings are each time inhabited by the same type of user, which is very unlikely in reality and which leads to an overestimation of the actual spread in aggregated energy use.

4.2.2 Results

Figure 4 (left) shows the empirical probability distributions of the total heating season energy use at the district level. All are best fitted with normal distributions (see Table 5). The mean values of the fitted distributions before retrofit differ by about 1%, while after retrofit, the mean values differ by only 2%. Or, both approaches predict almost equal mean aggregated energy use, both before and after retrofit. The spread for the individual dwelling approach is slightly higher before retrofit (due to the variation in building characteristics), but the difference with the representative dwelling approach remains quite small. This means almost all variation is defined by the user behaviour. This is an important finding in favour of the representative dwelling approach: if the user behaviour is indeed as variable as assumed in section 3, the spread in aggregated energy use might be predicted equally well by a single dwelling model and stochastic user behaviour than by 10 separate dwelling models with the same stochastic user behaviour.

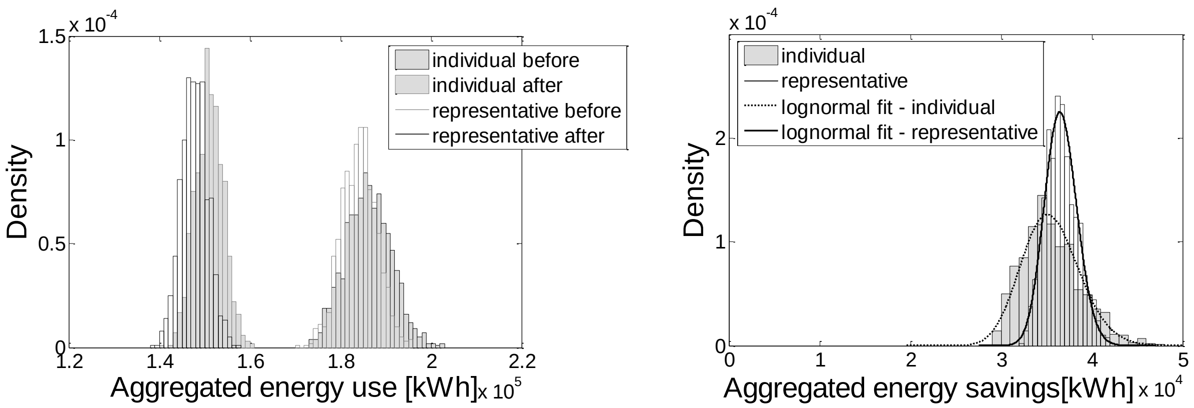

FIG 4. Probability distribution of total heating season aggregated energy use (left) and aggregated energy savings (right).

The district energy savings are also shown in Figure 4 (right). Both proved to be best fitted by lognormal distributions. The mean energy savings values practically equal the difference between the before and after values of Table 5 and also, the difference in mean value between the 2 approaches is very small. Due to the probabilistic approach however, additional information is available about the possible spread in energy savings, given the user behaviour from section 3. Now, the two approaches do differ from each other. The standard deviation of the individual approach is almost twice as large as the standard deviation from the representative approach. Based on the fitted distributions in Table 5, the probability that the predicted aggregated energy savings are lower than 33 MWh, is only 5% for the representative dwelling approach but still more than 25% for the individual dwelling approach. So, the representative approach could easily overpredict the amount of district energy savings. This might be important when also costs are to be involved in the analysis, because lower energy savings than expected lead to larger payback times and lower return on investment rates.

TABLE 5. Fitted probability distributions: normal ~N(μ ; σ) and lognormal ln(μ ; σ) with μ = mean and σ = standard deviation – in kWh.

	individual dwelling approach	representative dwelling approach
before	$\sim N(1.86 \cdot 10^5 ; 5055)$	$\sim N(1.84 \cdot 10^5 ; 3906)$
after	$\sim N(1.51 \cdot 10^5 ; 2974)$	$\sim N(1.47 \cdot 10^5 ; 2960)$
savings	~ln (35320 ; 3186)	~ln (36536 ; 1834)

5. Conclusion

Using a representative dwelling to represent a larger group of similar houses does not automatically lead to bad energy saving predictions. If rigorously composed to match the average building characteristics and when combined with probabilistic user behaviour, the mean predicted energy savings of the representative dwelling approach are almost equal to the mean energy savings predicted by the individual dwelling approach. However, if one is also interested in the calculated spread on the energy savings, the representative dwelling approach performs less, since no spread due to differences in building characteristics can be taken into account. For districts with a uniform housing population, e.g. low renovation rates in the past, the representative dwelling approach thus could be an option. For districts where a considerable part of the houses already has been renovated to a small or large extent, it could be important to gain more information about the spread on building characteristics and to include more dwelling types as is done in the individual dwelling approach.

References

Brohus, H., Heiselberg, P., Hesselholt, A., & Rasmussen, H. (2009). Application of partial safety factors in building energy performance assessment. *Eleventh International IBPSA Conference*, July 27-30 2009, Glasgow, Schotland.

Cyx, W., Renders, N., Van Holm, M., & Verbeke, S. (2011). *Report "IEE TABULA - Typology Approach for Building Stock Energy Assessment."*

Deurinck, M., Saelens, D., & Roels, S. (2012). Assessment of the physical part of the temperature takeback for residential retrofits. *Energy and Buildings*, 52, 112–121.

Firth, S. K., Lomas, K. J., & Wright, A. J. (2010). Targeting household energy-efficiency measures using sensitivity analysis. *Building Research & Information*, 38(1), 25–41.

Janssen, H. (2013). Monte-Carlo based uncertainty analysis: Sampling efficiency and sampling convergence. *Reliability Engineering & System Safety*, *109*, 123–132.

Peeters, L., Van der Veken, J., Hens, H., Helsen, L., & D'haeseleer, W. (2008). Control of heating systems in residential buildings: Current practice. *Energy and Buildings*, *40*(8), 1446–1455.