Towards A Comprehensive Tool To Model Occupant Behaviour For Dwellings That Combines Domestic Hot Water Use With Active Occupancy

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Abstract

In building simulation, deterministic reference load profiles are normally used to represent domestic hot water (DHW) demand. Limited studies are found in the literature about the stochasticity of DHW consumption. As an attempt to fill this need, a stochastic end-user DHW demand model was constructed with temporal coherency with a well known occupancy generator. The tool uses aggregated data from national surveys to effectively scale occupant behaviour models built in different parts of the world to produce the output for a given configuration. This tuning procedure is necessary to account for variations of occupant behaviour between different countries. The model displayed great accuracy in predicting the building DHW demand when its outputs were compared with measurements made in a multi-residential building in Quebec City, Canada. At its current status, the tool can be used for US, Canadian and UK dwellings, but the idea could be expanded for other locations.

Introduction

Residential buildings are responsible for 31% of world's energy demand (Saidur et al., 2007) and their consumption has been constantly increasing over the last few decades (Price et al., 1998). Fortunately, it is possible to greatly reduce energy use in buildings mainly by teaching individuals to adopt a low carbon lifestyle (Boardman, 2007; de Wilde and Coley, 2012). The energy consumption of a building turns around occupant behaviour. This has been seen in energy monitoring studies carried out on identical buildings, where the occupants' presence and their interactions with the buildings produce large disparities on the final bill (Emery and Kippenhan, 2006). Consequently, inadequate representation of occupant behaviour in building energy simulation often leads to inaccurate predictions (Branco et al., 2004), and this cascades down to inaccurate prediction of energy retrofit, misleading results of new designs and many others.

To fix this issue, multiple deterministic and stochastic models were developed to predict occupants' actions on several aspects of the building: HVAC systems (Nicol et al., 2004), window opening (Jeong et al., 2016), artificial lighting (Sadeghi et al., 2016), blinds and window opening (Haldi and Robinson, 2010), electrical appliances (Marszal-Pomianowska et al., 2016; Richardson et al., 2010) and hot water appliances (Jordan and Vajen, 2001). These studies show promising results when compared with field studies. Currently most of the models developed are built upon country dependent data and thus building professionals cannot employ them all around the world without inducing errors in occupant behaviour representation. As occupant behaviour depends on socio-economic factors, it is expected that cultural differences lead to differences in occupancy and thus occupants in various countries might act diversely (Schweiker et al., 2012). One solution to this problem is to replicate the monitoring process required for the development of these models in multiple countries so that they can be adapted for different lifestyles. This option is cumbersome as field survey monitoring asks for large time and financial resources. Re-doing the same task for multiple regions of the world is also unnecessarily repetitive.

Moreover, the tools presented above have been done independently. The modelling of the occupancy of Richardson and the window opening of Robinson, for example are in principle disconnected. The authors firmly believe that the building simulation community could benefit of a line of research with the purpose of the creation of comprehensive tools that merge all this aspects of human behaviour together.

This paper attempts to find an alternative manner of accounting for the variations in occupant behaviour between different countries by using a stochastic tool created with data coming from a specific country and adapting it for another country with a tuning procedure based on aggregated national statistics. In this attempt, the authors adapted to the Canadian lifestyle a domestic hot water (DHW) demand profile generator developed for the US by looking at national averages regarding the use of water in households.

DHW represents a substantial proportion of energy consumption in buildings. In the US, 18% of the energy demand in the residential sector is due to water heating (US EIA, 2009). Furthermore, as buildings are getting more efficient in terms of space heating and cooling, this ratio is expected to increase over the years, meaning that solutions to reduce building environmental footprint should consider the energy used for DHW.

The lack of interconnection between occupant models is also occurring on DHW models. Although some models consider its connection (McKenna and Thomson, 2016; Sandels et al., 2014), DHW demand tools usually do not look at both the number of occupants living in a household and the actual number of occupants in the household at a given time as a time series, even if the use of DHW should be proportional to these values. Instead, few models merely propose a simplified classification of the type of consumption in the dwelling (low, medium or high

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consumption). By combining a DHW model with a model that creates stochastic occupancy schedules in the building, more representative results are expected. This paper first describes the procedure used for both the incorporation of an active occupancy model into a DHW demand model and also the alterations made with national data to adjust these tools from a given country lifestyle (respectively the United Kingdom and the United States) to a Canadian one. To assess the accuracy of this novel methodology, in the last part of the paper, the profiles produced by the newly developed tool were compared with DHW consumption measurements made in a multi-residential building in Quebec City, Canada.

Methodology

In order to create a DHW demand tool that accounts for occupancy schedules of the dwelling, two occupant behaviour tools were merged together: one that projects occupancy (Richardson et al., 2008) and one that predicts DHW consumption (Hendron et al., 2010) both for residential buildings. It is important to consider occupancy in buildings when forecasting DHW use, as the number of events related to DHW use is expected to be proportional to the number of people present in the building.

The newly developed tool uses a time step of 10 minutes and only needs two inputs: first, the number of simulated dwellings and second, the number of days simulated (usually 365 days, i.e. one year). For every time step and dwelling, the outputs are the number of occupants and the volume of DHW being used in that time step.

To do so, the model starts by assigning a value for the number of people living in every dwelling using a probability distribution established from Canadian household statistics (Statistics Canada, 2011). With these values, the model generates one annual occupancy profile per dwelling. Based on this schedule, the tool predicts the DHW consumption by forecasting the events (start and volume). The summation of overlapping events in each time step gives the actual volume needed. Fig. 1 summarizes the procedure used by the model.

As the selected tools are based upon data coming from different countries, a scaling had to be done to adapt them for differences in behaviour. The following subsections explain how these models work, the methodology behind the tuning of these models and its impacts on the outputs.

Active occupancy model

Active occupancy is defined here as the periods when an occupant is physically active in their house (not sleeping). During this period, the occupant is not necessarily interacting with the built environment, but has the capacity to do so. A very popular tool found in the literature for the creation of realistic stochastic daily active occupancy profiles is the one developed by Richardson et al. (Richardson et al., 2008). As it is available online, this model is easily accessible for everyone and was thus chosen as the basis for the active occupancy part of the tool described in this paper.

Richardson's tool employs a first order Markov-Chain method to generate stochastic occupancy profiles with a 10-min resolution. A first Markov-Chain refers strictly to the current state to determine change of state and does not consider any preceding states – it is a memoryless methodology. As a result, only two variables determine the probability function for the number of active occupants in a dwelling at a given time step: the hour-of-day and the number of occupants during the previous time step.

To obtain these probability transition matrices, Richardson et al. use the results of a Time Use Survey, which contains 20,000 weekly United Kingdom household journals detailing time use by 11,600 people at a 10-min resolution (Ipsos-RSL and Office for National Statistics, 2003). The number of active occupants was found at each time step and the following, enabling the calculations of transition probabilities. This is an extensive work and such detailed data is not available in all countries, hence a need for a simple way to adjust Richardson's tool for other countries.

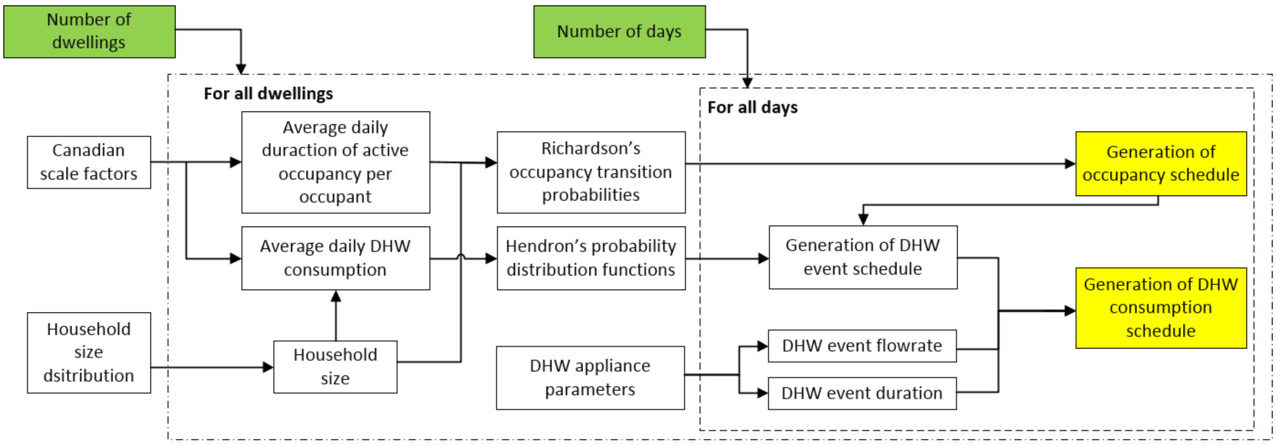

Figure 1: Schematic breakdown of the domestic hot water model showing the relationship between all components. Green boxes refer to inputs provided by the model user. Yellow boxes are the output of the model..

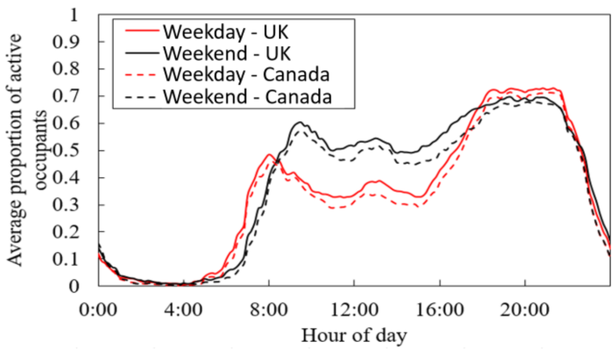

Figure 2: Comparison of aggregated daily active occupancy from Richardson's tool before (solid lines) and after (dashed lines) the suggested adjustement.

According to the UK Time-Use Survey, British citizens spend on average 1,003 minutes per day in their home and sleep for 476 minutes, meaning that they are actively living in their dwellings for 527 minutes per day. In Canada, these numbers are 990 minutes at home, 498 minutes of sleep and consequently 492 minutes of active occupancy (Statistics Canada, 2006). Accordingly, for Richardson's tool to be reliable in Canada, the probability transition matrices must be adjusted so that on aggregate, the time spent by occupants in the dwelling is reduced by 6.6%. Evidently, the major assumption behind this procedure is that other than the total amount of time spent awake in their home, people in different countries follow identical occupancy patterns, which might not be true in different regions of the world, but it is an acceptable premise considering the lack of data to adopt any other.

The adjustment made to Richardson´s model was tested with real data. For this, it was run 1,000 times before and after the adjustment for a weekday and a weekend day. Similar tests have shown that 1,000 simulations is an adequate number of runs to obtain aggregated results as little improvement in terms of accuracy is found afterwards (McKenna et al., 2015). A comparison of the averaged model output before and after the change is presented in Fig. 1.

The graph shows without surprise that the patterns of occupancy after the scaling (dashed lines) are very much like the ones observed with the original model (full lines). The only difference is that the dashed lines have a proportion of active occupancy smaller than the full lines as the integral of the new curves are equal to the targeted value.

Domestic hot water model

For this paper, the stochastic DHW tool developed by Hendron et al. is used to simulate consumption profiles together with occupancy profiles. Hendron´s tool is also available free of charge and includes realistic details such as vacation periods and seasonability (Hendron et al., 2010). This model divides hot water consumption in five major end-use categories: shower, bath, clothes washer, dishwasher, and sink. For these five categories, a probability of use at each hour is given based on two

Table 1: Average daily DHW use for five water appliances.

Water appliances	US aggregated data [L/day]	Canadian aggregated data [L/day]
Shower	73	59
Bath	18	40
Clothes washer	24	36
Dishwasher	15	9
Sink	65	81

datasets coming from dwellings from US (Hendron and Engrebrecht, 2009; Parker and Fairey, 2015). Adjustments are then applied to the probabilities using calibration scalars to reflect differences per type of day (weekday/weekend) and season. Once a hot water event is assigned a starting time, the flow rate and duration are obtained from different probability distribution functions (pdfs), providing the amount of water used in each hot water event.

Five alterations were implemented to fit Hendron's model with the tool developed in this paper. First, the resolution of Hendron's start-time pdfs for the five considered water appliances were adjusted from one hour to ten minutes so that it could work with the occupancy model. This increase in resolution was done by linear interpolation.

Second, the curves were adapted so that they could reflect a Canadian lifestyle instead of an American one (from which there were first developed). Table 1 shows the average daily volume of consumption by the five hot water appliances considered in the tool from US (Hendron and Engrebrecht, 2009) and Canada data (Natural Resources Canada, 2012), for a household of three people. In the US, the sum of these five appliances adds to a total of 195 litres of DHW per day. In the Canadian data, this value is 225 litres per day.

Consequently, if one uses an unaltered version of Hendron's model to simulate DHW consumption in a Canadian building, it would lead on average to underestimating the consumption by approximately 13%. The data from Table 1 was used to properly scale the probability distribution for each of the end-uses.

Next, a calibration scalar based on the number of occupants living in the dwelling was added (third modification). The probability of DHW use is directly proportional to the number of people and thus a five-people household is expected in the model to consume more DHW than one based on one-person. The Canadian building simulation software HOT2000 proposes to use a slope of 35 litres per person when accounting for occupancy during forecasts of daily hot water consumption (Natural Resources Canada, 2016). Subsequently, for every simulated household, the tool checks its size and assigned an appropriate value to this calibration scalar.

To have a consistent occupant behaviour model, there must not be DHW use for the shower, the bath and the sink when there is no one in the dwelling. Thus, a fourth change was implemented to ensure that the result does not

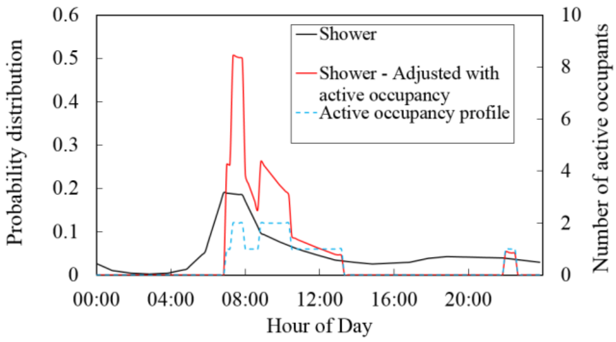

Figure 3: Example of probability distribution of a shower event before and after fitting the curve with active occupancy profile.

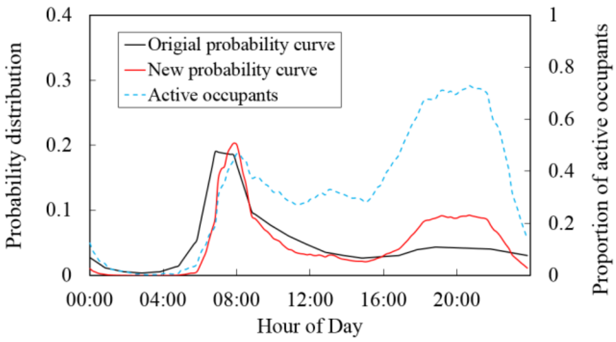

Figure 4: Aggregated probability distribution of a shower event before and after fitting the curve with active occupancy profile. Red and blue curves obtained after 1,000 simulations.

lead to incoherent outputs. For each occupant, the tool attributes the pdfs and then looks at the simulated active occupancy profiles of the household to change these pdfs to guarantee that the occupant is not consuming DHW when he is not awake in the dwelling. To ensure that the aggregated amounts of daily DHW use is unaffected by this change, the area under the new curves must be equal to the area under the old ones. Therefore, the modified probability distributions are multiplied by a correction factor.

Figure 3 offers an example of such an adjustment for occupancy for the probability distribution of shower use in a two-occupant house. It is clearly observable that there is zero chance of a shower occurring when zero occupants are in the building. At any other time, the new probability curve follows the patterns of the old one, but with increased values which depends on the number of occupants in the dwelling. These values are calculated so the overall DHW use is not modified. This procedure is repeated for every simulated day and appliance, and each day has different probability distributions according to the active occupancy profile.

To evaluate the influence of this modification, Fig. 4 presents the aggregation achieved by repeating this procedure 1,000 times. The graph exposes the impact of active occupancy, which is shown in blue, on the probability of a shower event. If there was no influence, the black and red curves would perfectly be superimposed. Yet, the morning peak happens an hour later than it does in the Hendron probability curve. This could be explained by the British origins of the occupancy model versus the American character of Hendron's tool. One could theorise that Americans leave their home one hour earlier than British. In the evening, the changes made on the pdf induced an increase in the probability of a shower event, as this period of the day represents the peak of active occupancy.

Finally, the fifth alteration introduced in the model takes low-flow water devices into consideration. As reducing buildings footprint is a priority in our society, low-flow water devices (showerheads, dishwashers, clothes washers and sinks) are becoming more widespread, which diminishes hot water consumption; these are therefore appliances worth studying. An analysis of retrofits suggests that low-flow sinks and showerheads reduce flow rates by a factor of 20% to 50% (Adye et al., 2014). Unfortunately, no more accurate studies were found and an educated guess of 20% of flow rate reduction was chosen for this new calibration scalar, which can be applied or not to the flow rate probability distribution of each hot water appliances considered by the tool, except for baths.

In the end, these adjustments provided a DHW forecasting tool which is directly connected with occupancy and accounts for lifestyle change and for the use of water savings appliances.

Results

Experimental data

To validate the procedure, the DHW output of the model was compared against measurements taken in a multi-residential building (social housing) in Quebec City, Canada. These measurements provide volume of DHW for each of the 40 dwellings of the building every 10 minutes. This dataset is independent from the tool – it was not used in the making of the model and therefore can be used for independent validation. This building was constructed with the objective of limiting energy consumption. Therefore, low-flow devices were installed in the showers and the sinks. However, tenants were not trained or educated regarding the energy performance of their apartments. Thus, measurements are expected to be representative of the everyday life of the building occupants. Unfortunately, no data provides the exact occupancy of the building, which makes it impossible to directly validate this part of the model. Nevertheless, a favourable comparison between the measured and simulated available data would provide an indirect verification of the occupancy model as it is tied to the DHW model.

The monitoring duration considered for the validation of the model is four months (January to April 2016). During this period, the building used a total 673,244 L, which translates into a daily consumption of 139.1 L per household, a number much smaller than the average Canadian value of 225 L for a family of four people. One dwelling was mostly unoccupied during the validation period, which could be seen by the fact that it had one single day of non-zero DHW consumption. Discarding this household, the sample size is 39 dwellings and the average becomes 142.7 L per day. The average standard deviation in the day-to-day consumption of a dwelling is 70.9 L.

In their monitoring study of 119 homes in Halifax, Canada, George et al. foreshadowed this difference in DHW consumption between the case study building and national aggregated data (George et al., 2015). This decrease can be explained by declining household sizes, by the use of water saving devices and by changes in occupant behaviour. The alterations made to the DHW tool should account for the first two explanations.

Figure 5a shows a side-by-side daily DHW consumption of the individual dwellings in a box-and-whisker plot. It confirms the substantial differences in use of hot water between households, increasing from an average of 17.5 L for the lowest consumer to a mean value of 495.9 L for the largest. There is also a large day-to-day variability between dwellings. Some households consume a very consistent volume of DHW day after day and others do not. For example, despite a similar median day, its narrower box illustrates that the day-to-day consumption in dwelling #22 is much more consistent than in dwelling #21. Several households appear to have developed steady DHW consumption habits and hence have a small day-to-day standard deviation. However, this does not seem to be the case for heavy consumers, as dwellings from #31 to #39 have large boxes and whiskers.

Simulation results

By setting the number of dwellings and number of days to be simulated to respectively 39 and 121, the demand of DHW of the case study building is predicted by the tool. The adjustment for low water devices is turned on to adequately represent the appliances found in the building. The simulations predict an average daily consumption of 141.0 L per dwelling, with an average daily standard deviation of 61.6 L.

Figure 5 displays the distribution of hot water use in the building. Two notable differences are found between Fig. 5a, obtained from measurements, and Fig. 5b, generated from simulations. First, the variation in DHW demand between the dwellings is much smaller in the simulations than in reality. Simulation results range from an average daily consumption of 91.4 L to an average of 221.9 L. For the simulations, the differences in DHW consumption between the dwellings are strictly driven by differences in household sizes, hence the lower variability in consumption than the one found with measurements. No consideration was made in the model for the type of consumers that make up the simulated households. In real life, some people typically use more DHW than others and thus the model could be improved in the future by accounting for that. Without this addition, and despite the stochastic aspect of the tool, over a large number of days,

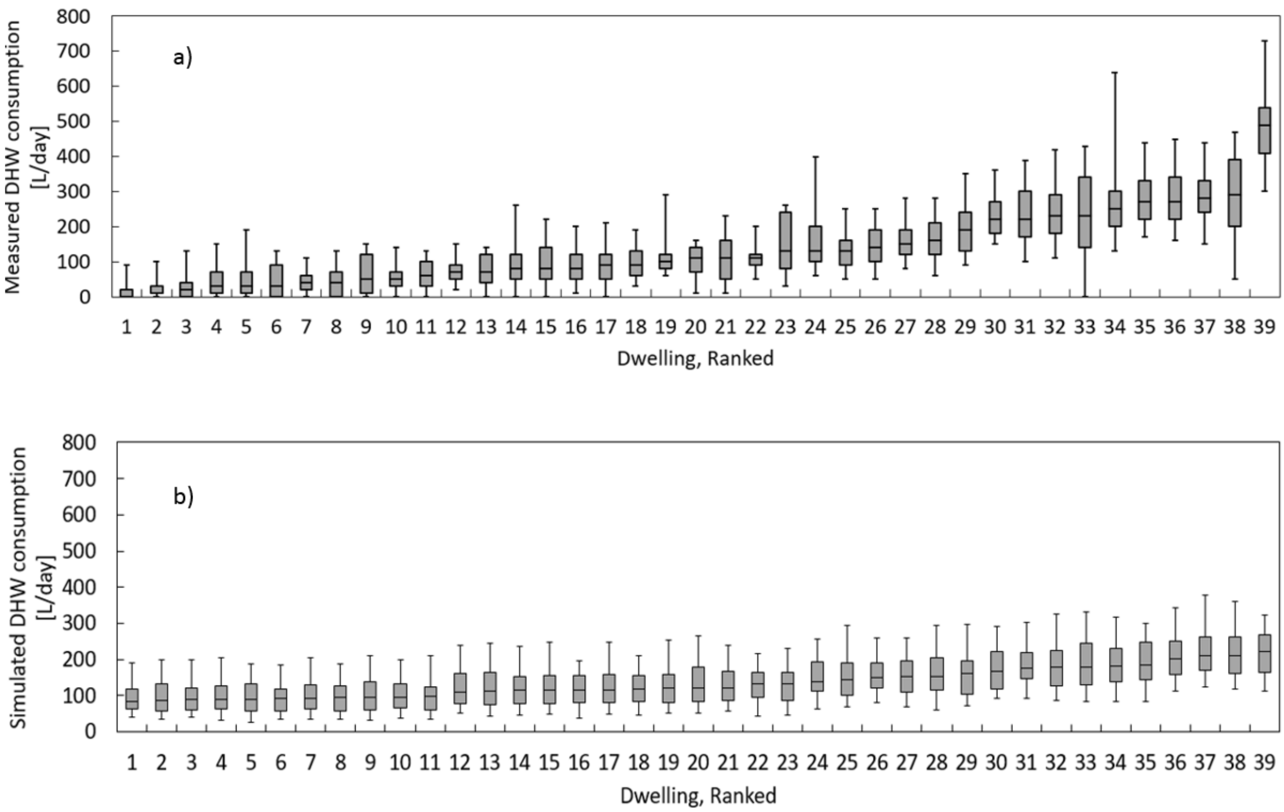

Figure 5: a) Measured and b) Simulated daily DHW consumption in the 39 dwellings during the validation period. Line within the box shows median day, length of the box shows the 1st and 3rd quartile and height of whiskers shows 5th and 95th percentile.

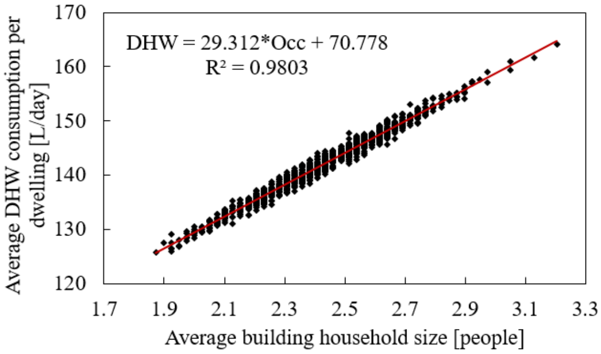

Figure 6: Effect of the average household size of the building on its DHW demand.

households of equal size will consume a highly similar total volume of DHW. An alternative to this drawback would be to generate a single day DHW profile for every household and replicate this profile for every day. In that way, the stochastic effects would not be cancelled or averaged over a high number of days. However, this alternative offers no day-to-day deviation in the DHW consumption of a dwelling, which is also not realistic. Another solution would be to simply infer differences in types of consumer with the addition of another calibration scalar.

Second, the day-to-day variability in each dwelling is very alike in all simulated dwellings, as evidenced by the similar length of the boxes and whiskers in Fig. 5b. Fig. 5a shows a different pattern for the measured data, in which variability is highly different between dwellings, as mentioned before. Since the tool is purely probabilistic, no daily routine is considered in the simulations.

Consequently, for all dwellings, the DHW consumption profile can completely change day after day. To test the model variability in DHW use for the complete building, its total annual consumption was simulated 1,000 times. During this test, the average daily consumption of the building ranged from 125.8 L per dwelling in the building profile that generated the lowest amount of DHW to 164.1 L, with a mean value of 141.9 L and a standard deviation of 6.2 L. These variations are purely due to changes in the number of people living in the building, as proved by Fig. 6 which gives the relation between household sizes and volume of DHW. Each dot provides the average household size and average daily volume of DHW for each simulation.

The linear regression shown in Fig. 6 has a coefficient of determination R^2 = 0.98. In reality, this value is expected to be lower due to divergences in types of consumers. For example, George et al. measured a coefficient of R^2=0.94 in their study when correlating consumption with household sizes (George et al., 2015).

Although this represents a high coefficient, it is not as close to a perfect fit as the model predicts. Nevertheless, the slope and intercept of the regression curve is comparable with those found in different DHW monitoring studies. A slope of 29.31 L per day per occupant is smaller than the targeted value of 35 that is used by HOT2000, but that is explained by the adjustment made for low-flow devices. It is also interesting to see the variability of household sizes in the building. Fig. 6 reveals that if the case study building follows typical Canadian distributions, then the minimal number of people living in the building is 73 people (1.87 occupants per household) and the maximum is 125 people (3.13). These values can be used to calculate the possible range of different building parameters, such as the electricity consumption or heat gains due to the occupants. The average building population found during the 1,000 simulations is 94.6 people with a standard deviation of 8.14 (an average household size of 2.43±0.21 people).

Impact of considering occupancy profiles

One of the main contributions of this paper is the merging of an occupancy profile model within a DHW consumption prediction tool by preventing the use of specific hot water appliances by an occupant when he is not predicted to be awake in the dwelling. This modification was made with the objective of developing a comprehensive occupant behaviour model. However, as confirmed by Fig. 4, this procedure affects the daily probability distribution of the starting time use of hot water appliances and thus it could modify the daily profile of DHW consumption in the building. This subsection analyses whether this change improved or degraded the accuracy of the tool.

To do so, a new intermediary tool was developed in which occupancy schedule is not considered. In essence, this intermediary model is Hendron’s tool with scale factors applied for household sizes and to adapt it to Canadian behaviours, so that the total volume of DHW should be the same between the intermediary and the complete tools.

Figure 7 presents the average daily DHW profiles generated by the complete and the intermediary tools and compares those profiles to the one observed in the case

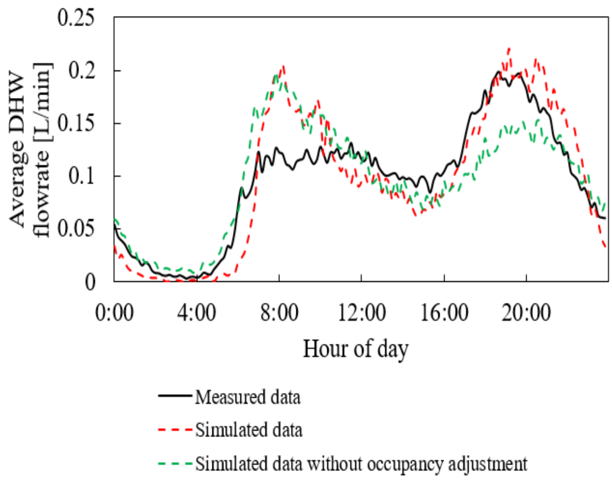

Figure 7: Average daily DHW profile from measurements (full line) compared to the one obtained by the model, with and without the adjustement for occupancy schedules (dashed lines).

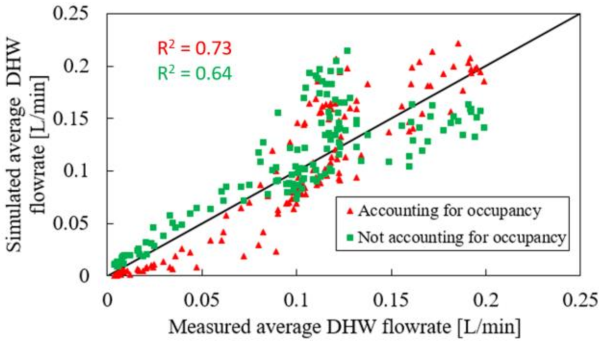

Figure 8: Comparison of simulated data with measurements. Red triangles represent data coming from the model with adjustment for occupancy schedules and green squares are data coming from the model without the adjustement. Simulated and measured values are in agreement when markers fall on the black line.

study building. The total DHW volumes of the simulated profiles are nearly identical to the measured volumes. The measurements show that there is a clear peak of consumption in the building during the evening. This peak is also present in the complete tool which predicts a flowrate that is nearly identical to the one measured. However, this is not true for the intermediary model as this model underestimates the evening peak by approximately 25%. A water heating system based on such a profile could potentially lead to a lack of hot water for the occupants during the evening. Nevertheless, in the early part of the day (from midnight to 7:00 AM), the adjustment for occupancy schedules has created an underestimation of DHW consumption. As foreshadowed by Fig. 4, in the measured dataset, the morning increase happens around 6:00 AM, while it happens at 7:00 AM in the simulations that accounted for occupancy schedules. Again, this could be explained by the fact that the occupancy schedules generated in the model are based on British patterns which might not exactly reflect Canadian lifestyle. A more accurate way to generate schedules that fit with Canadian patterns could fix this problem.

The main difference between the measured and simulated datasets is in the morning. With or without an adjustment for occupancy schedules, simulations predict a morning peak that is not seen in reality. It seems like the occupants living in the studied building do not follow a “usual” daily DHW schedule as morning peaks are seen in most DHW monitoring studies (Energy saving trust, 2008; George et al., 2015).

In short, the occupancy schedule adjustment improved predictions in the evening, but it also decreased accuracy during the night and beginning of the morning. Fig. 8 plots the simulated building DHW flowrate versus the measured one for all 144 time steps of the average day. Fig. 8 confirms the observations made from Fig. 7 since it is clear that the model accounting for occupancy is better at predicting consumption peaks (i.e. when the measured flowrate is above 0.15 L/min), but is less accurate in low-flow periods (i.e. below 0.09 L/min). Regression coefficients between the black line and the two simulated datasets are $R^2 = 0.64$ for the intermediary model and $R^2 = 0.73$ for the complete model, showing that accounting for occupancy schedules did improve the accuracy of the model. Moreover, linking DHW consumption with occupancy represents an initial step in the development of a comprehensive occupant behaviour model. Other behaviours, such as electricity consumption and window opening control, can all be merged together using the same procedure.

Ongoing and future work

Ongoing work is refining the model with the addition of a probability distribution curve which modifies the per capita DHW consumption of households so that the model can depict different types of consumers. This parameter is expected to follow a lognormal distribution (George et al., 2015). Validation of the tool against a British dataset is also currently made to test the idea with another cultural background (Energy saving trust, 2008). Once this is achieved, the objective is to add electricity consumption and set point temperature using a methodology similar to the one employed for DHW. The occupancy behaviour tool could then be linked to a dynamic building simulation software (such as Energy Plus or IES) to represent complete stochastic occupant behaviours that are in accordance with different country lifestyles. Work also needs to be done to make the tool entirely accessible for anyone to use.

Conclusion

This paper presents the first step of a new consistent and comprehensive occupant behavioural tool that uses scaling factors to account for differences in behaviour between countries. The part of the tool shown here is the one that generates DHW profiles for a given number of days and dwellings using a combination of previously made DHW and occupancy models. These two tools are stochastic models that are combined to ensure that no consumption happens when no one is in the building and that the total volume of DHW is coherent with the number of people living in the dwelling. Differences in lifestyle between countries are accounted for by multiplying probability matrices by calibration factors that are obtained using aggregated national statistics.

To validate the tool, its output was compared with measurements coming from a multi-residential building in Quebec City, Canada. Analysis of this dataset showed high variations of the average daily consumption between every dwelling. Furthermore, the day-to-day variability in a single household is very different from a dwelling to another, as if no family adopts the same behaviour concerning DHW. This demonstrates the need of considering stochasticity when modelling occupant behaviour in multi-residential buildings.

Simulations made from the developed tool did offer an accurate estimation of the building average consumption. However, it was unable to replicate the various patterns found in the measurements as it greatly underestimated the deviations between every household. The authors propose the addition of another probability distribution curve that covers all types of behaviour to fix this problem.

The simulated profiles were able to adequately depict the evening peak of consumption of the real building, but it also predicted a peak in the morning that is not seen in measurements. Accounting for occupancy schedules improved the accuracy of simulation results.

Overall, results presented in this paper are encouraging for the development of the occupant behaviour tool. It would be interesting to test the tool in a country that has a completely different cultural background (e.g. Japan or Brazil) to see if the tuning procedure can still offer satisfying results.

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