The Influence of Variation in Occupancy Pattern on Domestic Energy Simulation Prediction: A Case Study in Shanghai

Guangying Ren[1], Minna Sunikka-Blank[1], Xingxing Zhang[2]
[1] Department of Architecture, University of Cambridge, CB2 1PX, United Kingdom
[2] Department of Energy, Forest and Built Environments, Dalarna University, SE-79188, Sweden

Abstract

Uncertainties in occupant behavior lead to discrepancies between the actual energy demand and the predicted results. This paper aims to explore the effect of variation in occupancy pattern on domestic energy demand prediction. The smart meter data shows the large variation in the measured occupancy pattern, which is resulted from the impact of floor area, the number of occupants, occupants' habit of using appliance and energy saving attitudes. Single-zone simulation with internal load profiles of each household suggests that the variation in measured occupancy pattern would result in a large variation on domestic energy demand prediction. In addition, single-zone simulation with different level of internal load scheduling strategies shows the simulation accuracy is not obvious by using different level of profiles. It reveals that the level of internal load schedules to use depends on how much information we could obtain for simulation analysis, as well as the purpose and scale of the analysis. Another important finding is that nearly all simulation results give higher energy use than the actual demands, reflecting the pre-bound effect.

Introduction

One of the key factors of building energy consumption is occupant behavior, which is hardly simulated when it comes to residential buildings. There is a gap between the simulated energy saving and the real energy saving due to the prebound effect and the rebound effect. The rebound effect is defined as the situation when a proportion of the energy saving after a retrofit is consumed by additional energy use; and the prebound effect is defined as the situation before a retrofit, when less energy is consumed than expected (Sunikka-Blank and Galvin, 2012). Martinaitis et al. (2015) indicated that the use of different occupancy profiles is related to the building performance simulation, and the collection of more occupancy information could improve the accuracy of model predictions.

On the other hand, by taking behavioral factor into consideration, the modeling process becomes more complicated and the model running process is also more time-consuming. A modeling process often involves subjective judgement in making modeling assumptions. In order to build up simulation model more cost-effectively, it is necessary to reduce the number of thermal zones by combining multiple rooms into one zone. However, the simplication procedure made in the model can unavoidably impact the accuracy of model output, which may possibly bias design decisions.

Several studies have investigated the effect of thermal zoning on building energy prediction. Korolija and Zhang (2013) compared the annual energy use intensity predicted by detailed simulation models (modeling every room as a single zone) with those predicted by simplified models (modeling each floor as a single zone) for residential buildings. The simulation results disclose that the simplications in thermal zoning can reduce simulation time by 30% on average, but result in the mean absolute relative error of 10.6% in predicting annual heating demand. They selected five representative dwellings in the UK to form the base models, and used the National Calculation Method (NCM) (BRE, 2015) to set default occupancy density, equipment loads and lighting loads for each zone, with two schedules (working family and constantly occupied) for occupancy pattern and domestic appliance use. Heo, Ren and Sunikka-Blank (2016) also examined the effect of simplication in thermal zoning by reducing multiple zones to single zone for the entire house. The results demonstrate the heating demand was under-estimated by 26% from multiple- to single-zone model. They used the NCM to set occupancy density, equipment loads and lighting loads to test the effect of thermal zoning for a case building, and then used electricity consumption data collected from 9021 domestic customers by Customer-Led Network Revolution (Barteczko-Hibbert et al., 2015) to test the adequate level of internal load schedules from smart meter data used for single-zone simulation. However, these two studies have their own limitation because of the use of the hypothetical case buildings. Korolija and Zhang simulated the model with the input occupancy variables from national standard, which can not capture the variation in occupant behavior. Heo et al. used the actual internal load profiles from different buildings for simulation of the same case building, so it ignored the impact of floor area and other important parameters.

There are several definitions of smart meter, and the most popular one is defined as the meter device itself is advanced and supported by a two-way communication system (Haney, Jamasb and Pollitt, 2009). Dent, Aickelin and Rodden (2011) pinpointed that extracting the typical electrical usage patterns within households could help assess the impact of initiatives in order to reduce overall energy usage.

Several studies have been done on extracting occupancy profiles. K-means algorithm was applied to compute a set of representative electricity profiles from a large number of internal load data collected from domestic buildings in Ireland (Mcloughlin, 2013). In order to deal with more than thousands of electricity daily profiles, cluster analysis was used to effectively capture variability in the actual internal load profile and extract the representative profile for each household. Different from Mcloughlin's study, which used the daily internal load profiles, this paper employed the average internal load profiles of each household for improving simulation efficiency. Even if peak value of individual daily profile is smoothed and not captured by the average profile, the missing information of peak value is still acceptable to generate a set of profiles that capture the major variation and evaluate the effect of the variation on annual energy consumption – the purpose of this study.

In order to avoid the limitation in previous studies, real buildings were investigated for this case study. This study not only had smart meter data for each single household, but also provided the detail information of that household, including construction year, floor plan layout, domestic appliance and the number of occupants. In addition, the context of this study is important, as China has taken serious actions to reduce the carbon intensity, aiming to reduce its carbon intensity by 40-45% below 2005 levels by 2020 (Zhou et al., 2011).

This paper aims to explore the effect of variation in occupancy pattern on domestic energy demand prediction. Firstly, the variation in measured occupancy pattern was analyzed through the smart meter data from 126 flats in Shanghai. Secondly, the effect of variation in measured occupancy pattern on energy demand prediction was investigated through single-zone simulation with actual internal load profiles of each household. Third, four levels of internal scheduling strategies were tested: (1) the average profiles of flat in the same floor area; (2) the average profiles of flat in the same number of occupants; (3) the average profiles of flat in the same floor area and the same number of occupants; (4) the average profile of all households.

This study hypothesized the large variation in occupancy pattern could lead to a large variation in energy simulation prediction, which was explained in details in the following sections. The next section introduces general information of the case study. Section three provides overview of the smart meter data and explores the variation in measured occupancy pattern. Section four presents the simulation analysis to explore the effect of variation in occupancy pattern on domestic energy demand prediction. Section five tests the adequate level of internal load profiles used for single-zone simulation. The final section summaries findings and limitations of this study.

Case study

The case study used the smart meter data from 126 flats in Shanghai, built in 2013. The case study also provided information of household plan layout, floor area, number of occupants, and appliance information. There were 2 types of layout for the 126 flats: 62 cases in Type (a) with floor area of 45m^2 and 64 cases in Type (b) with floor area of 60m^2, with 1-2 residents. Figure 1 presents the layout of Type (a) and Type (b), in which, pink color represents the bedroom, dark green represents the lounge, light blue represents the kitchen and yellow represents the toilets. The appliances were pre-installed before residents moved into the flat, with 1 air-conditioner for flat Type (a) and 2 air-conditioners for flat Type (b). This case study is appropriate for this research aim, as it can eliminate the impact that is not caused by occupant-driven factors. There is also a need to mention that there are still many uncertain variables existed, but will be not discussed in this paper.

Figure 1: Plan layout of each flat type: a(left), b(right)

Shanghai is located in the hot summer and cold winter climate region in China. The design of residential buildings should meet the requirement in the national building standard, named Design Standard for Energy Efficiency of Residential Buildings in Hot Summer and Cold Winter Zone (JGJ134-2010) (MOHURD, 2010). Therefore, many unknown parameters are assumed according to the building standard, which is a common method dealing with unknown parameters in previous studies (Caputo, Costa and Ferrari, 2013; Jones, Lannon and Williams, 2001; Li et al., 2015; Parekh, 2005). The material is assumed as the minimum requirement in the standard, with U-value of 1 W/m^{2}K for the wall and 2.8 W/m^{2}K for the window. The heating temperature is assumed as 18°C and cooling temperature is assumed as 26°C, with air change rate of 1 ACH. In addition, the heating period is from 1 Dec. to 28 Feb., and the cooling period is from 15 Jun. to 31 Aug. The air-conditioners are used for both heating and cooling in Shanghai, with the cooling COP of 2.3 and the heating COP of 1.9.

The smart meter data collecting frequency is set at 15-minute interval. The record period is from August 2013 to December 2015. As the current smart meter technology is still unstable, some of the data was lost during the recording period. As a result, we selected a group of relatively complete electricity data with more than 70 recorded days of each household for analysis.

Measured occupancy pattern

Figure 2 presents the actual daily profiles (top) and the electricity intensity profiles (bottom) of all recorded days of all households. It can be seen from Figure 2 (top) that, generally, the internal load profile for Type (b) is higher, as the air-conditioning area for Type (b) is larger. When the total electricity demand is divided by the floor area, shown in Figure 2 (bottom), the electricity intensity for flats Type (a) and (b) reflects some similarity, but Type (a) flat has higher peak values in electricity intensity. Thus, floor area is an important impact factor on energy consumption.

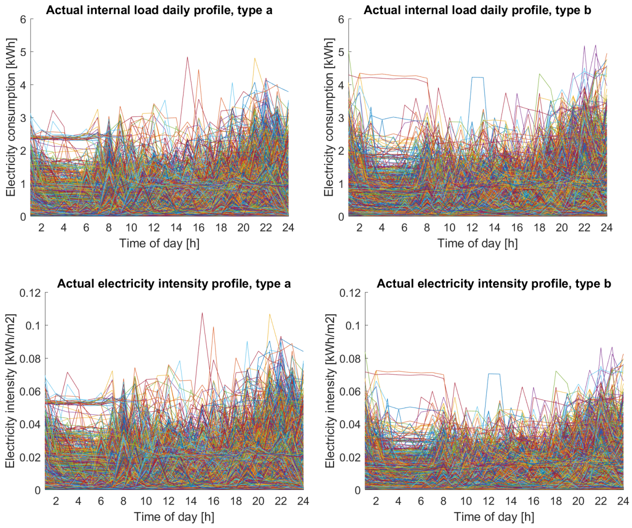
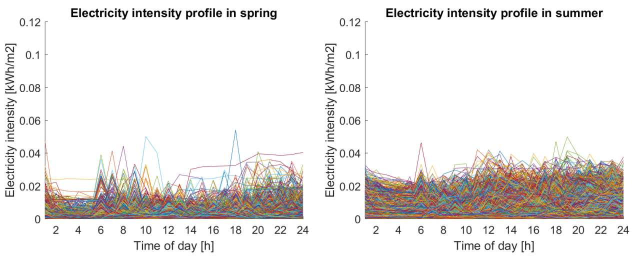


Figure 2: Actual internal load profile (top); and actual electricity intensity profile (bottom)

Figure 3 shows the daily profiles of electricity intensity in spring, summer, autumn and winter. It illustrates that the electricity consumption in winter is much higher than summer, and the electricity intensity in summer and winter is higher than non-air-conditioning period. It implies that, despite other impact factors, electricity used for heating is higher than cooling. Figure 3 also shows the occupancy patterns vary dramatically for different households at different days. In terms of the electricity intensity in winter, during the night period, from 0:00 to 8:00, some occupants constantly use air-conditioners for heating, but the magnitude varies from 0.01 to 0.07 kWh/m^2 per hour; some occupants do not use air-conditioners during night; and some occupants switch on air-conditioners at the specific time, as some peaks are identified during this period.



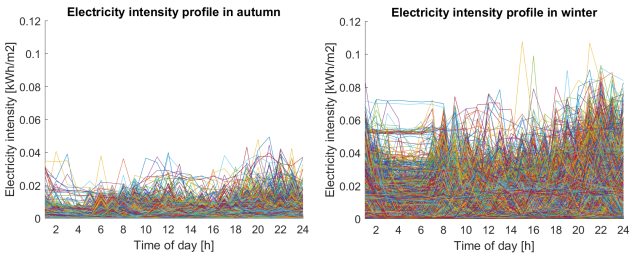


Figure 3: Actual electricity intensity profile in spring, summer, autumn and winter

Figure 4 presents the daily profiles for households with 1 occupant and 2 occupants, and shows the impact of the number of occupants on electricity consumption. The electricity consumption for households with 2 occupants is much higher than 1 occupant. For instance, during the night period, the maximum constant consumption for households with 1 occupant is about 1.5 kWh per hour, while the consumption reaches more than 4 kWh per hour for some households with 2 occupants. Thus, the number of occupants is an important impact factor on energy consumption.

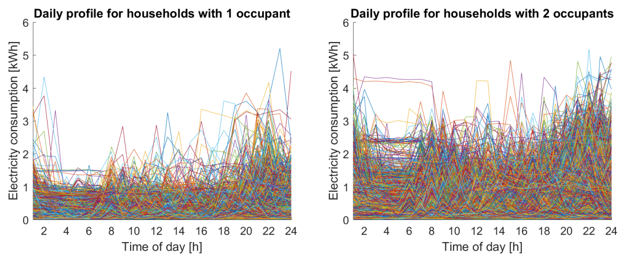


Figure 4: Daily profile for households with 1 occupant (left) and 2 occupants (right)

Figures 2-4 provide the overview of the smart meter data, which demonstrate the electricity consumption in residential buildings is related to floor area, seasons and the number of occupants. In the next, the average profiles of each household would be analyzed to explore the variation in occupancy pattern between each household. The average profile is calculated by the mean value of all recorded day data of each individual household at each hour of the day.

Figure 5 shows the average internal profiles for flat Type (a) and (b), which reflects the large variation in the occupancy energy usage pattern. The average profiles range from 0 to 0.8 kWh per hour, with two peaks at 8:00 in the morning and 22:00 in the evening. After a constant period during night time, small peaks occur at 8:00, and higher peaks occur during 18:00 to 24:00, but the magnitude of the average profile is slight different. Generally, the average profile for Type (b) is higher than Type (a), as flat Type (b) is larger than Type (a) with larger air-conditioning area and more air-conditioners.

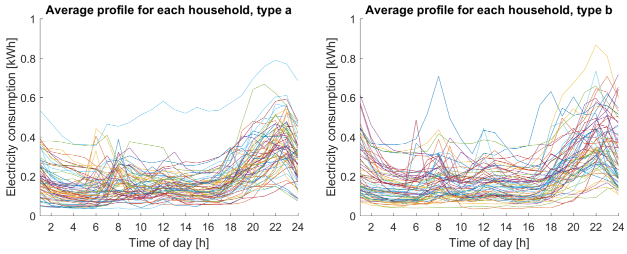


Figure 5: Average profile of each household, include Type a (left) and Type b (right)

Figure 6 presents the average profiles in different groups classified by floor area and the number of occupants. All the average profiles have two peaks, with one peak at 6:00-8:00 in the morning and a higher peak at 18:00-22:00, but each case varies. The magnitude of households with 1 occupant (top) is lower than 2 occupants (bottom), but the difference between floor area is smaller than the difference between the number of occupants. It can be inferred that the impact from the number of occupants on electricity consumption is higher than impact from floor area.

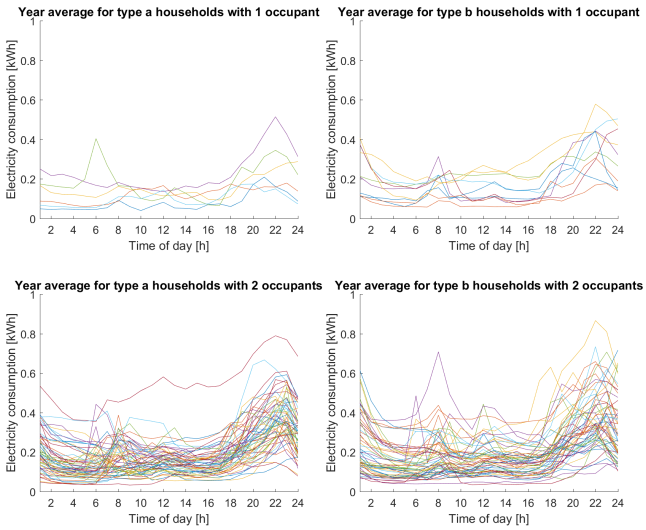


Figure 6: Average profile for Type a (left) and b (right) with 1 (top) and 2 occupants (bottom)

It can be seen from Figure 6 that, even within the same group, the average profiles vary among each household. For instance, in the group of flat Type (b) with 2 occupants, the minimum consumption at 22:00 is about 0.1 kWh, while the maximum consumption at 22:00 is more than 0.8 kWh. This reflects the factor that, apart from floor area and the number of occupants, occupants' habit of using domestic appliance is also an important factor on energy consumption. Thus, it can be concluded from this section that the large variation exists in the measured occupancy pattern, resulted from the impact from floor area and the number of occupants, as well as occupants' habit of using domestic appliance.

Effect of occupancy pattern on prediction

This sections aims to investigate the effect of variation in occupancy pattern on energy prediction, through single-zone simulation with internal load profiles of each household. The occupancy pattern is extracted from the smart meter data of each individual household. In addition, single-zone simulation would be conducted in two simulation models, according to the flat type of each household, with floor area of 45m^2 and 60 m^2.

In order to extract heating and cooling profiles from total electricity consumption, the following steps will be conducted: firstly, calculate the average electricity use at each hour in June (transition season) for each household; secondly, calculate the average electricity consumption at each hour in August (cooling season) and December (heating season); thirdly, use the average electricity demand in cooling season and heating season to minus the average electricity demand in transition season to calculate the average heating and cooling demand for each household at each hour of the day.

Figure 7 shows the cooling and heating profiles of each household for each flat type. It agrees with the previous finding that the residents use more electricity for heating than cooling. In addition, compared with heating profile, the cooling profile is flatter throughout the day, which suggests that cooling consumption is used more randomly throughout the day, but the heating is mainly used during the night. It agrees with the fact that the Chinese residents wear many cloths at home in Winter to fight against the low temperature during the daytime, but they need to switch on the air conditioners when they sleep.

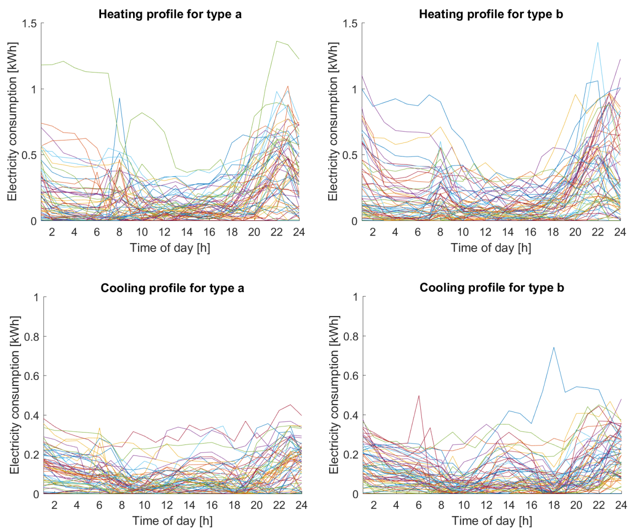


Figure 7: Average heating (top) and cooling (bottom) profile, for Type a (left) and Type b (right)

It can be concluded from Figure 7 that the large variation exists in heating and cooling profiles of each household. The highest consumer for heating is 10 times more than the lowest consumer, which indicates that occupant behavior for heating consumption varies dramatically and should be considered and simulated carefully. When comparing the average heating profile between Type (a) and Type (b), generally, during 20:00 and 24:00, the demand value is higher for Type (b) than Type (a), which reflects larger heating or cooling area.

Multiple simulations have been conducted in EnergyPlus to investigate the effect of variation in occupancy pattern on energy demand prediction. Figure 8 compares the actual annual demand from smart meter data (red), with the annual electricity demand prediction from single-zone simulation with internal load profiles (blue). When the actual annual demand is small, the predicted annual demand is relatively small. In other words, the output is positively related to the input profiles, as the input schedule is extracted from the actual electricity demand. Furthermore, the large variation in measured occupancy pattern also leads to a large variation in energy demand prediction. The predicted annual demand ranges from 2000 kWh to 5500 kWh for each household in Type (a), and ranges from 4000 kWh to 6000 kWh for each household in Type (b).

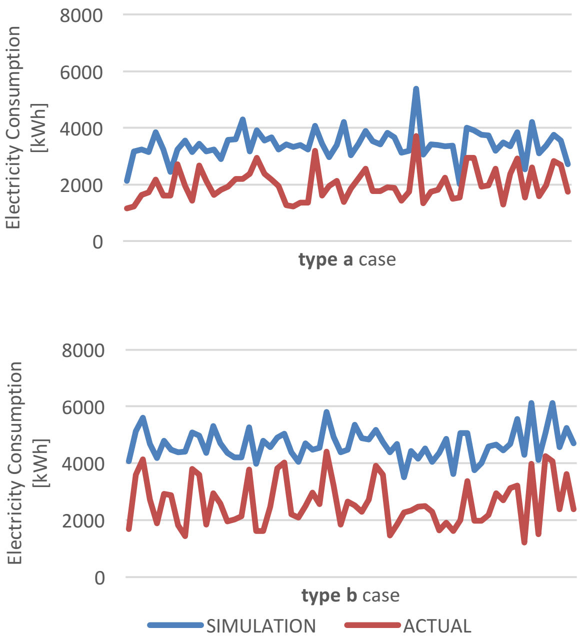


Figure 8: Single-zone simulation in Type a (top) and Type b (bottom), compared with actual data

An important finding is that all the predicted results is higher than the actual measured data, which reflects the prebound effect that less energy is actually consumed than predicted. The difference might be resulted from other unknown and stochastic parameters, but this study aims to explore the effect of occupant-driven load only and will not investigate other uncertain parameters.

Level of internal load profiles for prediction

This section aims to explore the adequate level of internal load profiles for single-zone simulation. Four levels of internal scheduling strategies are tested, from the actual profiles of each household, to (1) the average profiles of flat in the same floor area, to (2) the average profiles of flat in the same number of occupants, to (3) the average profiles of flat in the same floor area and the same number of occupants, and finally to (4) the average profile of all households. In addition, the traditional simulation method of multiple-zone simulation with information from national standard JGJ134-2010 was also used for comparison. There is a need to note that the occupancy schedule is not mentioned in any simulation guide that for the specific context in China, such as CIBSE for the UK and ASHARE for the US. The traditional simulation method requires simulators' experience to adjust internal load schedules. Annual electricity demand is used as a performance indicator, and all the simulation results will be compared with the actual annual demand to test the accuracy of each level of internal load profiles used for simulation.

Table 1 presents each level of internal load scheduling strategies, from multiple- to single-zone model with different input occupancy profiles. Step 1 is the multiple-zone simulation with input parameter from national standard. Steps 2-6 are single-zone simulation with different strategies and occupancy schedule profiles: Step 2 uses the average profiles of each household (126 schedules for 126 simulations); Step 3 uses the average profiles of each category by floor area and the number of occupants (4 schedules for 4 simulations); Step 4 uses the average profiles of each category by the number of occupants (2 schedules for 4 simulations); Step 5 uses the average profiles of each flat type (2 schedules for 2 simulations); and Step 6 uses the average profiles of all households (1 schedule for 2 simulations). Step 2 is the simulation test that has been done for the previous section, and the detail simulation results will also be analyzed here.

Table 1: Each level of internal load scheduling

Step	Notation	Occupancy schedule
(0)	0	Actual annual demand
(1)	1-a	Multiple-zone with Chinese standard, JGJ134-2010
	1-b	
(2)	2-a	Average profiles for each household: 126 simulations
	2-b	
(3)	3-a-1	Average profiles for group in **flat type** and **number of occupants**: 4 schedules, 4 simulations
	3-a-2	
	3-b-1	
	3-b-2	
(4)	4-a-1	Average profiles for group in **number of occupants**: 2 schedules, 4 simulations
	4-a-2	
	4-b-1	
	4-b-2	
(5)	5-a	Average profiles for each **flat type**: 2 schedules, 2 simulations
	5-b	
(6)	6-a	Average profiles of all households: 1 schedule, 2 simulations
	6-b	

The heating and cooling profiles were extracted with the methods mentioned in the previous section, according to the criteria of floor area and the number of occupants. Figure 9 presents the input schedule profiles of Steps 3-6 for single-zone simulation. The input schedules from the category of Type (a) households with 1 occupant (3-a-1) has the lowest input value, as this category has the smallest floor area and smallest number of occupants. In the opposite, generally, schedules from the category of Type (b) households with 2 occupants (3-b-2) has the highest input value. The cross effect of floor area and the number of occupants has the highest impact.

In addition, the category of households with 1 occupant (4-1) ranks as the second lowest among all input schedules. The input schedule for Type (a) and Type (b) (5-a and 5-b) is similar, which also agrees with previous finding that the impact from the number of occupants on energy demand is higher than impact from floor area. It leads to the conclusion that behavioral factor plays a more important role than building envelope in energy consumption. The input schedule of all households (Step 6) is located in the middle, between the maximum and minimum profiles.

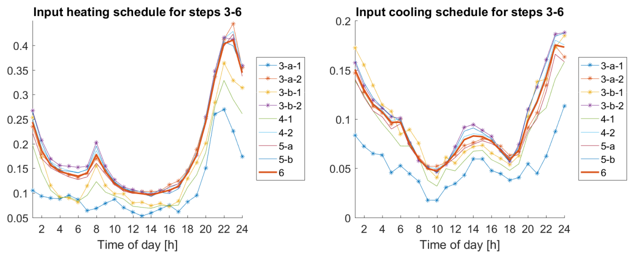


Figure 9: Input schedule profiles for Steps 3-6

Multiple simulations have been conducted in EnergyPlus to test the level of internal scheduling strategies required for single-zone simulation. Table 2 lists the actual annual demand and the predicted annual demand. There is a need to note that Steps 0 and 2 have 126 results, so the annual demand is present in the MIN, MEAN and MAX value of all the 126 values. Step 1 uses the input parameter from standard, which means that just one schedule would be used for two simulations. For Steps 2-6, the number of simulation runs is listed in Table 1, so the number of results is the same with the simulation runs. For Steps 3 and 4, as they also consider the number of occupants in simulation, four simulation runs would be conducted for each step with 4 results.

Table 2: Predicted annual demand (kWh)

<table>
<tr><th>Step</th><th colspan="6">Type (a)</th><th colspan="6">Type (b)</th></tr>
<tr><td></td><td colspan="2">MIN</td><td colspan="2">MEAN</td><td colspan="2">MAX</td><td colspan="2">MIN</td><td colspan="2">MEAN</td><td colspan="2">MAX</td></tr>
<tr><td>0</td><td colspan="2">1160</td><td colspan="2">2000</td><td colspan="2">3709</td><td colspan="2">1219</td><td colspan="2">2624</td><td colspan="2">4402</td></tr>
<tr><td>1</td><td colspan="6">4206</td><td colspan="6">6623</td></tr>
<tr><td>2</td><td colspan="2">2020</td><td colspan="2">3420</td><td colspan="2">5378</td><td colspan="2">3513</td><td colspan="2">4671</td><td colspan="2">6127</td></tr>
<tr><td></td><td colspan="3">a-1</td><td colspan="3">a-2</td><td colspan="3">b-1</td><td colspan="3">b-2</td></tr>
<tr><td>3</td><td colspan="3">3371</td><td colspan="3">3584</td><td colspan="3">4785</td><td colspan="3">4847</td></tr>
<tr><td>4</td><td colspan="3">3514</td><td colspan="3">3623</td><td colspan="3">4695</td><td colspan="3">4806</td></tr>
<tr><td>5</td><td colspan="6">3563</td><td colspan="6">4837</td></tr>
<tr><td>6</td><td colspan="6">3609</td><td colspan="6">4791</td></tr>
</table>

The actual demand (Step 0) varies among all households, with the average value of 2000 kWh for Type (a) and 2600 kWh for Type (b), which suggests that the actual annual demand is positively related to the floor area. The maximum actual annual demand is more than 3 times of the minimum value, which reflects the large variation in annual demand, even in the flats with the same floor area. Table 3 provides the simulation accuracy of each step when compared with the actual annual demand of each household. The difference is calculated by using the predicted result minus the actual demand, and then divided by the actual demand. The simulation accuracy varies from 2% to 252% for single-zone simulation, depending on impact factors such as the number of occupants and appliance use habit.

Table 3: Accuracy of each step compared with actual

Step	Type (a)			Type (b)		
	MIN	MEAN	MAX	MIN	MEAN	MAX
1	0.13	1.10	2.63	0.50	1.52	4.43
2	0.20	0.80	2.03	0.19	0.92	2.52
3	-0.03	0.91	1.93	0.10	1.04	2.98
4	-0.02	0.94	2.03	0.09	1.02	2.94
5	-0.04	0.78	2.07	0.10	0.84	2.97
6	-0.03	0.78	2.07	0.09	0.84	2.97

According to MIN, MEAN and MAX values, generally, the simulation difference for Type (a) is smaller than Type (b). For Type (a), the MIN value ranges from 2% to 20%, MEAN value ranges from 78% to 110%, and MAX value ranges from 193% to 263%. For Type (b), the MIN value ranges from 19% to 50%, MEAN value ranges from 84% to 152%, and MAX value ranges from 252% to 443%. There is a need to note that the MAX difference of Step 1-b is 443% (6623 minus 1219, and then divided by 1219), and it is due to the actual demand for that household is so small (larger floor area with 1 occupant). The large difference for the Type (b) extreme case is from the factors like energy use consciousness, appliance use habit and the number of occupants. It reflects the fact that the large variation in occupant behavior results in the large variation in actual consumption, which will also lead to a large variation in simulation accuracy. Thus in order to simulate more accurately, it is important to take behavioral factors into consideration. The important finding is that simulation accuracy varies more dramatically for flats with larger floor area.

The simulation difference for Step 1 is larger than Steps 2-6. The MIN value for Step 1 is similar with Steps 2-6 for Type (a), varies from 2% to 20%, and the MIN value for Step 1 (50%) is much higher than Steps 2-6 (2-19%) for Type (b). The MAX value for Step 1 (263%) is a little higher than Steps 2-6 (193-207%) for Type (a), and the MAX value for Step 1 (443%) is much higher than Steps 2-6 (252-298%) for Type (b). The MEAN value for Step 1 is larger than Steps 2-6 for both Type (a) and (b). The comparison of simulation accuracy indicates that, by taking behavior factor into consideration, single-zone simulation with smart meter data (Steps 2-6) is more accurate than the traditional simulation method (Step 1). The use of smart meter data could be used to capture occupancy variation.

This section aims to explore the adequate level of internal load profiles used for single-zone simulation. Among Steps 2-6, the simulation accuracy is not obvious among each step. It leads to the conclusion that the level of internal load scheduling is depending on how much information we could obtain for analysis, as well as the purpose and scale of the analysis. For instance, for the analysis of retrofit options for a single household, the single-zone simulation with average profiles of that particular household from smart meter data (Step 2) is recommended. For the design of building with unknown residents, single-zone simulation with the similar group of residents (Steps 3-5) is recommended.

Conclusion

Occupant behavior in residential buildings contributes to a large uncertainty in energy demand prediction. This paper explored the effect of variation in occupancy pattern on domestic demand prediction by a case study of smart meter data from 126 flats in Shanghai. It was demonstrated the large variation in occupancy pattern would lead to a large variation in energy prediction. Section three proved the large variation in measured occupancy pattern, which was resulted from the impact from floor area, the number of occupants and the occupants' habit of using appliance. Section four shows that the large variation in occupancy pattern lead to the large variation in domestic energy demand prediction. The predicted annual demand ranged from 2000 kWh to 5500 kWh for each household in Type (a), and ranges from 4000 kWh to 6000 kWh for each household in Type (b). Section five shows the simulation accuracy was not obvious among Steps 2-6, which leads to the conclusion that all levels of internal load scheduling strategies are acceptable and the level of internal load scheduling is depending on the how much information we could obtain for simulation analysis.

One important finding is the residents used more electricity for heating than cooling, and the highest consumption for heating was ten times more than the lowest one. It indicates that occupant behavior for heating varied dramatically and should be considered and simulated carefully. Another important finding is that almost all simulation results give higher energy use than actual consumption data from smart meter data. It suggests the prebound effect, which is an indication of how much heating energy would need to be consumed in a particular dwelling for that dwelling to have a comfortable indoor temperature and air quality in all rooms, throughout the whole year compared to the actual consumption. Due to the prebound effect, most retrofits bring less fuel saving than the engineering estimates. A homeowner's or landlord's decision as to whether to invest in energy efficiency measures greatly depends on the payback time. Therefore, the financial feasibility of thermal retrofit measures, and the effectiveness of fiscal policy instruments, greatly depend on accurate actual energy consumption figures. It should also be noted that one limitation is that many other unknown and stochastic variables in the simulation model did not be involved in this study, such as building materials. As this paper only investigated the effect of occupant-driven load on energy demand prediction, during the simulation process, other unknown parameters were assumed according to building standard, and those unknown parameters will be investigated in future studies to improve the simulation efficiency.

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