Allocating Occupancy Rates to the Micro Census Using Time-Use Data

Marcelo Esteban Muñoz Hidalgo[1,*]

[1]HafenCity University, Hamburg

ABSTRACT The model aims to describe an essential method for simulation of user influence on heat demand of small urban areas. This papers presents first efforts towards a tailored spatial microsimulation model that selects representative households from the micro census for a specific urban area fitted to an aggregated cross tabular demographic information. The selected families are allocated to geo-referenced buildings of the corresponding urban area, see (Munoz Hidalgo & Peters, 2014). The core of the paper deals with the generation of time schedules for the individual occupants based on their demographic characteristics. In order to reproduce a plausible time schedule for the buildings I use the official time-use survey from Germany "Zeitbudgeterhebung". This data set contains detail demographic information of single families. This information is used to allocate occupational schedules to families in the micro census. The time budget data set contains detail information about the time spend on specific activities. The model generates a simplified sub-hourly time schedule identifying occupancy rates of individual families in the building. This method opens the possibility to further investigate into several fields of application such as the use of demographic characteristics in: (1) thermal simulation models or (2) heat balancing methods, which typically requires the historical profile of individuals and have traditionally been difficult to acquire, leading the community to perform the simulation with standardized individuals. The approach is applied to assess: (1) the effects of user behaviour on heat consumption; and (2) the consequence of this effect in the performance of heat supply infrastructure. The results of this simulation are presented in this paper aiming to establish a discussion platform in both communities: the microsimulation community and the energy simulation community.

KEYWORDS
Occupancy; Sub-hourly schedules; Micro census; Time-use survey.

*Corresponding author email: marcelo.hidalgo@hcu-hamburg.de

USING FAMILY SPECIFIC OCCUPANCY RATES TO SIMULATE HEAT CONSUMPTION

A significant variation between estimated heat demand and monitored heat consumption among residential buildings with similar physical characteristics has lead the scientific community to the conclusion that this variation has to be explained trough occupant behaviour (Guerra Santin, Itard, & Visscher, 2009; Haldi & Robinson, 2011; Durand-Daubin et al., 2013; D'Oca, Fabi, Corgnati, & Andersen, 2014). The aim of this paper is to present a strategy to use time-use data to enrich the population census, different families taken from the census are allocated to a generic building with a simple geometry for the estimation of heat demand. The estimation of heat demand is performed with the well established building simulation software EnergyPlus[1]. The generated occupancy rates are parse as input files to the building simulation model in form of a csv file. This file contains 52560 (144 x 365) record points, 144 points for each day, because the data from the time-use dataset describes events in a 10 minute interval. For the integration of building occupants at an urban scale I propose to allocate synthetic families, with their corresponding time budget, into the digital cadastre. The biggest challenge in these endeavors is to develop robust models able to create plausible scenarios for this merge. First steps in this direction have been taken (Munoz Hidalgo & Peters, 2014). This paper marks an important step towards this goal.

THE USER INFLUENCE ON HEAT CONSUMPTION

The influence of the user on heat demand is a topic of much debate among the community. There is little empirical data available at: (1) the require resolution, needed to identify difference between behavioral patterns during the day; and (2) required amount of data, needed to control for all other variables influencing heat demand (Zhun Yu, Benjamin C.M. Fung, Fariborz Haghighat, Hiroshi Yoshino, & Edward Morofsky, 2011). An important factor for the simulation of energy demand seems to be occupant presence (Guerra Santin et al., 2009). The later authors observe this effect in their work, (Page, Robinson, & Scartezzini, 2007) developed an interesting method for the integration of this parameter into simulation models generating stochastic occupation patters using Markov chains. The integration of user behavior into building simulation models can be achieved, difficulties arise by the validation of such simulations as empirical data at the needed temporal and disaggregation resolution is difficult to recover. The integration of behavior models into well-established energy demand models have presented into two forms: (a) probabilistic and (b) deterministic approaches, the latter being the "native" method for common simulation models (D'Oca et al., 2014). A good example of this distinction can be found in the simulation of window opening (Borgeson & Brager, 2008), the integration of user behaviour models (e.g: natural ventilation rate through opening windows) into energy demand models has pose a challenge for models, because resulting models from empirical observation deliver probabilistic models which are hard to integrate into the "classic" deterministic architecture of conventional building simulation models.

[1] http://apps1.eere.energy.gov/buildings/energyplus/

(Bourgeois, 2005) develop the model SHOCC (Sub-Hourly Occupancy Control) which can be directly used with the common thermal simulation model ESP-r.

THE DATA

For the presented method in this paper I use two data sets: (1) the micro census[2]; and (2) the time-use survey[3] Both data sets contain record for the German population. The micro census contains 489 630 individual entries. Each entry in the data set corresponds to a real person living at the time in Germany. The individual records can be group into families with help on one of its attributes. The data set has a detailed description of each individual, describing the individual with help of 529 attributes. Out of this 529 attributes I use 11 to fetch a representative individual form the second data set, the time-use survey. Similar to the micro census the time use survey consists of individual records of people. Each record contains a wide set of attributes, for the method described below I make use of just a small section of the survey. In order to handle this data set in a more efficient way, I divided the survey into 11 different tables. Two of this tables are used to generate the needed data for the analysis presented below. The first table describes the characteristics of the individuals that took place on the survey. This table contains 397 attributes and 13 691 records. The second table contains more records because each individual may have recorded a time use journal for more than one day. This table contains 148 attributes, 144 of these attributes represent the location of the individual in a 10 minute interval. The other four attributes are: (1) an internal unique ID; (2) a household ID; (3) the individual ID; and (3) a day ID.

ALLOCATING OCCUPANCY PATTERNS TO INDIVIDUALS

For each individual described in the micro census a representative record from the time-use dataset is selected. In table 1 the available attributes present in both datasets: (a) the micro-census; and (b) the time-use data set are listed by relevance. The order of the attributes is important for the selection of a matching record in the time-time use dataset because of two reasons: (1) the number of records in the time-use data is smaller than of the micro census and; (2) the attributes classes are not equal for both data sets. It is possible that the developed algorithm can't find a matching using all the attributes as query constrains, in such a case the algorithm drops the last constrain and performs the query with one constrain less, this procedure is performed until at least one matching record is recovered from the database. In the case than more than one journal is recovered an average is constructed upon all retrieved records. The recover data contains information regarding the location of the individual in a 10 minute step for workdays and weekends (day types). This information is simplified to two one dimensional vectors for each day type. Each vector of size 144 represents the probability of being at home.

[2] forschungsdatenzentrum.de/bestand/mikrozensus

[3] forschungsdatenzentrum.de/bestand/zeitbudget

Table 1: Attributes used to allocate occupancy schedules to individuals from the census

#	Time-use ID	Microcenssus ID	Attribute name
1.	P27X	EF131	Working hours
2.	P2610	EF171	Work-at-home
3.	VO_TE_N	EF129	Full-time or part-time job
4.	P281	EF149	Work on Saturday
5.	P282	EF150	Work on Sunday
6.	PH01B2X	EF44	Age
7.	PH01E	EF49	Family status
8.	BERUF_N	EF117	Occupational status
9.	P11	EF287	Attending school
10.	PH01C	EF46	Gender
11.	P29X	EF436	Net-income

GENERATING A SCHEDULE FILE FOR THE SIMULATION

Based on the matched profile from the time-used data a file for the entire simulation year is generated. Two files are given as input for this computation describing the probability of being home at: (1) weekdays and (2) weekends. Based on this files the occupation patters for the entire year is generated. Figure 1 shows this probability for the average individual and for two sample households, see below for details on the definition of households. The file containing the presence of the single individual for the entire year in a 10 minute interval is generated based on the retrieved information from the time-use data set. This data-set delivers the probability of the specific individual of being home at a particular hour of the day. This probability is used as base to generate the schedule of the individual. In order to avoid fluctuations during time period with out a clear probability (50%) a transition probability is added to the equation, labeled *trans* in equation 1 and equation 2. Because out of the micro census I can group the individuals into families, the generated schedule used as input for the thermal simulation model is the average occupation of the building for the number of persons living in the house.

$$B_t(i,dt) = \begin{cases} 0 & \text{if } rnd > P_t(i,dt) + trans(t-1) \\ 1 & \text{if } rnd < P_t(i,dt) + trans(t-1) \end{cases} \tag{1}$$

$$trans(t) = \begin{cases} +0.4 & \text{if } B_t = 1 \\ -0.4 & \text{if } B_t = 0 \end{cases} \tag{2}$$

Where:

B_t	Determinant of being home at time step t
$trans$	Transition probability
P_t	Probability of being home at time step t
i	Unique individual from the micro census
dt	day type (Workday/Weekend)

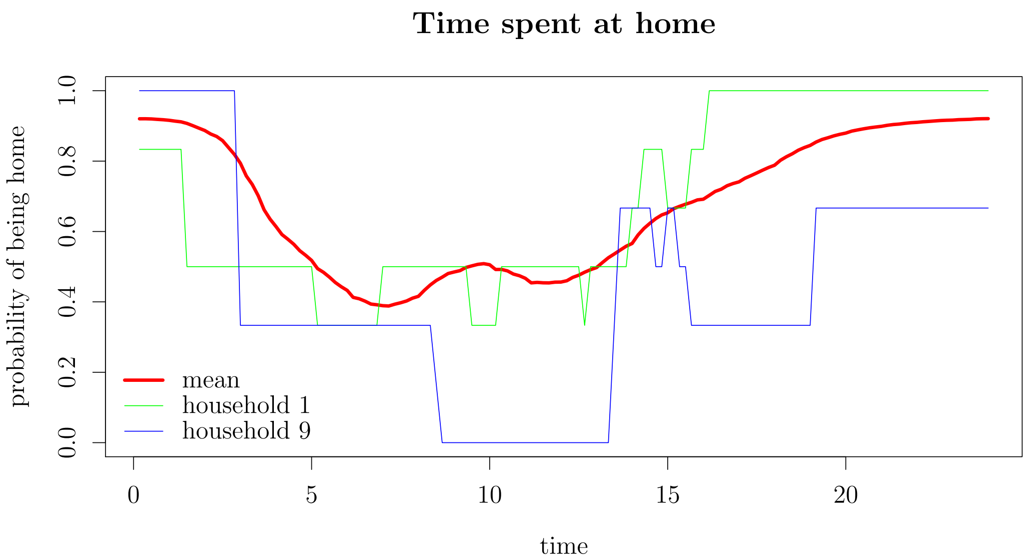

Figure 1: Average probability of being at home and two probability curves for two individual households

BUILDING GEOMETRY USED IN THE SIMULATION

For the purpose of this paper I defined a simple building geometry, A box of 6x8 meters with a celling height of 2.7 meters. A double glazed window was located on each side of the building. I aim to expand this approach by defining the building characteristics, including geometry and heat transmission coefficient of components through the use of the available digital cadastre for the city of Hamburg. Using the digital cadastre to acquire geometrical information of the individual buildings is not the only advantage of the digital cadastre, because the buildings are geo-referenced an allocation of representative synthetic families to the building stock is possible (Munoz Hidalgo & Peters, 2014). A detail description of the building stock geometry and schedules of its occupants is the development goal I am working on. The presented contribution represents an important step to achieve this goal.

ESTIMATING HEAT DEMAND WITH FAMILY SPECIFIC OCCUPATIONAL SCHEDULES

For the simulation of heat demand the energy simulation software EnergyPlus, was used. The *.idf input file used for the simulation is dynamically generated with the new data. For now, only two variables of the input file are modified for the different simulations: (1) the generated schedule for the specific family, third variable in listing 1; and (2) the number of occupants, or in this case household size, listed as the fifth variable on listing 2. In order to show the function of this method I have only used the generated schedule to control for internal gains, this method can be expanded to control other relevant parts of the simulation, e.g: ventilation rates, appliance used, lighting or temperature set points. For the define building I run 100 simulations with the first 100 families in the micro census. This type of simulation could also been achieved with the use a stochastic model. The aim of the presented method is not to simulate possible spreads of heat demands for a single building but aims to simulate building agglomerations while taking into account the specif socio demographic characteristics of its residents. The efforts presented in this paper make a significant contribution toward the development of urban heat demand models which take the user behaviour into account. The resulting heat demand estimation from the simulation is depicted in figure 2. There is a significant variation in the consumption of heat for the different family types. I expect to see a similar variation at an urban scale. Such a heat demand model may prove interesting for the proper dimensioning of decentralized heat supply systems.

```
Schedule:File,
    OCCUP,                      !- Name
    Fraction,                   !- Schedule Type Limits Name
    shedules\shedule.csv,       !- File Name
    1,                          !- Column Number
    0,                          !- Rows to Skip at Top
    8760,                       !- Number of Hours of Data
    Comma,                      !- Column Separator
    no,                         !- Interpolation
    10;                         !- Minutes per item
```

Listing 1: Definition in the .idf input file for the schedule controlling the presence of occupants during the simulation

```
People,
    SPACE1-1 People 1,          !- Name
    ZONE ONE,                   !- Zone or ZoneList Name
    OCCUP,                      !- Number of People Schedule Name
    people,                     !- Number of People Calculation Method
    3,                          !- Number of People
    ,                           !- People per Zone Floor Area
    ,                           !- Zone Floor Area per Person
    0.3,                        !- Fraction Radiant
    0.55,                       !- Sensible Heat Fraction
    ACTIVITY_SCH;               !- Activity Level Schedule Name
```

Listing 2: Base code used in the input .idf file for the simulation of internal heat gains

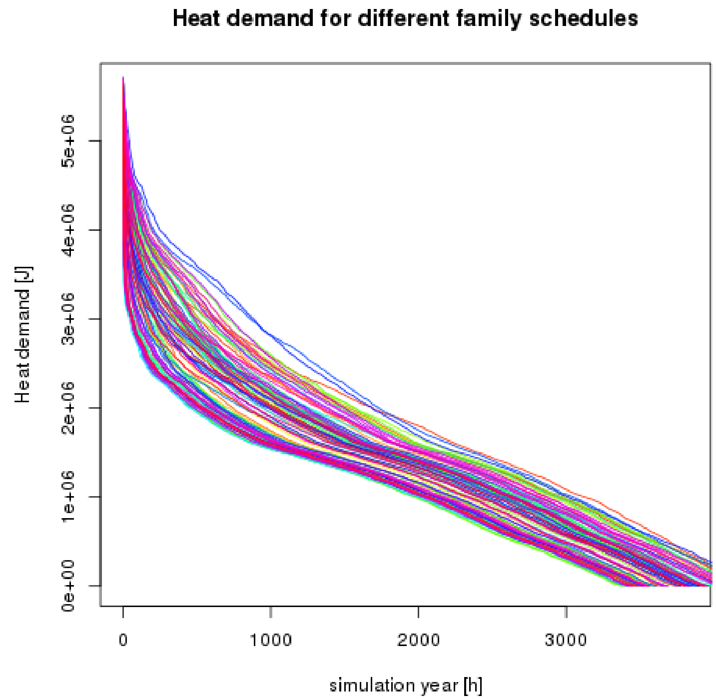

Figure 2: Simulated heat demand for 100 different occupation schedules of 100 different families occupying the generic building

FUTURE PATH

In the presented approach the generated occupation schedule distinguish only between workdays and weekends, this method can be expanded to distinguish occupational patterns between seasons. This method can also be expanded to other type of simulation models. The simulation of electricity demand can directly profit from this approach. The available data in the time-use survey delivers not only information about the location of single individuals over time but describes the specific activity as well as appliances used in the household. I expect that this type of information, in combination with a spatial microsimulation (that is the selection of representative individuals from the micro census for specific urban areas) make a contribution towards the reduction of the variation between simulated heat demand and monitored heat consumption. When occupants have control over the system, they can adapt, and this can lead to a significant reduction of energy (Bourgeois, 2005; Toftum, Andersen, & Jensen, 2009; Fabi, Andersen, Corgnati, & Olesen, 2012), specially on new or retrofitted buildings where heat transmission losses through the wall and through ventilation are rather low. We need models able to capture this influence for the proper design of future supply systems.

Acknowledgements

This research was founded by the *Federal Ministry of Economic Affairs and Energy (BMWi)* in the framework of the research project: *EnEff:IBA - 03ET1081A* and by the German Academic Exchange Service (DAAD) in the framework of the program: *Year Stipend for Doctoral Students 2014/15 (57044990).*

References

Borgeson, S., & Brager, G. (2008). *Occupant control of windows: Accounting for human behavior in building simulation.* Retrieved 16.08.2012, from `http://www.cbe.berkeley.edu/research/pdf_files/Borgeson2008-OperableWindowSimulation.pdf`

Bourgeois, D. J. (2005). *Detailed occupancy prediction, occupancy-sensing control and advanced behavioural modelling within whole-building energy simulation* (Unpublished doctoral dissertation). Université Laval, Québec.

D'Oca, S., Fabi, V., Corgnati, S. P., & Andersen, R. K. (2014). Effect of thermostat and window opening occupant behavior models on energy use in homes. *Building Simulation*. doi: 10.1007/s12273-014-0191-6

Durand-Daubin, M., Huebner, G. M., McMichael, M., Shipworth, D., Shipworth, M., & Summerfield, A. (2013). Heating patterns in English homes: Comparing results from a national survey against common model assumptions. *Building and Environment, Volume 70*, *70*.

Fabi, V., Andersen, R. V., Corgnati, S., & Olesen, B. W. (2012). Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment*, *58*(0), 188–198. doi: 10.1016/j.buildenv.2012.07.009

Guerra Santin, O., Itard, L., & Visscher, H. (2009). The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings*, *41*(11), 1223–1232. doi: 10.1016/j.enbuild.2009.07.002

Haldi, F., & Robinson, D. (2011). The impact of occupants' behaviour on building energy demand. *Journal of Building Performance Simulation*, *4*(4), 323–338. doi: 10.1080/19401493.2011.558213

Munoz Hidalgo, M. E., & Peters, I. (2014). Constructing an Urban Microsimulation Model to Assess the Influence of Demographics on Heat Consumption. *International Journal of Microsimulation*, *7*(1), 127–157.

Page, J., Robinson, D., & Scartezzini, J.-L. (2007). Stochastic simulation of occupant presence and behaviour in buildings. In *10th Conference of International Building Performance Simulation Association* (pp. 757–764).

Toftum, J., Andersen, R. V., & Jensen, K. L. (2009). Occupant performance and building energy consumption with different philosophies of determining acceptable thermal conditions. *Building and Environment*, *44*(10), 2009–2016.

Zhun Yu, Benjamin C.M. Fung, Fariborz Haghighat, Hiroshi Yoshino, & Edward Morofsky. (2011). A systematic procedure to study the influence of occupant behavior on building energy consumption. *Energy and Buildings*, *43*(6), 1409–1417. doi: 10.1016/j.enbuild.2011.02.002