A MODEL OF OCCUPANTS′ ACTIVITIES BASED ON TIME USE SURVEY DATA

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ABSTRACT

In this paper we present a method to simulate residential building occupants' activities, which can be directly used to predict occupants' presence and as an input to models of occupants' behavior, resulting in more coherent and accurate predictions of buildings' energy demands for heating, ventilating and air-conditioning as well as for lighting and electrical appliances. First we describe a stochastic model of the activity chains of residential building occupants and the calibration of this model using French time-use survey data (for the period 1998/1999). This model is based on three time-dependent quantities: (i) the probability to be at home, (ii) the conditional probability to start an activity whilst being at home, and (iii) the probability distribution function for the duration of that activity. We then present results from the validation of this model based on the aggregated time use survey dataset as well as for disaggregations of the survey population; the objective here being to enable predictions of specific segments of a given population. We conclude by presenting an algorithm to guide the implementation of this activity model within building simulation software.

INTRODUCTION

Some of the activities of residential building occupants have a direct bearing on the behaviors of interest to the building simulation community: the use of lights and appliances (both water and electrical) as well as of windows and shading devices (Rijal et al., 2008; Haldi and Robinson, 2009, 2010; Robinson and Haldi, 2011). For example, the activity cooking is rather likely to involve the use of a cooker and thus the opening of a kitchen window or alternatively the use of a ventilation device to evacuate pollutants. The cooker may also, for the braver amongst us, be used concurrently whilst we bathe. We are less likely to open the bathroom window whilst bathing than we are when we have finished, this time to evacuate excess moisture. Some research has already been done which is dedicated to ascribe the electricity needs of electrical appliances to residential activities (Tanimoto and Hagishima, 2011; Widén et al., 2011; McQueen et al., 2005). A robust way of handling this complexity is to model occupant' activities based on measured time-use survey (TUS) data.

In this article, we introduce the preliminary research that we have conducted in this field, describing an approach which is sufficiently tractable to be easily implemented in building simulations, and which is sophisticated enough to capture the significant human behavioral patterns when performing residential activities. Furthermore, the approach is focused on smoothing the artifacts which occur in TUS datasets due to subjects' tendencies to record rounded time values, or other misapprehensions and imprecisions.

In the next section of this article we present our modeling methodology and give an overview of the data used to calibrate the models. We then present some initial simulation results and associated validation tests, based on comparing simulated outcomes with survey responses, for both the aggregate dataset and for disaggregatations of the survey population. We then introduce an algorithm for the implementation of our preliminary model within building simulation software and conclude with an outlook regarding future work to further refine this preliminary model.

METHOD

Time Use Survey Data

In order to calibrate our model, we use the data of a French time-use survey (TUS) that was conducted from February 1998 to February 1999 by the French National Institute of Statistics and Economic Studies (Blanc, 2011). This information is included in electronic format in a data base containing the TUS data of many different countries (Fisher et al., 2009). The survey contains the information gathered from 12000 households and over 15000 individuals. The respondents completed questionnaires (resolution 10 min) describing the chronological course of events of the activities (out of a list containing 41 different categories; *cf.* (Fisher et al., 2010)) performed during one particular calendar day starting and ending at midnight. For reasons of clarity and readability we have merged together activities with similar impacts on energy demand. Those with low frequency of occurrence and/or negligible impact on building physics were merged to the category "other". This leads to $N_{\mathrm{act}} = 20$ different residential activity types (see the legend of Figure 2). Additional information that was recorded in the TUS includes the date of the recording, the gender, the age and the information in which type

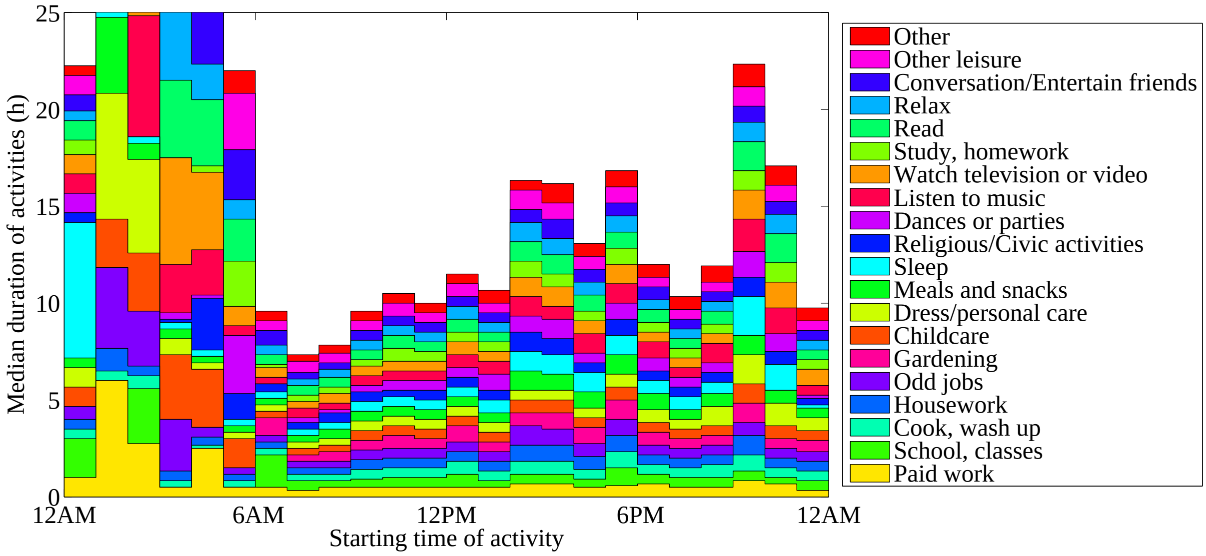

Figure 1: (color on-line) Stacked medians of the durations of residential activities of the TUS that were started during the hour interval given on the x-axis. Activities which are performed for less than 0.5 % of the time throughout the day are not shown. The y-axis is bounded to a maximal value of 25 h.

of place the person is present (at home, workplace, school, etc.). Furthermore, there is much more information specifying household-level characteristics, as well as personal characteristics of demographic variables, employment and education and health. The day the data was recorded is relatively uniformly distributed, ranging from 10.5 % for Mondays to 16.9 % on Thursdays. The months are also relatively uniformly covered, ranging from 7.6 to 11.0 %, apart from March, August and December which lie between 4.1 and 5.6 %. 47 % of the respondents are male, and 24.6 % are retired.

In Figure 1 we show a summary of median durations of residential activities of the TUS as a function of the hour of the day when they were started, indicated by the height of each single-colored area. The scarcity of events during the night time amplifies the weight of erroneous recordings in the data base leading to a much longer mean duration during the night time (we assume that the activity type in the data base has sometimes been mistaken for another one in the data base; during the night time this leads very likely to a replacement of sleeping by another activity, which increases the mean duration of the other activity substantially). Therefore, we do not show the whole range of activities between 12 am and 6 am to focus on the rest of the day which is more reliable. At the end of the day the means decrease because of the truncation of the questionnaires which stop recording after midnight.

In Figure 2 we show a stacked histogram of the numbers the activities have been started in the whole TUS as a function of the time interval on the x-axis. Between 1 am and 5 am the total number of started activities is considerably lower than during the rest of the day. This intuitive situation can also be explained by the fact that sleeping is the activity which is most often started in the two intervals before 1 am and which has a high average duration at that time of day (*cf.* Figure 1). As a summary of the Figures 1 and 2, it can be seen that the probability to start an activity varies more with the time of day than does the average duration of the activity.

Methodology

The central variable of interest is the probability to perform an activity j depending on the time t, which we will denote by $p_j(t)$. These probabilities are shown in Fig. 3 (left). We apply a stochastic approach to model individuals' activity chains throughout their day. In our model, we use two distinct processes which enable predicting whether a certain activity is performed whilst someone is at home. First, we consider the time-dependent conditional probabilities $p_{s,j}(t)$ to start a certain activity j whilst being at home, and second, the corresponding probability distribution functions (PDFs) $f_j(t)$ of the duration the activity j lasts. When the duration is drawn from the continuous PDF in the simulation, the value is rounded to the 10 min resolution of the simulation afterwards.

To assign residential activities to an individual, we need to know whether that person is at home. Although the latter is to be modeled stochastically, we use the recorded occupancy data of the TUS in order to evaluate the performance of the activity model itself as a post-process of a separate occupancy model. In this approach, there are censored (truncated) events at the beginning and the end of the calendar day of the questionnaire as well as when an individual leaves his residence. This is modeled in the simulation by forcing an activity to end as soon as the individual leaves his/her residence.

In general, the mentioned stochastic quantities can be

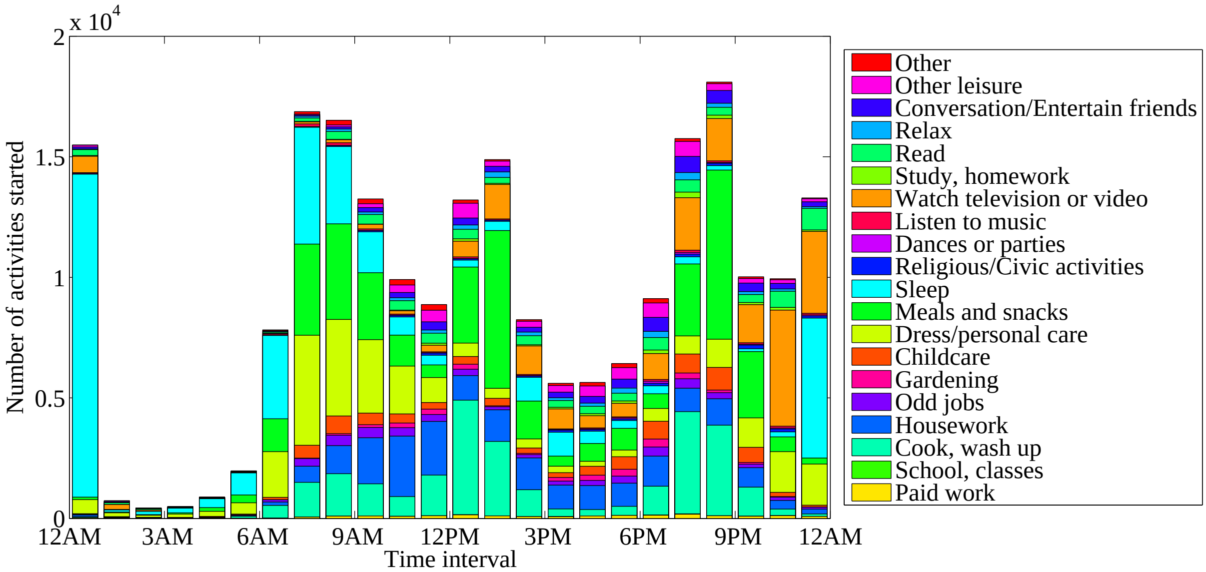

Figure 2: (color on-line) Stacked histogram of the total counts of activities that where started in the corresponding time interval shown on the x-axis.

strongly dependent on the time of the day. However, because some activities occur very rarely in the TUS during a certain period of time, there might not be enough data to calibrate a model meaningfully with a high time resolution. We have thus derived the conditional probability to start an activity j whilst being at home $p_{s,j}(t)$ at an hourly resolution from the according frequency distributions from the data. To get smooth results in the simulations we have defined the starting probability $p_{s,j}(t)$ to be equal to the linear interpolation of these values for the different time steps.

The measured hourly values as well as the time values regarding the 10 min time step of the simulations are set to the center of the corresponding time intervals. However, at the end / the beginning of the day we have kept the derived value of the whole hour interval for the last / first three time steps afterwards and we did not interpolate with the values of the next / previous day, due to inconsistencies in the TUS, which will be described in more detail later.

The PDFs of activity durations were also derived based on the activities started at each hour interval. However, representing the PDF by the measured frequency distribution of the TUS implies the need of many input parameter values for the simulation program. Furthermore, there is very often a bias in the questionnaire as humans are not perfectly precise when recording the times of their activity chains. This implies that the rounded values (30 min time steps) occur more often, which is very unlikely to best reflect reality in general. Therefore, we have fitted the measured duration PDFs (of all occurrences in one hour time intervals) by Weibull distributions using maximum likelihood estimation. In this way we estimate the values and the confidence intervals of the two parameters determining the scale and the shape of the Weibull distribution. To determine whether these theoretical distributions differ in successive time intervals for a given activity j, we have performed a two sample z test checking whether the two values are significantly different. If they are not, the same has been done for all pairs of the set which also includes the parameters of the subsequent time interval. This procedure has been repeated, as long as we did not find at least one pair where the value of at least one of the scale / shape parameter was significantly different. Afterwards, we have again fitted the Weibull distributions based on all the occurrences which fall into these eventually extended time intervals. This procedure prevents the PDFs $f_j(t)$ from a non-assignment in intervals around t where there is no start of the activity j in the TUS data. The drawback of this procedure is, that in case of a rare event where the average duration varies substantially in subsequent time periods but where no events where recorded in some hour intervals of the TUS, this can lead to a uniform PDF in all those time intervals. However, this is an error related to data scarcity, not to a mis-specification of the methodology.

When evaluating the specifics of the sleeping activity there is one particularity in the French TUS: More than 98 % of all the events when this activity has begun in the time interval between 11 pm and midnight fall on the last 10 min (*cf.* Fig. 1), which is clearly an artifact of the survey method. Either it could be due to an imprecision or misunderstanding when the questionnaires were filled out or to the uncommon character of the day such a questionnaire has to be filled out. This information was of use to deduce a realistic way of modeling sleeping, most time-consuming residential activity. It is worth noting that other TUS datasets largely solve this issue of correctly identifying when sleeping activities started, by covering the period

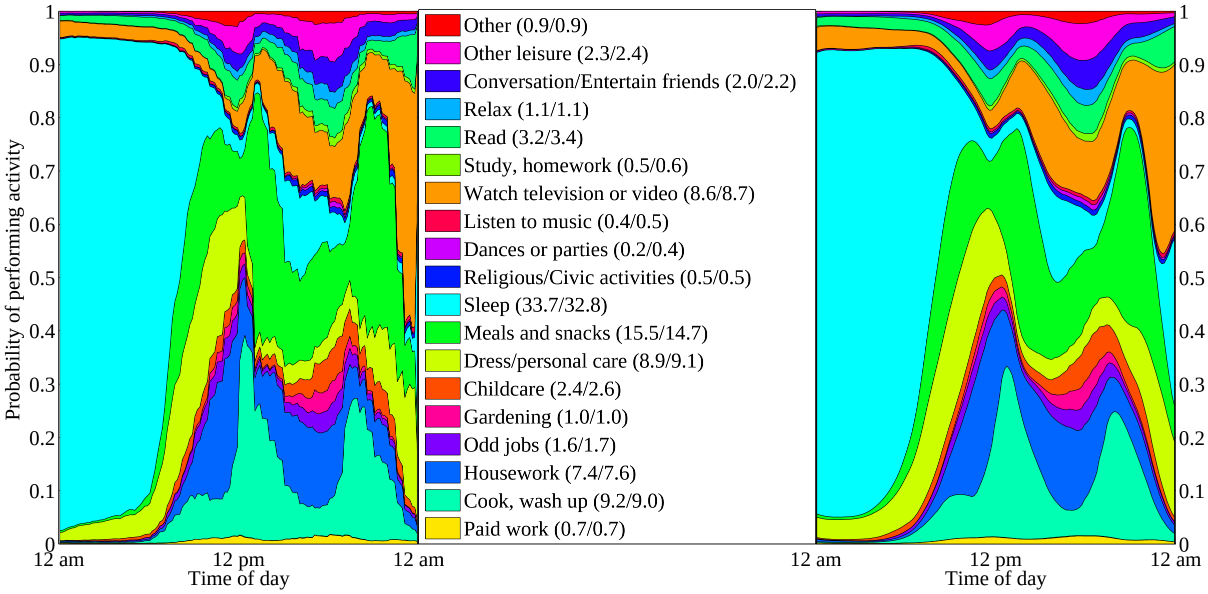

Figure 3: (color on-line) Activity profiles whilst being at home. On the y-axis the cumulative frequency distribution is shown. Left: Time use survey. Right: Simulated. The two values in parentheses show the overall percentage (rounded to one decimal place) that the corresponding activity has been performed throughout the whole day (in the TUS / in the simulation).

from 4 am until 4 am. The problem when one wants to fit a Weibull distribution is that most of the sleeping events at night are censored (because they start before midnight), thus yielding a very poor fit. Thus, we have considered the sleeping events after midnight as not being censored yielding a realistic mean of over 7 hours. Apart from that we have checked for the non-zero percentage of sleeping events before midnight being censored in all hourly intervals, yielding 98 %, 40 %, 25 % and 7 % for the last, the second, the third and the fourth last hour interval, respectively. In the simulation, this leads to the particularity that as soon as the activity sleeping starts we choose a long sleep duration from the last mentioned distribution with a probability being equal to the above-mentioned ratio of censored events in the corresponding interval.

When one wants to predict activity chains of individuals, the dependence of people's behavior on, *e.g.*, the individuals' characteristics or the weekday is of great interest. However, the calibration of a model of residential activity chains for sub-populations is problematic due to the scarcity of events as the sample size decreases. Regarding the fitting of the empirical frequency distributions of durations with Weibull PDFs, this can lead to a substantial decrease of the quality of the predictions. Therefore, we apply the following hypothesis: we derive the Weibull fits of the activity durations of the sub-populations in the same manner as explained above. However, as soon as both of the fitted Weibull parameters are not significantly different from those of the entire sample population (according to the two-sample z-test; see above), we take the two values of the latter. In this way we prevent the simulations to be based on a set of events which is less representative of human behavior in general than the set of the whole sample, taking into account that the predictions are based on a sample which also includes individuals who are not in the corresponding sub-population.

RESULTS

We present a comparison of the activity profiles of the simulation (Figure 3, right) and the data that has been measured in the TUS (Figure 3, left). The simulation results have been generated by taking the average values of 100 simulation runs. These profiles show the shares of the different activities that are performed when the individuals are at home. The measured profiles of many activities show the peaks at the hours and the half-hours due to the rounding of the respondents which was mentioned in the previous section. Moreover, the previously mentioned strong increase in the likelihood of sleeping is visible at 11.50 pm. In the parentheses of the legend we show the mean percentages for which the corresponding activity occurred throughout the whole day, rounded to one decimal place. Here, the largest discrepancy between measurement and simulation is present for the activity "dances or parties" which is overestimated by 83 %.

The differences of the shares of different activities of the simulation results $p_{j,\mathrm{sim}}$ and the TUS $p_{j,\mathrm{obs}}$ on an hourly aggregated basis (in this way the rounding artifacts in the time specifications are leveled out) are shown in Figure 4. The largest difference of 12.4 % occurs for sleeping in the last time interval. However, this is due to the fact that the probability to start an activity has been derived on an hourly basis, whereas in the TUS strong increases during the last 10 min of the day (cf. Figure 3). This increase has a strong weight

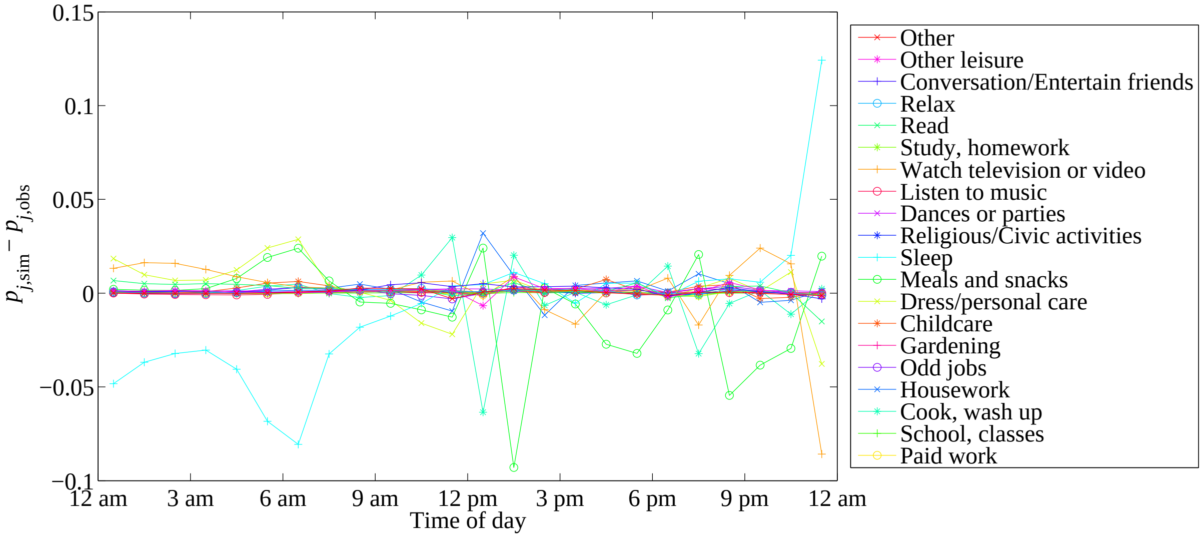

Figure 4: (color on-line) Differences of the predicted ($p_{j,\mathrm{sim}}$) and observed ($p_{j,\mathrm{obs}}$) shares of different activities on an hourly aggregated basis. The lines are drawn to guide the eyes.

when the starting probability is derived and thus the model overestimates the percentage of sleeping people in this interval. Furthermore, the number of people who are sleeping during the night is underestimated by the simulations. This is due to the fact that the simulation duration is set to 24 h, implying that the individuals who began their sleep before midnight are not accounted for in the simulation (an easily resolved artifact of this particular simulation). There are also noticeable underestimations of the share of people having meals and snacks between 1 and 2 pm of 9.3 % and up to 5.5 % in the evening hours. We still have to study in detail for which reasons these discrepancies occur. The activity ”watching TV” is underestimated by the simulations (-8.6 %) during the last hour interval of the day. This underestimation is caused by the overestimation of sleeping in this interval, which suppresses the likelihood of performing other activities, as it can also be observed in the underestimation of the activities ”Dress/Personal care“ or “Read books“ within this interval. Furthermore, this is also observable in the first time intervals of the night, where the lack of the individuals who started sleeping before midnight (because of the simulation duration which was set to 24 h and starting at midnight) amplifies the occurrence of other activities.

The ratio of the simulated and the measured percentages of the different activities is shown in Figure 5. For better readability, we have set the maximal value of the y-axis to 3 and we have only put activities which have a mean share of more than 2 % during the day. The maximal value is reached for the activity ”dances and parties“ which takes a value of about 22 at 12.20 pm (not shown, due to the small mean share of this activity). This is due to the data scarcity of events that the time-dependent PDF is based on leading to a uniform distribution during many hours according to the calibration algorithm for the PDFs (taking into account too many subsequent time intervals) that was depicted in the previous section. The problem of data scarcity is apparent by the fact that out of the activities which have a mean share in residences of more than 1 %, only ”Sleeping“ exceeds this barrier in the last hour of the day, due to the reasons that were depicted in the previous paragraph.

The profile of the simulation is in good agreement with the measured data. The advantage of the time-dependent PDF can be observed, *e.g.*, in the sleeping proportion during night time, where the probability of a short duration would be disproportionally high if one fits the data with a time-independent Weibull distribution, meaning to take also into account all the short duration naps that usually take place during the day.

Individual profiles

We present an evaluation of the performance of prediction of different versions of algorithms in the tables 1 and 2. These algorithms have been tested for different disaggregations of the sample population. The criterion according to which the disaggregation was chosen is shown in the first column. The different criteria in these lines specify whether, the respondent was retired, living in an urban area, belonging to a specific income class, or having access to zero, one or more motorized vehicles.

These sub-populations were then simulated as it is described above. The results of the whole sample population were then evaluated. These values are shown for three different types, corresponding to three different ways how we have calibrated the PDFs of the algorithm: (i) when the Weibull parameter values of the sub-populations are not tested for significant difference to the ones of the whole sample, (ii) the case where the PDF is derived independently of the starting time, and (iii) when the Weibull parameter values are

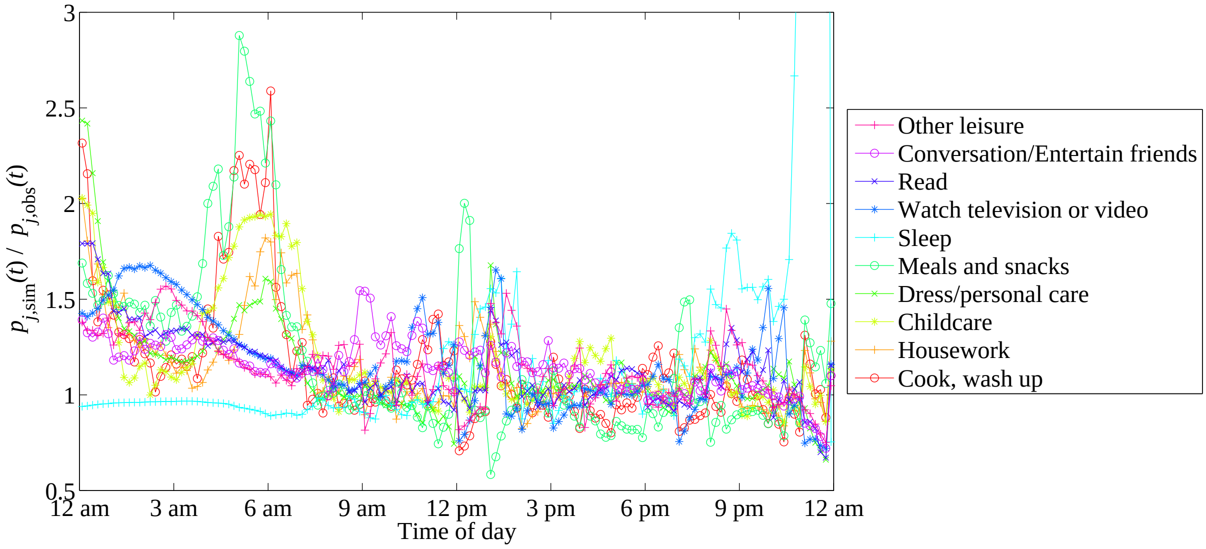

Figure 5: (color on-line) Ratio of the shares of different activities of the simulation results and the TUS $p_{j,\mathrm{sim}(t)}/p_{j,\mathrm{obs}}(t)$. For clarity reasons, the upper value of the y-axis is bounded to 3 and only activities with a mean share of more than 2 % are shown. The lines are drawn to guide the eyes.

derived as described in the previous section (having a time-dependent PDF which is afterwards tested for significant difference to the corresponding PDF of the whole sample population and if necessary replaced).

Table 1: Mean correctly predicted share of the activity profile of different versions of the algorithm (in %).

disagg. criterion	(i) no stat. sign. test	(ii) t-indep. PDF	(iii) t-dep. PDF; stat. sign. test
retired	85.5	23.8	85.4
urban	85.6	23.8	85.5
incorig	84.9	23.8	78.5
vehicle	85.5	23.8	78.6

In Table 1 the share of the activity profiles which is correctly predicted is shown for the different algorithms. The mean share of correctly predicted activity profiles can be calculated from the curves which are shown in Figure 4. The mean value of all curves above zero corresponds to the mean over-estimation per activity share by the simulation, which is equal in magnitude to the underestimation per activity share by the simulation. In type (iii) the accuracy of prediction is up to 8 % worse than that of type (i). However, in these tests we have calibrated the simulations with the same data set which is used for the validation. Presumably, the accuracy of (iii) would be better in case of a cross-validation with a different data set. Furthermore, data scarcity impinges on the relative accuracy of (iii) more than the one of (i). The fact that the differences between (i) and (iii) are small is an indicator that the calibration with a larger data set would be of great increase the differences of individuals' behavior. Furthermore, it is evident that the time-dependence of the PDFs is crucial for accurate predictions. The fact that the values do not differ significantly amongst the different chosen disaggregations is a sign that the retained criteria, are not associated with a strong difference in residential behavior.

In Table 2 we show the overall share of the time steps where the activity is correctly predicted for the individual activity chains. The best performing is again the one where the Weibull distribution are not tested for statistical significance to the ones of the entire sample population. There, the best result is obtained for the disaggregation according to different income classes. This is probably due to the fact that in this case there is the largest number of different categories and thus, the PDFs could be adapted more closely to the behavior of different people. The simulations of type (iii) with a time-independent PDF of durations are again those with the worst performance. However, on an individual level, decisions on which activity is currently performed are influenced on much more things than the time, *e.g.*, other individuals, future plannings, *etc.* Therefore, the improvement of the quality of the predictions due to a description of the PDFs as a function of time in comparison to the other algorithms is less considerable.

Table 2: Mean share of correctly predicted activities of all activity chains of different versions of the algorithm (in %).

disagg. criterion	(i) no stat. sign. test	(ii) t-indep. PDF	(iii) t-dep. PDF; stat. sign. test
retired	53.14 ± 0.13	52.35 ± 0.28	53.14 ± 0.13
urban	53.07 ± 0.13	52.08 ± 0.28	52.99 ± 0.13
incorig	53.32 ± 0.15	52.18 ± 0.28	53.00 ± 0.13
vehicle	53.13 ± 0.13	52.15 ± 0.28	52.92 ± 0.13

DISCUSSION

Some behavioral patterns are not captured by the model, e.g. the coherence in the succession of activities, which could be taken into account by describing the probabilities to start an activity as transition probabilities from one activity to another. One example would be the increased probability to start eating when the cooking is finished. In this case the stochastic model would be represented by a Markov chain based on transition probabilities $p_{ij}(t)$ $(i, j = 1, \ldots, N_{\mathrm{act}})$. The order of the Markov chain should be also higher than one in some cases, *e.g.*, for the sequence "Personal care" $\rightarrow$ "Sleeping" $\rightarrow$ "Personal care" during the night time. Unfortunately, reliable estimates for such models would require an extremely large data set. However, the transition probabilities influence the activity chains rather on a disaggregate level and less on the aggregate, where the appearance of consecutive activity shares is well captured by the time-dependent starting probabilities.

Nevertheless, the results of the simulations may be considered as satisfying. The general trend of activity profiles of the aggregate population is well reproduced. We have made considerable progress towards a better matching, after defining the PDFs of activity durations as being time-dependent. However, the biggest difficulty in modeling this behavior is that the questionnaire data does not perfectly represent reality, as is evident at the beginning and the end of the day, when the shares of different activities in TUS profile are often very different (cf. Figure 3, right/left) although they should be equal in reality by definition (as soon as all different weekdays are represented with the same share in the TUS, as is approximately the case). This is the reason why we have also set the simulation duration to 24 h, in order to make the results better comparable to the TUS. When one wants to use this model, e.g. in building simulation programs, it will produce more realistic results when the simulation duration is extended. Clearly we would like to avoid these kinds of artifacts, making it necessary to estimate which particular behavior is real and which one is due to systematic errors of the experiment. Nevertheless, the simulations based on the time-use surveys are a powerful tool to derive detailed statistical information about activities that occur at a given time of the day in residential buildings.

Moreover, the methodology which is shown here to derive the specific behavior of individuals with specific characteristics seems to be a good compromise between parsimony and statistical significant explanatory power. If the data set for the calibration of the model can be expanded, this will extend the applicability of the model as a tool to predict individuals' behavior in residential buildings.

Integration into Building Simulations

The model that is presented in this paper can be integrated into any dynamic building simulation tool. We will describe here the steps that are to be executed, to derive the activity chains whilst an occupant is at home. We assume that the information of the residential presence/absence chains is provided by a preprocess for the occupants in the simulation.

1. The occupancy status (absence/presence) at time t_i as well as the time of the next change t_{i+1} is retrieved.
2. - **case 1:**
     The occupant is absent. The activity until the end of the occupancy state duration is set to null. The time is incremented to the next occupancy state $t_i \mapsto t_{i+1}$.
   - **case 2:**
     The occupant is present. An activity j is chosen based on the corresponding starting probability at that time $p_{\mathrm{s},j}(t)$. A time increment Δt_j is chosen according to the PDF at that time $f_j(t)$ (limited by $t_{i+1} - t_i$ if necessary, corresponding to a censoring of the activity by a departure of the occupant). The time is incremented to $t_i + \Delta t_j$.
3. As long as the time has not reached the maximum simulation time, the simulation returns to step 1.

According to the level of detail which is of interest and the extent of TUS data which is available, one can calibrate the PDFs according to aggregate population means. The more realistically one wants to describe the specific behavior of certain building occupants depending on their personal characteristics, and the more extended the calibration data set is, the more reasonable it is to calibrate the PDFs according to the corresponding sub-populations of a TUS sample. However, apart from the presence modeling which is required by this methodology as a pre-process, another pre-process is then needed which assigns individual characteristics to building occupants on a statistically coherent basis.

CONCLUSION

The purpose of this work is the development of a time-dependent model to predict residential occupants' activities. We used time-use survey data to calibrate the model. In this our aim is to have a structure which is sophisticated enough to capture the peculiarities of individuals' behavior. On the other hand, the model was designed to be as parsimonious as possible, in order to make it a promising candidate for building simulation. Furthermore, attention was also given to prevent the model from being influenced by non-significant statistical fluctuations. This is of major importance when the properties of the behavior of sub-populations is investigated, as the sample size is decreasing and many activities are rarely performed during the day.

The predicted activities can be directly used as inputs for the prediction of quantities of relevance for building simulation and thermal comfort prediction. This includes metabolic heat gains, vapor production, pollutant emissions, comfort temperature and illuminance, among others. We are planning to use this model as a pre-process for a model predicting the use of electrical appliances, as the probabilities of the latter is clearly strongly dependent on the activities that are performed (Robinson et al., 2011). The interest in this is the possibility of predicting the time-dependent distribution of the electric power demands of entire districts. As the socio-demographic characteristics of districts are very likely to vary strongly, the whole modeling methodology could make it possible to adapt the electricity supply infrastructure of small scale power plants more adequately. However, more progress is still needed to achieve these goals. Regarding the data scarcity, we are also planning to test the probabilities to start an activity of subpopulations for statistical significant difference to the entire population mean. In this our quest would be helped if it is proven to be viable to combine complementary TUS datasets, either from other time periods or from other countries with comparable lifestyles.

ACKNOWLEDGEMENT

We gratefully acknowledge the financial support received for this work from the Swiss National Science Foundation.

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