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A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison

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ABSTRACT

User behaviour plays a key role in the energy demand of residential buildings, and its importance will only increase when moving towards nearly Zero-Energy homes. However, little detailed information is available on how users interact with their homes. Due to the lack of information, user behaviour is often included in building performance simulations through one standard user pattern. To obtain more accurate energy demand simulations, user patterns are needed that capture the wide variations in behaviour without making simulations overly complicated. To this end, we developed a probabilistic model which generates realistic occupancy sequences that include three possible states: (1) at home and awake, (2) sleeping or (3) absent. This paper reports on the methodology used to construct this occupancy model based on the 2005 Belgian time-use survey. Using hierarchical clustering, we were able to identify seven typical occupancy patterns. The modelling of individual occupancy sequences based on this method enables to include highly differentiated yet realistic behaviour that is relevant to building simulations and can be used for individualised feedback based on peer comparison. The model's calibration data is available for download [1].

1. Introduction

To reduce energy use in buildings, we need accurate modelling methods for energy demand that take into account both building characteristics and user behaviour. The current energy performance calculation method ISO 13790 [2] focuses primarily on building characteristics. The result of this method is a theoretical energy consumption for a standard user. However, once the dwelling is occupied the actual energy consumption may differ greatly from the predicted theoretical consumption. Wide variation of the energy consumption of dwellings with similar building characteristics indicate that this difference is caused by the diversity of user behaviour [3–5].

User behaviour influences the energy demand of a building both passively and actively. On the one hand, the presence of people in a building will lead to passive effects such as the change of heating or cooling demand, depending on the hygrothermal conditions in the building. On the other hand, active effects include the operation of control devices (e.g. window opening, lighting control, thermostat setting), the use of electrical appliances (e.g. computers, washing machines) or the consumption of hot water (e.g. shower, cleaning) [6]. Both effects are closely related: the presence of people is required for the majority of the control actions and the use of appliances or hot water. Understanding both the passive and the active effects of user behaviour is needed when modelling nearly Zero-Energy homes because these buildings are primarily heated by the sun, metabolic heat of the users and heat emitted from electrical home appliances. However, these effects are difficult to predict because they are not based purely rational choices, but rather on user habits and preferences.

For the modelling of user behaviour we may distinguish between deterministic and probabilistic approaches [7–9]. The deterministic approach typically assumes a direct causal link between one or multiple drivers and an action. Control actions are often modelled with fixed action typologies. For example, a window will always be opened if the indoor temperature threshold is exceeded. Internal gains are typically calculated based on a fixed occupancy schedule that describes the number of people present at

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a given time. This approach is the simplest way of integrating user behaviour, but it has two important limitations. On the one hand, fixed schedules lead to fully repeatable and predictable behaviour. Consequently, the variations of behaviour are lost. On the other hand, it is not realistic to assume that users make perfectly rational choices, for example towards the control of the indoor environment. In many cases, personal preferences or habits play an important role in the decision making [10].

Probabilistic models typically use statistical data to predict the likelihood (or probability) that certain action occurs. Similar to deterministic models, these models take into account correlations between observed behaviour and indoor climate related variables such as the indoor temperature. However, whereas deterministic models include direct causal links between drivers and actions, probabilistic models predict the probability that an action occurs. As a result, these models capture more variations in behaviour than deterministic models and they include behaviour that cannot be explained by external, objective variables. Many probabilistic models focus on one specific activity, for example the opening of windows [11–13] or lighting control [14,15]. Other models predict the presence of users based on individual's characteristics [16–18].

We developed a probabilistic model that generates individual occupancy sequences that include three possible states: (1) at home and awake, (2) sleeping or (3) absent. The model was calibrated with a Belgian time-use survey, that contains detailed information on the whereabouts and activities of 6400 respondents from 3455 households during one weekday and one weekend day. For each of the respondents we analysed the occupancy data from their survey entries. The model combines strong elements from existing occupancy models [16,18,19], while extending it with a tool to distinguish between a set of seven occupancy patterns that show significantly different behaviour. To detect these occupancy patterns, we used hierarchical agglomerative clustering algorithms. By calibrating the probabilistic model with these occupancy patterns the variability of the resulting occupancy sequences can be limited. This empowers the user of the methodology to test different scenarios that are based on realistic behaviour without having the drawbacks of a deterministic model.

This paper presents the methodology used to develop a probabilistic occupancy model. First, it discusses the time-use data that were used to calibrate the model. Second, it reports on existing probabilistic occupancy models as well as our own model. Third, it introduces the concepts of hierarchical clustering that were used to partition the data into patterns. Finally, the paper presents the occupancy patterns that result from the model and the strategy used to verify the model.

2. Material and methods

A wide range of parameters may influence user behaviour that ultimately determines the energy consumption. In literature, building related parameters such as the dwelling type, surface area of the dwelling and appliance holdings are frequently proposed to have strong explanatory power [18–22]. Household related variables that are often put forward are income, number of household members, household composition and age [16,18–22]. McLoughlin [23] ranked the explanatory variables based on the number of citations in literature and discovered that dwelling type, household income, appliance holdings and the number of occupants appear most frequently. However, he also suggests that this could partially be explained by the ease with which these explanatory variables can be collected. Furthermore, he notes that many of these variables are multi-collinear. For example, the age of the head of the home (HoH) appears to have an inverse effect on energy consumption. This may be due to the fact that middle-aged HoHs generally have more children living in the home, resulting in a higher energy consumption. Retired HoHs are likely to spend more time at home, explaining an even higher energy consumption. In other words, as stated by Yao and Steemers [24], many of the explanatory variables are directly or indirectly related to the number of people and the amount of time spent at home. This finding confirms the need for models that predict the occupancy of users.

2.1. Time-use survey

We derived realistic occupancy data from the combined Belgian Time-Use Survey (TUS) and Household Budget Survey (HBS) that were conducted in 2005 [25]. The combined surveys TUS and HBS include 6400 respondents from 3455 households. In the TUS all household members over twelve years old were asked to complete the diary for the same two days; one weekday and one weekend day. In these diaries the respondents described their activities and movements from 4:00 AM until 3:50 AM the next day. The Belgian diaries use a continuous registration system with fixed time slots of 10 min. The continuous registration system forces respondents to provide at least one activity for each time slot, preventing gaps in the time-use pattern. For each of these time slots, the respondent could enter up to two activities, a primary activity and a secondary activity, so that multitasking could be captured. The activities are described by the respondent in their own words, and afterwards recoded into 272 activity codes. Furthermore, for each activity the respondents mentioned if they were at home and if they were accompanied by someone. In addition to the TUS, a HBS was conducted that comprises both individual and household questionnaires. The former include information about the age, position within the household, education, income and employment, whilst the latter contain details about the family home, the ownership of (electrical) appliances and vehicles, as well as their expenditures on goods and services.

The extensive TUS and HBS datasets allow us to analyse general occupancy patterns and to study relationships between behaviour and socio-economic characteristics. To this end, we generated three-state occupancy patterns for all 6400 respondents by extracting the activity and location data from their diaries.

Average occupancy data for the entire population can easily be deducted from the TUS database, but more specific occupancy patterns are needed to understand the diversity of user behaviour. The average occupancy pattern for the Belgian TUS dataset (Fig. 1) shows three coloured zones that represent the three occupancy

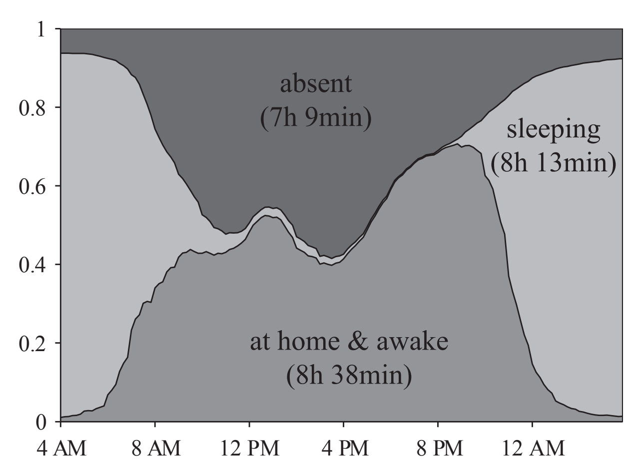

Fig. 1. The average occupancy profile indicates the overall probability that individuals are at home and awake, sleeping or absent.