Agent-based behavioural models for residential buildings in dynamic building simulation: state-of-the-art and integrated model assembly

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RESUME. Les conditions limites internes d'une simulation de la performance d'un bâtiment sont souvent simplifiées en imposant des profils déterministes et indépendants du bâtiment, ce qui conduit à une sous-estimation de l'incertitude sur la performance énergétique. Cet article fournit un bref aperçu de la littérature disponible sur les modèles de comportement multi-agents pour les bâtiments résidentiels. Ces modèles sont évalués à partir d'une description générale du comportement des occupants, qui peut être qualifié de stochastique, adaptatif et individuel. Cet aperçu met en évidence le manque de maturité de ce domaine de recherche. Néanmoins, un modèle intégré du comportement est proposé, prenant en compte l'occupation, l'utilisation des équipements électriques, la température de consigne, l'éclairage artificiel, l'utilisation des protections solaires, les ouvertures des fenêtres et l'utilisation de l'eau chaude sanitaire.

MOTS-CLÉS : bâtiments résidentiels, modèle du comportement, consommation énergétique.

ABSTRACT. The internal boundary conditions for building performance simulation are often simplified to deterministic building independent schedules. As a result, simulation studies underestimate the degree of uncertainty on the energy performance of actual buildings. This article presents a concise overview of the literature available on empirical agent-based behavioural models for residential buildings. Based on a general description of occupant behaviour in buildings, which can be described as stochastic, adaptive and individual, the available models are evaluated. From this review, it is clear that this research field is not quite mature yet. Even so, an integrated behavioural model, aimed at generating realistic internal boundary conditions for building energy performance simulation, is proposed. The model comprises presence, electrical appliances use, temperature set points, lighting use, shading use, window-opening and domestic hot water use.

KEYWORDS : residential buildings, behavioural model, energy use.

1. INTRODUCTION

During the past decades, several dynamic Building Energy Simulation (BES) tools have been developed, providing virtual test environments to study energy efficient measures on both the building level and the systems level during the conception stage, for the construction of new buildings as well as retrofitting of existing buildings. However, when simulating any system, the definition of the boundary conditions at which it operates is as decisive for the simulation results as the model of the physics of the system itself. This is especially true for buildings, where the boundary conditions vary largely. Building simulation boundary conditions can be subdivided in external – all geographical influences – and internal conditions – related to occupancy and building use. This paper focuses on the latter. The internal boundary conditions are often simplified to deterministic building independent schedules, based on measured or estimated averages. As a result, simulation studies underestimate the degree of uncertainty on the energy performance of actual buildings (e.g. (Schnieders and Hermelink 2006)) and overestimate the impact of retrofitting measures (e.g. (Hong 2006)). The former is particularly the case in very low-energy designs, where the relative influence of the building use rises, as solar heat gains and internal heat gains are more effectively conserved and thus the energy performance is more sensitive to the presence and activities of the occupants (Wilke 2013). Acknowledging the need for a more realistic and higher resolution definition of internal boundary conditions, a remarkable rise in empirical studies trying to quantify occupancy and occupant behaviour has been seen in the recent past.

This paper attempts to give a global literature overview of those empirical studies, from the point of view of usability in coupling to BES tools for energy performance calculations. The general aspects of occupant behaviour in residential buildings are discussed first (section 2) to create a framework for evaluation. The state-of-the-art of all relevant subfields of behavioural research is discussed in the subsequent section (section 3). The best available models in each subfield are selected and assembled in an integrated behavioural model structure (section 4). Such an integrated model, combining the results of field studies in all relevant behavioural subfields in a coherent manner, has not yet been proposed before, to our knowledge, though modelling frameworks have been presented for residential user behaviour, e.g. by Kashif et al. (2013).

The focus of this research lies solely on residential buildings, aiming specifically on low-energy designs. Only agent-based behavioural models are included in this study – which represents the lion share of the publications. These are models in which the actions and driving forces for these actions of individual occupants are explicitly modelled. The reasons for this methodological limitation are (i) the aim for a behavioural model usable on different scales, ranging from a single building to the national building stock, (ii) the aim for a model that is extrapolatable to dwellings beyond the studied building set, to be able to study the effect of the introduction of new technologies, changing climatic conditions etc., and (iii) to allow all aspects of occupant behaviour to be integrated consistently in a comprehensive model (see section 4), to take possible causal links between different aspects into account. The down-side of agent-based models is the large amount of empirical data necessary to construct, calibrate and validate them.

2. GENERAL ASPECTS OF OCCUPANT BEHAVIOUR

2.1. NATURE OF OCCUPANT BEHAVIOUR

An important finding in the context of occupant behaviour was that "the use of controls is clearly influenced by physical conditions, but their use tends to be governed by a stochastic rather than a precise relationship" (Nicol 2001). Occupant behaviour is thus *adaptive* and *stochastic*, to which it could be added that it is *individual*, in that respect that behaviour is "governed by different but distinct habits" (Andersen et al. 2011). This last aspect of individual variability depends on many characteristics, such as socio-demographic, physiological or cultural conditions. The behavioural models discussed in this paper will be evaluated on the proper incorporation of each of these 3 essential features, in the form relevant for each subfield (see 2.2).

The modelling methodology typically applied for agent-based behavioural models is the Markov chain. A first-order Markov process is a discrete random process where the state of the next time step only depends on the state of the current time step. Thus, at each time step, a randomly drawn number is compared to a probability of transition, which depends on the physical environment – thus introducing the stochastic and adaptive aspect. The process is called inhomogeneous when the probability functions are time-dependent. The individual aspect can be integrated by defining several probability functions for different occupant types. Since these models only depend on the previous time step, the duration of the modelled behaviour cannot be captured coherently (Wilke 2013). This drawback can be resolved by applying a hybrid higher-order Markov process, in which the durations are explicitly modelled (often based on survival analysis) and the transition between activities is modelled in the traditional manner.

2.2. SUBFIELDS OF BEHAVIOURAL RESEARCH

The actions of occupants, relevant to building engineering, can be divided into 3 categories (Fabi et al. 2011): actions to adapt the environment, actions that produce internal heat gains and actions to adapt the occupant to the environment (e.g. drinking or changing the clothing level). Given the focus on energy performance simulation, the latter category can be discarded here – though its influence on thermal comfort calculations is of course key. It represents a set of variables that are often unknown and will therefore create an added variability in the adaptive action probabilities. The aim of the integrated behavioural model is to serve as internal boundary input for dynamic simulation concerning all aspects of residential energy use, namely electrical appliances, lighting, domestic hot water and heating and cooling energy. These inputs are produced in the form of time series.

Based on the foregoing remarks, the subfields of behavioural research to be integrated in the model are identified as: presence, use of electrical appliances, system temperature setting, lighting, window- and door-opening, shading device use and domestic hot water use.

3. STATE-OF-THE-ART OF BEHAVIOURAL SUBMODELS

3.1. PRESENCE/ACTIVITY

The presence of people induces metabolic sensible and latent heat gains as a direct effect on the building's energy balance. More importantly, given the premise of agent-based modelling, predicting the presence is an essential preprocessing step for the other aspects of occupant behaviour, as discussed in the subsequent subsections. As presence and activity modelling are often treated simultaneously in the literature, they are discussed together in this subsection.

	Number of activities	Explicit duration modelling	Socio-demographic variability	Long absences	Correlated activities within household
(Tanimoto et al. 2008b)	32	Yes	Yes	No	No
(Richardson et al. 2010)	7	No	No	No	Yes
(Widén and Wäckelgård 2010)	9	No	No	No	No
(Wilke 2013)	20	Yes	Yes	No	No

Table 1 : Overview of presence/activity models' distinctive properties.

Several agent-based models incorporating the stochastic aspect have been proposed during recent years. At the basis of all agent-based residential presence models lie Time Use Surveys

(TUS),questionnaire studies in which people meticulously record their activities throughout a 24h cycle.

Table 1 shows an overview of the existing stochastic activity models. None of them combines the essential features of individual variability and activity correlation within a single household. Furthermore, since at the basis of all models lie TUSs, typically executed for a single week day and weekend day, none of the models take into account irregularities such as long absences or gatherings.

3.2. APPLIANCE USE

Accurately modelling the electrical power demand of the residential sector has long been of interest to the field of electrical engineering research. This has led to a multitude of empirical models, though often aimed at generating end-use curves without explicit links to the occupants. Given the agent-based approach adopted here, only models deriving the electrical energy use from activity modelling are considered. Table 2 summarizes the most important features of these models.

	Sharing of appliances within household	Probabilistic power use per appliance	Appliance ownership probability sampling	Socio-demographic variability in appliance ownership	Inclusion of activity independent appliances
(Tanimoto et al. 2008b)	Yes	No	Yes	No	Yes
(Richardson et al. 2010)	Yes	No	Yes	No	Yes
(Widén and Wäckelgård 2010)	Yes	No	No	No	Yes
(Wilke 2013)	Yes	Yes	Yes	Yes	No

Table 2 : Overview of electrical appliances models' distinctive properties

Again, none of the models offer an integral solution combining all essential features, though the model of Wilke (2013) can relatively easily be complemented with activity independent energy use, e.g. by refrigerators. Tracking each and every appliance found in a household is, at least for the time being, impossible due to a lack of longitudinal empirical data linking activities and appliances use. Therefore, each of the considered models contains a 'rest electricity use' term that can be used to calibrate the models to comply with aggregated data on dwelling-averaged end-use.

3.3. TEMPERATURE SET POINTS

In this subfield, the user supplied thermostat set point is of interest, as this is evidently a decisive influence on the internal temperature and thus the heating energy use. The findings of Andersen et al. (2011), that thermostat settings are very different between dwellings but consistent for each household, suggest it is not necessary to update the set point at each time step, but that is sufficient to update its value seasonally or even sample a single household set point at the start of the simulation.

In principle, sampling this set point should be done from a distribution dependent on many known influence factors, such as socio-demographics. To our knowledge however, quantified correlations of this nature are not yet published. The best available sources are based on an extensive empirical study in English homes reporting a mean heating set point of 21.1°C with standard deviation 2.5°C (Shipworth et al. 2010), later refined to a mean of 20.6°C (Huebner et al. 2013). These results are comparable to the reported desired temperatures in a set of passive houses, ranging from 17°C to 25°C with a mean of 21.5°C (Schnieders and Hermelink 2006).

In summary, a thermostat set point for each household can thus be sampled from an empirical Gaussian distribution, though without linking it to the household characteristics. This implies a loss of information leading inevitably to an overestimation of the variability, though its magnitude is unknown. Furthermore, a dependency of the set temperature on the outdoor climate is not incorporated, which means the adaptive aspect is neglected in this subfield.

3.4. LIGHTING USE

Electric lighting forms an important aspect of domestic electric energy use and at the same accounts for a substantial share in the diurnal and annual variation (Widén et al. 2009). The latter is due to the fact that lighting use, in contrast to appliances use, includes a strong adaptive aspect, due to its dependency of the available daylight.

Only 2 models can be found that incorporate this adaptive aspect in an agent-based approach – i.e. an approach in which the lighting use depends on the active occupancy. The model of Widén et al. (2009) includes a proportional dependency of the lighting power use on the outdoor illuminance level, while that of Richardson et al. (2009) uses an outdoor irradiance threshold to produce a binary input for lighting use. It should be noted that both approaches represent an indirect accounting of the adaptive aspect, as it is in the end the indoor daylight illuminance level that will drive occupants to act. The model of Richardson et al. (2009) is somewhat more detailed, as it models each individual light bulb, the occurrence of which is sampled at the start of the simulation period from an empirical data set to include the variability between households – though the sampling is random and thus does not explain the variability.

3.5. SHADING USE

There are currently no agent-based models of residential blind use available. More in general, empirical studies producing quantified results on the influencing factors are very rare. Andersen et al. (2009) confirmed the adaptive and individual aspect of shading use by finding statistically significant of solar radiation and socio-demographic variables on self-reported shading use.

Due to this existing gap in research, the use of shading devices by occupants can only be modelled in a simplified manner. The main principles can be derived from the findings of studies performed in office buildings, which are much more numerous, though no consensus model exists yet (Van Den Wymelenberg 2012): shading use is relatively inert (once the shading device is lowered, it stays in that position all day) and depends on direct irradiation on the façade and, evidently, the presence of the inhabitants. Varying the irradiation threshold before action allows the inclusion of individual variability.

3.6. WINDOW-OPENING

Roulet et al. (1991) defined transition probabilities with a 10 minute time step for window opening and closing depending on the outside conditions. The authors deduced Markov Chains for each of the 16 orifices in the façade, both windows and doors, thus effectively treating them as independent. The individual variability was acknowledged by defining an ‘average user’, a ‘closer’ and an ‘opener’. Given the fact that the study was published in 1991, it can be assumed that the measurements were performed in housing units not yet equipped with a mechanical ventilation system. This, unfortunately, renders the results all but unusable for application in low-energy dwellings typically equipped with mechanical ventilation systems, as the type of ventilation system greatly influences window operation by occupants (Erhorn 1986).

The work of Andersen et al. (2013) resolves this last issue, as it proposes separate Markov chain models per ventilation system based on measurements in Danish housing units. The transition probabilities depend on physical variables – thus including the adaptive aspect – and to a limited extent on socio-demographics – partly incorporating the individual variability.

3.7. DOMESTIC HOT WATER USE

In principle, modelling the domestic hot water use through an agent-based approach is methodologically comparable to the modelling of electrical appliances use (3.2), by linking the activity (3.1) to the use of equipment. Ideally, the probability of occurrence of this equipment is modelled dependent on household variability and the use of hot water at each activity is sampled from a probability distribution. However, the only existing agent-based models, that of Tanimoto et al. (2008a) and Widén et al. (2009), provide only deterministic volumes and supply temperatures linked to the relevant activities, such as showering or washing the dishes.

4. INTEGRATED BEHAVIOURAL MODEL AND BES COUPLING

Figure 1 shows a schematic overview of the integrated behavioural model and its coupling to BES tools. The arrows indicate the information flow, of which the dotted arrows in grey are currently non-existent but pertinent links. The integrated behavioural model, implemented in Matlab, thus produces the internal boundary conditions for the building simulation. Note the bidirectional coupling between the windows use model: as this behaviour depends on the occurring conditions inside, a real-time coupling is necessary. The behavioural submodels currently implemented are those of Wilke (2013) for presence, activity and appliances, of Huebner et al. (2013) for temperature set points, of Richardson et al. (2009) for lighting use, of Andersen et al. (2013) for window-opening and of Tanimoto et al. (2008a) for domestic hot water use. Shading use is implemented in the simplified way described above (3.5).

The determination of static parameters in the preprocessing step can be readily integrated in an uncertainty analysis.

5. CONCLUSIONS AND FUTURE OUTLOOK

This article presents a concise overview of the literature available on empirical agent-based behavioural models for residential buildings. Based on a general description of occupant behaviour in buildings, which can be described as stochastic, adaptive and individual, the available models are evaluated. Even though models properly including the three aforementioned features are not yet available for each behavioral subfield and causal links between subfields are often still lacking, an integrated behavioural model, aimed at generating realistic internal boundary conditions for building energy performance simulation is proposed.

In future work, this behavioural model will be further developed and applied in uncertainty analyses of the performance of residential buildings.

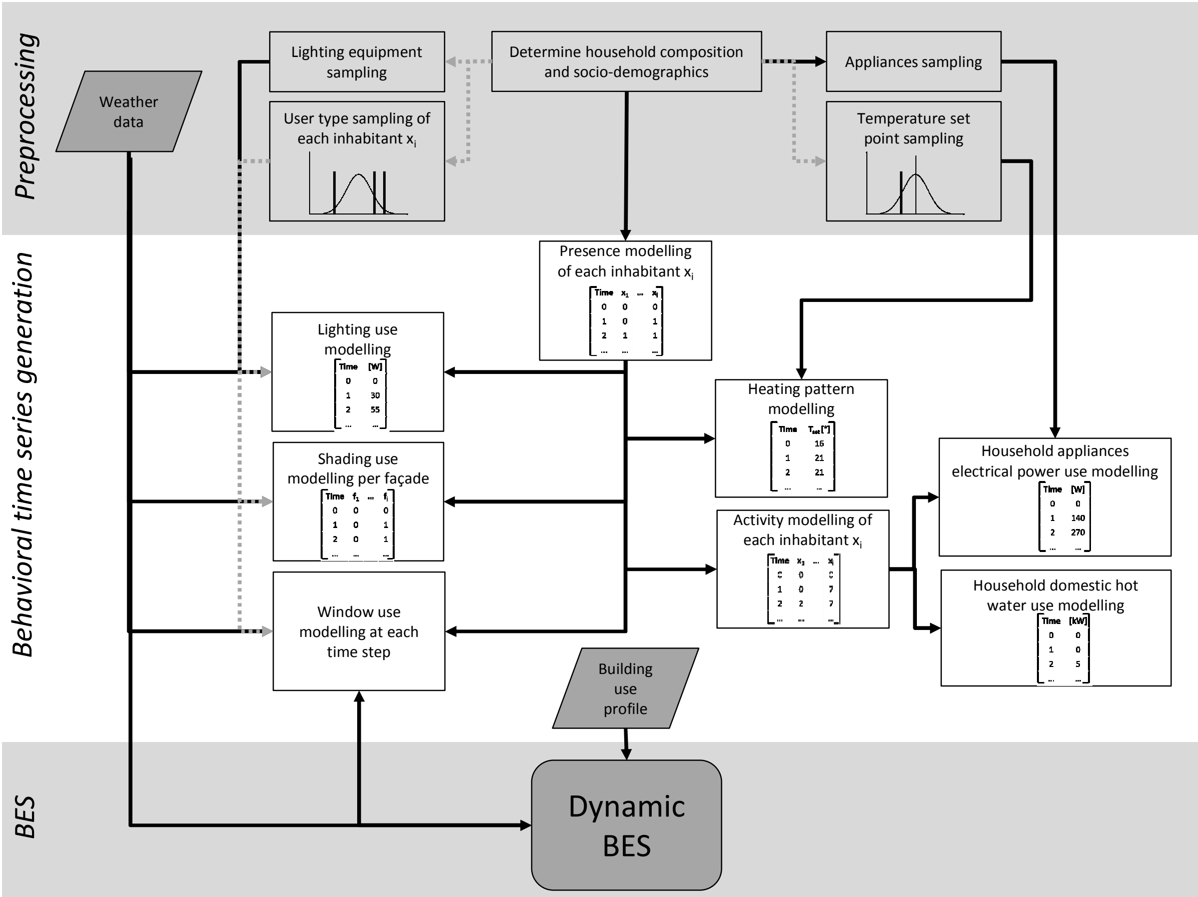

Figure 1: Schematic overview of integrated behavioural model for residential building use

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