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On The Multi Agent Stochastic Simulation Of Occupants In Buildings

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This paper introduces a new general platform for the simulation of occupants' presence and behaviours. Called No-MASS (Nottingham Multi-Agent Stochastic Simulation) this generates a synthetic population of agents, predicts their presence and, in the case of residences also their activities and inferred locations, as well as their use of windows, lights and blinds. Using the Functional Mockup Interface No-MASS is coupled with EnergyPlus: EnergyPlus parses environmental parameters to No-MASS which in turns parses back the energetic consequences of agents' behaviours. After describing the architecture of No-MASS and the form of the integrated models, we demonstrate its utility through two use cases: a house and an office. We close by outlining how No-MASS has been extended to more comprehensively simulate the behaviours of agents occupying multiple buildings; including behaviours for which data is scarce, social interactions between agents, and a generalisation of No-MASS to simulate electrical devices and their interactions.

Keywords: Multi-Agent; Stochastic; Behaviour; Energy; Simulation

1. Introduction

Predicted building performance continues to deviate, sometimes considerably, from that which is observed post-build. The reasons are many and complex. We can categorise these as: (type I) errors in modelling deterministic phenomena or indeed the neglect of these phenomena, (type II) errors in the inputs to these deterministic models, (type III) errors in modelling stochastic phenomena or indeed the neglect of these phenomena, (type IV) errors in the inputs to these stochastic models. Type I errors might include ignoring thermal storage in the modelling of heat diffusion, assuming thermophysical properties to be constant in the dynamic modelling of heat diffusion, or assuming that heat diffuses exclusively in one direction. Type II errors might relate to the characterisation of the bulk thermophysical properties of building materials, or assuming that multilayer constructions are perfectly homogenous and known; where as in reality workmanship is imperfect and unknown. Type III errors can be sub-categorised according to whether stochastic perturbations to heat flows in buildings are a) climatic, or b) human-behavioural in nature. Type IIIa errors might relate to wind pressures across the envelope and the corresponding impacts on convective heat transfers and infiltration, or the effects of cloud cover on transmitted shortwave irradiation. Whereas, type IIIb might relate to occupants' presence and associated metabolic heat gains, interactions with the envelope (e.g. windows and blinds), lights, appliances and systems. Finally, type IV errors relate to the empirical coefficients that are estimated for the models that are structured to address type III errors and their suitability to the particular context under consideration. Thus, and as with deterministic phenomena, we distinguish between the model structure and its ability to capture the underlying stochastic phenomena in principle, and the calibration of this model to a particular

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circumstance. This paper focuses on the development and application of a new simulation platform conceived to systematically improve upon the representation of type IIIb and associated type IV errors in building simulation. In this we begin by reviewing empirical evidence in support of the impacts of human behaviour on building performance, and the corresponding progress that has been made in the development of stochastic models of human behaviour to address these impacts, before presenting and demonstrating the application of our new platform.

1.1. *The need for stochastic behavioural models and platforms*

In their study of 22 identical residential houses in Germany, Maier, Krzaczek, and Tejchman (2009) have identified a factor of two variation in heating demand. Meanwhile, post occupancy evaluations of UK EcoHomes have found that occupants' planned behaviour accounts for a variation of 51% in heating demand between dwellings (Gill et al. 2010). Altering the heating controls using an occupant comfort measure (predicted mean vote), Andersen, Olesen, and Toftum (2007) found that a simulated building could vary in energy use by 324% from a low consumption scenario to a high consumption scenario.

The quest to reduce the performance gap, and thus to predict the above variations, has led to models addressing the stochastic nature of occupants' behaviours, integrated within building performance simulation software. These range from hard coded integration in the case of lighting behaviour models in Reinhart's (2004) Lightswitch2002 algorithm to Haldi and Robinson's (2011b) integration of occupant presence, window and blind models into CitySim. More recently, Vorger (2014) hard coded models of presence, activities, approximate use of heating systems, windows and blind interactions within the building simulation software Pleiades+COMFIE. In line with empirical findings, Haldi and Robinson (2011b) found with CitySim that variations in stochastic behaviour accounted for a factor of two variation in heating demand. Likewise, when comparing an ideal and worst case occupant scenario to demonstrate the range of influence occupants have, Roetzel et al. (2011) found that there was a factor of 2 difference in the simulated annual energy use for both heating and cooling. Bonte, Thellier, and Lartigue (2014) found a similar factor of two variation arising from the integration of models of blinds, lights, windows, temperature setpoints and clothing into a building simulation tool.

Although these efforts have usefully demonstrated the potential impact of stochastic behaviours (and models of them) on building performance, and that these closely concur with empirical observations, they are software specific and lack generality. This criticism was partially addressed by Bourgeois, Reinhart, and Macdonald (2006) who developed a general solution for the integration of lighting, windows and blind models with ESP-r, called Sub-Hourly Occupant Control (SHOCC). In a similar way, Gunay, O'Brien, and Beausoleil-Morrison (2016) implemented several data-driven stochastic models into EnergyPlus using the in-built EMS functionality. But this approach is also software specific and does not support more complex features. Robinson, Wilke, and Haldi (2011) suggest that a comprehensive behavioural modelling framework should support:

- The definition of archetypes and archetypal behaviours to account for diversity between occupants.
- Social interactions between members of a population and the corresponding implications for their behaviours.
- Behaviours that are conditional on others having already been exercised or indeed on proximity to the building envelope or system, with corresponding implications for interaction probability.

With the objective of addressing these limitations, our approach is to use multi-agent stochastic simulation. To combine stochastic models into a single package that can be used to support building and urban performance simulation using a range of software; whilst facilitating the modelling of interactions between agents (whether these be occupants, electrical devices or both) and of interactions for which data is scarce (e.g. due to privacy, cost or complexity constraints).

1.2. *Multi-Agent Simulation (MAS): Background*

Multi-agent simulation is a tool that has been developed primarily in the social sciences to effectively model human interaction (Bonabeau 2002; Zhang, Siebers, and Aickelin 2011). Its use in the social sciences has typically been to study behaviours that emerge from bottom up interactions, allowing the creator to make and encode judgements as to what has caused these emergent behaviours and whether they correspond with expectation from social theory. An agent should have the following properties; they should be autonomous, have social ability, perceive and react to the environment and be proactive with their choices (Wooldridge and Jennings 1995). Each agent has rules and behaviours, making them excellent at modelling group and individual interactions (Axtell 2000). Multi-agent simulation has been used to represent people in a variety of application areas. Epstein and Axtell's (1996) SugarScape simulates a simple society where inhabitants need to eat resources in an artificial world to survive. Each agent moves around a plane looking for and consuming sugar based on predetermined rules. These models demonstrated how societies can develop over time, congregating around areas of resource. The model was expanded to include sugar and spice as resources that could be traded, from which the authors showed that the prices of both converged to an equilibrium, as economic theory would predict. Meanwhile Axelrod (1997) tested agents, employed in combination with a genetic algorithm, against a prisoner's dilemma scenario (should you defect against or cooperate with your accomplice who has the same options); finding that 95% of all populations evolved towards the optimal *tit-for-tat* strategy, demonstrating the effectiveness of agents in exploring alternative decisions. Traffic flow within cities has also been modelled with agents, allowing traffic planners to make informed decisions to improve congestion (Nagel, Beckman, and Barrett 1999; Balmer, Axhausen, and Nagel 2006). Each agent in these scenarios occupies a vehicle, with their own goals and decisions to make. Another example is a city wide disaster scenario, evaluating traffic flow during an evacuation and the effects of different city road layouts (Ring, Grid, etc.) on evacuation time (Chen and Zhan 2006). Finally, Siebers and Aickelin (2011) model the effects of changes in employee empowerment on customer satisfaction in shops.

Agent cognition is often based on the Belief-Desire-Intention (BDI) system described further in Rao and Georgeff (1995); D'Inverno et al. (1998); Bratman (1987). In this system an agent has beliefs about the current state of the environment and related desires about what they want to achieve, committing their intent to take an action that moves them towards achieving their desires. A belief-desire-intention system allows us to encode behavioural interactions that will likely occur under specific circumstances and to test their impacts. For example, what if an occupant closed a shade for privacy while showering; how would it effect the building's performance?

1.3. *MAS applied to modelling occupant behaviours*

The BDI methodology has been used in the context of building performance simulation, where agents obtain a belief about the state of the current environment from a building performance simulation tool. In this vein, Andrews et al. (2011) combine the Radiance ray tracing tool with agents, to simulate interactions with lighting and shading. Agents build up their understanding of the environment with data from Radiance (room illuminance) then, based on their assigned personal characteristics, develop plans of action and act on the plan that maximizes their utility (satisfaction). To simulate diversity each agent was given an archetype of either green activist, good citizen, healthy consumer or traditional consumer. These archetypes were developed from questionnaires administered to building occupants, to better understand their preferred lighting levels and the energy use they are comfortable with. The agents' assigned archetype would effect their desire thus altering their intended method of interaction. Kashif (2014) uses a similar approach to predict the use of fridge-freezers, where an occupant would first perceive their hunger, second conceive a desire based on social normals, household rules and culture. They then perform an action, remove food from the freezer, increasing the electrical load on the fridge, and then cook.

These approaches attempt to encapsulate the human decision making processes involved in each activity. But they can lead to very complex and unwieldy models that have a weak empirical basis. Paradoxically this is also their strength, that with relatively little data reasonably reliable aggregate behaviours can be simulated. Come what may it is important that for empirical studies results have a high degree of certainty and that agents' rules and behaviours are grounded with data based on reality (Gimblett 2002). In recent years there has been a move from models based on social theoretical rules and behaviours, to those derived from observation (Janssen and Ostrom 2006). By using previously developed stochastic models of occupant behaviour it is possible to predict agent behaviours based on solid empirical evidence.

As an alternative to the BDI approach, Liao, Lin, and Barooah (2012) use room occupancy data to inform their agents' behaviours for the prediction of presence across multiple rooms and occupants; albeit concluding that for larger numbers of agents, it is often difficult to obtain high quality data from which to infer reliable rules. The model was also developed for a very specific use case of university buildings where students and professors have very different schedules. It has yet to be seen if this method can be applied to other building uses. Furthermore, these agents do not have the properties (social ability, reactivity and pro-activness) required by Wooldridge and Jennings (1995) to be formally designated as agents.

1.4. *Towards software-independent platforms for occupant behaviour modelling*

More recently, Langevin, Wen, and Gurian (2014) use data taken from a one year study of an air conditioned office to develop rules that allow an agent to proactively restore thermal comfort based on thermal sensation, through changes to clothing, the operation of windows/fans/heaters and by changing set point temperatures. These values are then parsed to the dynamic building simulation program EnergyPlus using the Building Control Virtual Test Bed (BCVTB). The Langevin agents are only as good as the realism given to the agent attributes specified for the model (such as clothing levels), the corresponding comfort model and the limited thermal inhomogeneity in the simulated indoor environment. With thermal discomfort as the trigger for a specified behaviour (based on the stationary ISO 7730 model), an error in the (dis)comfort prediction will inevitably undermine the faithfulness of the predicted interactions and their consequences. An improvement would be to more explicitly represent the dynamic relationship between environmental stimuli and interactions for prediction.

More recently, Lawrence Berkeley National Laboratory have embarked on an ambitious research programme to develop a comprehensive interoperable platform for the co-simulation of occupants' behaviours and their energy and comfort consequences. Informed by a review of behavioural modelling frameworks and of data-driven models of occupants' stochastic behaviours, Hong et al. (2015a) propose a Drivers - Needs - Actions - Systems framework to structure the occupant modelling task. The logic underpinning this DNAS framework has much in common with the BDI framework that has gained so much traction in social simulation research: drivers are in principle comparable to agents' beliefs of the current state of the environment, needs to agents' desires that express their preferred state, and actions (and thence systems these being more general than the name implies) to the commitment of agents' intents to act to achieve their desires. But this logic diverges somewhat as Hong et al. (2015a,b) elaborate their DNAS framework and develop an XML Schema (obXML) from it. In particular, the seemingly MAS-inspired roots of the DNAS framework are not truly retained in their (initial) schema and the examples demonstrating its application; because the schema does not appear to support the formulation of BDI-inspired goals and the definition and execution of plans to achieve them: it is restricted to the use of data-driven stochastic models. Hong et al. (2016) go on to demonstrate the use of obXML with a preliminary occupant modelling tool that is coupled with Energy Plus (using the Functional Mockup Interface

(FMI) co-simulation standard, of which more later). Called obFMU, this solves equations predicting the probability with which windows are opened / closed, lights are switched on/off and air conditioning systems are switched on/off and translates these into actions that are then parsed to Energy Plus. This is a very promising start, but both obXML and obFMU need further development to handle: i) more complex forms of data driven stochastic model, ii) alternative modelling strategies (e.g. BDI-type rules, machine learning techniques), iii) rationale informing appropriate model (and coefficient) selection, iv) agent representations of occupants, the generation of agent populations, the assignment of attributes influencing their behaviours and the handling of social interactions between agents, and v) rationale informing the orchestration of calls to models (e.g. the sequencing of behavioural actions).

In contrast with previous strategies to model occupants' behaviour that have tended to be based either on data-driven stochastic models or BDI rules, usually integrated with a specific dynamic building simulation program, we propose a more general framework. The virtues of both modelling approaches can be combined (data-driven where data is abundant and BDI or machine learning algorithms where it is not) and interfaced with a range of building simulation programs; whether at the building or the urban scale. To this end and in the first instance, we integrate existing models of occupants' activities, metabolic heat gains, use of windows, lights and shading devices within a bespoke platform that we call Nottingham Multi-Agent Stochastic Simulation (No-MASS). In common with obFMU, these agents' interactions are parsed, also using the FMI standard, to a building simulation program (at present EnergyPlus), which in turn parses environmental parameters to No-MASS, to impact on future behaviours. This provides a generic way to integrate existing and future stochastic models, speeding up time from model development to integration and thus availability of missing models for use by the broader simulation community, increasing their usefulness. The remainder of this paper is dedicated to describing this new framework, from population generation, through parameter assignment to simulation (pre and runtime). Use cases exploring the simulation of No-MASS with EnergyPlus for a house and an office are then presented to demonstrate its utility. We conclude by summarising the additional functionally that has been developed for the more comprehensive simulation of building performance, referring the interested reader to the relevant companion papers.

2. No-MASS

There remain many gaps in our ability to model occupants' stochastic behaviours (such as their interactions with heating and cooling systems, hot water devices, curtains, their use of windows to evacuate pollutants, etc). However we do have a sufficient core set of rigorously formulated and validated models with which to evaluate the proof of principle of No-MASS as a platform for addressing type IIIb and IV errors and thus of evaluating the robustness of buildings' performance. In this section we introduce No-MASS, the models included and how it is implemented. Also described is how No-MASS may be coupled with other (than EnergyPlus) simulation programs using the Functional Mockup Interface (Nouidui, Wetter, and Zuo 2013).

2.1. *Concept*

The initial family of models integrated with No-MASS includes models of occupants' activities (Jaboob 2015), presence and corresponding metabolic heat gains (Page et al. 2008), window interactions (Haldi and Robinson 2009), shading interactions (Haldi and Robinson 2010) and lighting interactions (Reinhart 2004). These models were chosen as they have been empirically verified, are well known to the authors of this paper and were readily available. Simulations with No-MASS follow the process outlined in the conceptual flow-diagram in Figure 1. A number of pre-processes are first performed. Initially an agent population is created, with each agent assigned a profile that influences their subsequent behaviours. For example, socio-demographic characteristics influence the probabilities with which time dependent activities will take place. Couples may have different activity profiles than single adults living alone and elderly agents may perform different actions at different times compared with younger adults: there is a greater chance that an elderly retired occupant will be present and cook during the day, whereas a younger occupant will more likely be out at work. Furthermore the probability of being present at a given time step and the corresponding location may vary with socio-demographic characteristics. This location may correspond to the agents' office when occupying (and sleeping in) a non-residential building or their bedroom for sleeping when occupying a residential building.

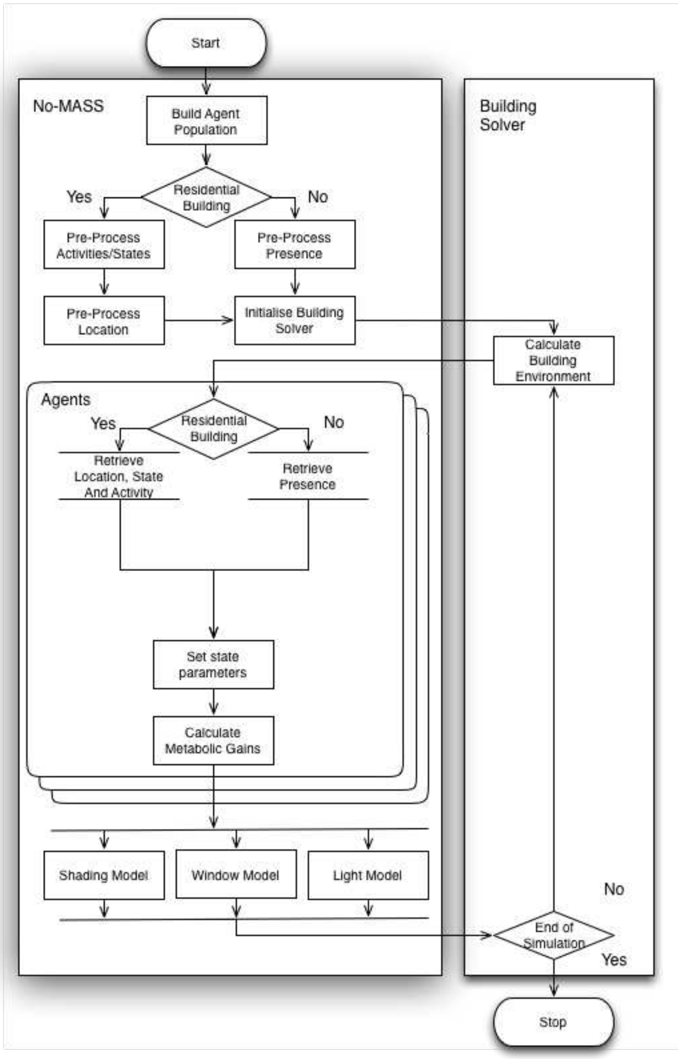

Figure 1. No-MASS conceptual flow diagram illustrating the sequence of calls to No-MASS models and the parsing of data between No-MASS and EnergyPlus

Once the agents are defined we can pre-process those models that do not utilise transient environmental inputs, such as models that depend on time only. Here we distinguish between residential and non-residential buildings. For residential buildings we process the activity that an agent will perform and the corresponding location at each time step; whereas in non-residential buildings, a separate presence model is used to calculate whether an agent is present in a given zone at each time step. The presence and activity profiles are predicted independently for each agent. Once these pre-processes are complete EnergyPlus is called to simulate the building's energy flows for the first time step. At the end of each subsequent time step, No-MASS is called by EnergyPlus.

Environmental conditions are parsed from EnergyPlus to No-MASS, which then uses these to predict our agents' behaviours. Each agent is called independently and at random. For residential buildings the pre-processed activity and location for the present timestep is retrieved and used to calculate the metabolic gains for that agent and location. In non-residential buildings only the pre-processed presence is retrieved to calculate metabolic gains. Next agents' interactions with shading devices, windows and lighting are predicted, the sequencing of calls to these models being randomised. The outputs from all models are then parsed back to EnergyPlus, which resolves the energy consequences of these interactions when simulating the building's energy flows during the next time step, so that there is no within timestep iteration. This process continues until the end of the simulation period.

2.2. *Activity model*

The activity model (Jaboob 2015) predicts the time-dependent probability that one of a set of ten groups of activities will be performed in the home. These activities include sleeping, passive, audio/visual, IT, cooking, cleaning, metabolic, washing appliance use, personal washing and absence from the building. They are modelled as a time-dependent Bernoulli process using multinomial logistic regression. As the probabilities are only dependent on time it is possible to generate a 10 by 24 matrix giving the probability of performing each activity at a given hour; though the corresponding model can also be re-called within the hour for sub-hourly simulation timestep, using appropriate interpolation. As well as a model predicting activities for an average member of the population (estimating model parameters using the entire dataset) models have been estimated for subpopulations of the time use survey dataset from which they are derived, to give probabilities that depend for example on age, employment status, season or day of the week. The relevant sub-model used for each agent is assigned when the agent population is generated. This is then pre-processed, assigning a state to each timestep within the simulation. This is achieved by drawing a random number at each timestep for each agent. Where that number falls within the range of probabilities for that hour, the corresponding activity is assigned to the relevant agent. These are then stored for retrieval at run time.

Note that this process is only considered for residential buildings and does not apply to the simulation of non-residential buildings, for which the corresponding time use survey data is not available.

2.3. *Agent states*

During a simulation our (residential) agents are assigned one of ten activity-dependent states. No-MASS uses a state machine, which is a way of defining programmatically the states an agent may be in and the possible transitions from each state to the next. Dependent on the state, values of agents' personal characteristics and location are modified: Table 1. These values are taken from ISO 7730 (ISO 2005). In the case of the more constrained environments of non-residential buildings we set the metabolic rate to 116 and Clo to 1. Although daily clothing level choices are known to vary with mean outdoor temperature (Haldi and Robinson 2011a), in present case, in which our focus is on the impacts on energy simulation of behavioural models using environmental stimuli rather than perceived comfort as explanatory variables, this would only impact on variations of metabolic heat gains (of which more later) - the effect being small enough that we do not take this into consideration. Rather we dynamically calculate metabolic heat gains using fixed clothing levels.

State	Location	Clo	Metabolic rate (W/m^2)
Sleeping	Bedroom	2.55	46
Passive	Living Room	0.7	58
Audio/Visual	Living Room	0.7	70
IT	Office	0.7	116
Cooking	Kitchen	0.7	116
Cleaning	Kitchen	0.7	116
Washing self	Bathroom	0.3	116
Washing appliance	Kitchen	0.7	116
Metabolic	Living Room	0.7	93
Absent	NA	NA	NA

Table 1. Agent states with corresponding locations and values

2.4. *Presence and location*

We have two methods for calculating presence within a building, the choice of which depends on the type of building. For residential buildings, presence (or rather absence) is predicted directly by the activity model (as noted above). Furthermore, based on the activity being performed [or the agent's state], we can infer a location. For example, if the agent is in the sleeping state it can be assumed that they are in their bedroom. But this may not always hold true. For example, if an agent is predicted to sleep during the day (and retired folk do this with relatively higher probability) they may do so in the living room. Thus we may in the future need archetype-dependent assignment probabilities to account for such eventualities. To allocate agents to a zone within EnergyPlus we define an external schedule of occupancy for each zone in the EnergyPlus configuration file. EnergyPlus then assumes that a value for each schedule will be received by its external interface at each time step. For the simulation of non-residential buildings a presence model (Page et al. 2008) predicts when an occupant is present within their office, based on a time-inhomogeneous Markov chain, using a mobility parameter μ and a time-dependent profile of the probability of presence p(t) as input. By default No-MASS uses the parameters for p(t) and μ give in (Page et al. 2008). Since this model uses no environmental parameters, it may be run as a pre-process, generating a sequence of presences and absences for each agent. For the time being long term absences due to illnesses, vacations or work related business trips are not stochastically predicted. Page's Page et al. presence model does not account for seasonality but the underlying profile could. The residential locations are based on the activity model (Jaboob 2015) that accounts for both seasonality and types of day, based on representative time use survey data (in both socio-economic and temporal terms).

2.5. *Metabolic gains*

Metabolic gains are calculated using Fanger's PMV model, as described in ISO 7730 (ISO 2005), based on the standard physical (air temperature, radiant temperature, relative air velocity and relative humidity) and personal (clothing level and metabolic rate) parameters. With the exception of an assumed relative air velocity of 0.1 m/s, the physical parameters are supplied by EnergyPlus; whereas the state-dependent personal parameters are as defined in Table 1 (with external work taken to be 0W). As EnergyPlus takes a single metabolic rate for all agents within a zone, we calculate the zone average for all agents present. We set this within EnergyPlus through the zone activity schedule, which multiplies this average gain by the number of present occupants to determine the total metabolic heat gain for all occupants.

2.6. *Window actions*

We use the model of Haldi and Robinson (2009) to predict interactions with windows. This is a hybrid model, predicting transitions in opening status using a presence-dependent Markov chain and, in the cases of transitions to the open state, predicting the duration for which the window stays open using a Weibull distribution. The predictors at arrival are indoor temperature, outdoor temperature, absence duration and rain presence. During occupancy they are indoor temperature, outdoor temperature, length of presence and rain presence, whilst at departure the predictors are indoor temperature, daily mean outdoor temperature, length of departure and a dummy parameter to represent whether the window is at the ground floor level (which reduces the probability of windows being left open at night). With the exception of the presence-related parameters and the ground floor parameter the values of these predictors are supplied by EnergyPlus via the Functional Mockup Interface. No-MASS determines the occupants' presence status and calculates the future presence and past absence durations when needed. Absence duration is computed within No-MASS by rewinding the array of chains of presence and absence from the current timestep; and the opposite for the duration of departure. For example when modelling the probability with which window will be closed at departure as a function of the anticipated duration, No-MASS forward-winds the pre-processed agent-dependent presence array until the next arrival to determine the absence duration. The ground floor parameter is given as an input to No-MASS at runtime, as a boolean value per zone, set to true if the zone is at ground level otherwise false. This is defined in a simulation configuration file, of which more later, as it can not be supplied by EnergyPlus. By default the model is estimated from data relating to an aggregate population (i.e. using all empirical data for all members of the population surveyed), so that each agent uses the same model coefficients to predict window opening behaviour.

Within EnergyPlus we again create an external schedule for windows, setting the value to be either 1 for fully open or 0 for fully closed for each time step (in the future it would be useful to include predictions of opening proportion, based for example on the model described in Schweiker et al. (2012)).

2.7. *External shading actions*

The shading action model (Haldi and Robinson 2010) predicts lowering and raising probabilities, which are also based on Markov chains. Like the window model, predictions are estimated using data for an aggregate population. Upon an agents' arrival the first step in this model is to determine the probability with which a raising or lowering action from the indoor illuminance supplied by EnergyPlus at a suitable daylight reference point within the zone and the unshaded fraction at the previous timestep. If the shade is lowered or raised we then predict whether the shade is fully raised or lowered. If the shades are only partially raised or lowered, we calculate a new unshaded fraction, using a Weibull distribution whose parameters are dependent on the prior unshaded fraction. Otherwise, shading remains unchanged. A similar process but with different probabilistic models occurs whilst occupants are present. The outcomes from these models allow us to set the shading fraction in EnergyPlus. The current version of EnergyPlus (8) only allows shades to be either fully open or fully closed. As such, it does not provide a function to overwrite an external shade fraction value from an external interface such as No-MASS. The EnergyPlus source code was therefore altered to provide a function that reduces the radiation transmitted through the window in proportion to the fraction that the shade was closed, this function can now be accessed from an external interface at each timestep (see Appendix A for the source code changes).

2.8. *Lighting*

The prediction of the use of lights within No-MASS is based on the Lightswitch-2002 algorithm (Reinhart 2004). We take the indoor illuminance E of the zone from EnergyPlus for the current time step and compute the probability of turning the lights on when the agent arrives or whilst they are present, and thus whether this action takes place. When all agents vacate the zone we predict whether the lights will be turned off, as a function of the anticipated duration of their absence, calculated by forward-winding from the time of departure until the time of return. For absences below 0.5 hours we assume that lights remain on, where as for absences exceeding 12 hours the lights are assumed to be turned off (Pigg, Eilers, and Reed 1996). The consequent lighting status (on-off) is set within EnergyPlus at each timestep as a lighting schedule for each zone within the building.

2.9. *On behavioural diversity and generalisability*

The behavioural models that we have described in 2.6 (windows), 2.7 (shading) and 2.8 (lighting), to demonstrate the utility of No-MASS have each been estimated (or rather their coefficients have been) for particular circumstances: laboratory offices in the case of windows and shades and a combination of office and school class rooms in the case of lighting; but in Schweiker et al. (2012) it was demonstrated that the window opening model of Haldi and Robinson (2009) could be reliably used to model residences as well as offices. This implication was deemed to be general: so long as the modes of interaction are similar and the local stimuli are properly accounted for then a model developed from observed behaviours in one setting can be used to predict those of another. Thus the models for predicting the use of windows, blinds and lighting should be applicable to both residential and non-residential cases. The models implemented do not yet cover all interactions to non-residential cases, so long as the above condition is satisfied. Examples of where this condition is not satisfied (using the models we currently employ) include the closing of windows in bathrooms whilst bathing for privacy and their subsequent opening to reject moisture; the opening of windows while cooking in kitchens or upon awakening in bedrooms to reject odours. A belief-desire-intention system will be implemented in the future to cover this wider range of occupant interactions which are relatively habitual in character. For the purposes of this paper we have only used model coefficients estimated from aggregate datasets in conjunction with these fixed effects models. However, we do demonstrate the modelling of behavioural diversity in a companion paper, in which we also account for social interactions between members of our agent population (Chapman, Siebers, and Robinson 2017), where this capability is more fitting.

3. Implementation

No-MASS was built from the ground up, having tested a number of current multi-agent simulation development platforms, including Repast Simphony and Anylogic. Although these platforms are very useful they come with significant overheads, typically requiring a large library of graphical user interface routines to be imported, making it more difficult to package a No-MASS equivalent with simulation tools such as EnergyPlus and the DesignBuilder interface to it. C++ was chosen as the development language as it is simple to integrate with EnergyPlus, our (first) chosen building simulation tool, which is also developed in C++. Using the same language allows for easy communication between the two tools. EnergyPlus is well tested and well documented, allowing us to readily understand how to connect to it. There are also two interfaces that allow other tools to interact with it, without altering the EnergyPlus source code. The first is through the building controls virtual test bed (BCVTB) and the second is through the Functional Mockup Interface (FMI). The No-MASS platform connects to EnergyPlus using FMI (Nouidui, 2014), which is an open standard so that No-MASS could in principle be integrated with any other FMI compliant simulation tool. We chose this over the BCVTB as it allows direct communication through C++ double arrays using predefined calling points. The calling points are well documented, with No-MASS only using the *initialise* function, the *receive an array of doubles* function for the environmental variables and the *send an array of doubles* function for the occupant interactions.

The array of values that No-MASS receives at each time step is defined in the XML file ModelDescription.xml. At the beginning of the time step the following environmental variables are received: horizontal sky illuminance, rain status, outdoor drybulb air temperature, zone drybulb air temperature, zone relative humidity, indoor radiant temperature and indoor illuminance. Returned to EnergyPlus are the number of occupants in a zone, their metabolic gains, the window status, the blind shading fraction and the lighting status.

Following a timestep sensitivity study (Figure 2), we use by default a simulation timestep of 5 minutes. Time steps greater than 5mins tend to lead to unstable control actions and corresponding indoor temperatures in the case of window openings, whilst indoor/outdoor temperature differences are relatively large. Note that this timestep length has no impact on the the behavioural (window shading and lighting) models, for these are time (though not occupancy status) homogeneous, but the presence/ activity models do require interpolation the corresponding probabilities within the timestep to then predict the corresponding presences/ activities.

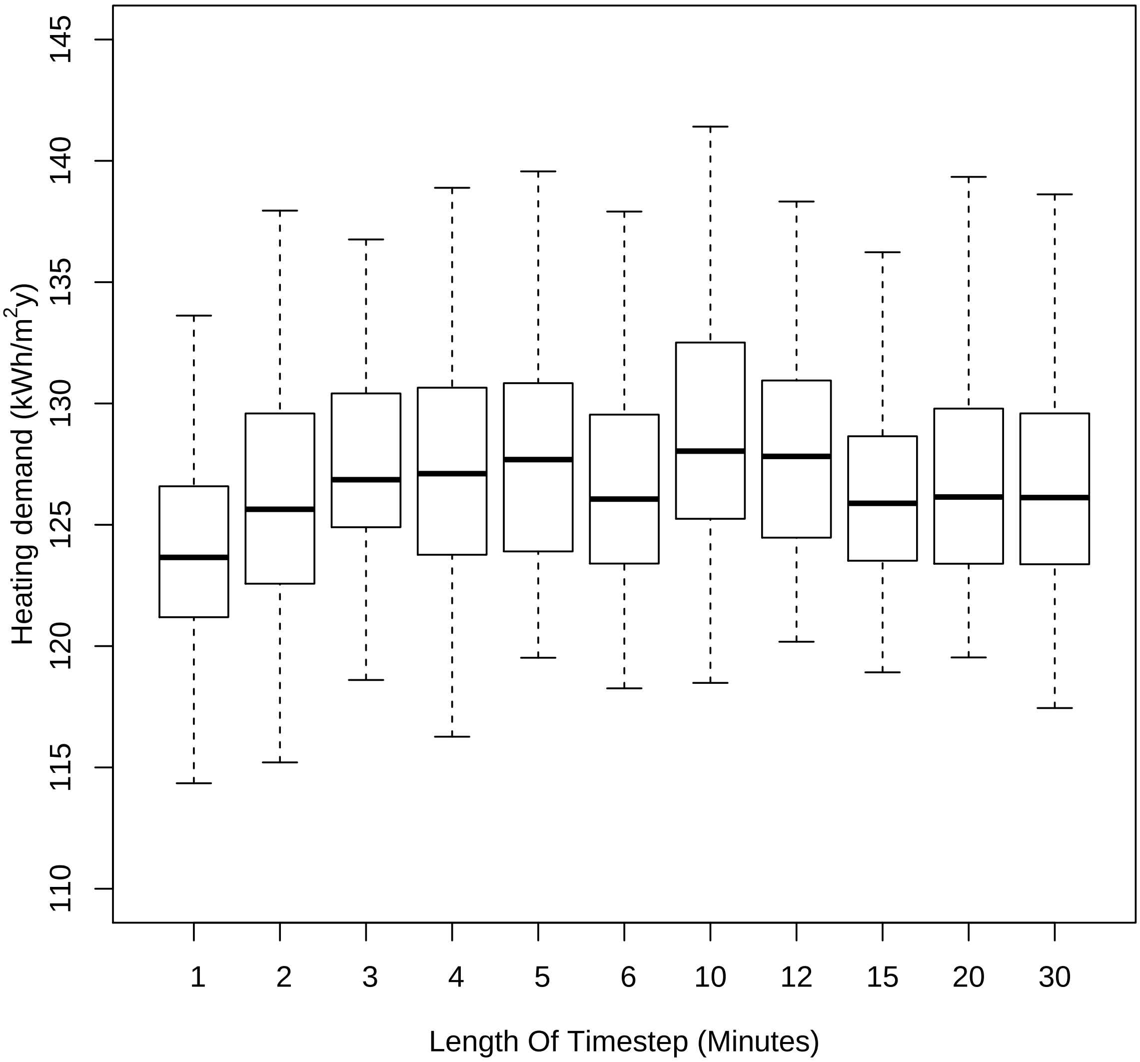

Figure 2. Time Step Sensitivity Analysis: a comparison of predicted annual heating demand for different simulation timestep lengths. Performance predictions tend to stabilise at a timestep of 5 minutes.

No-MASS has been developed as both a Linux shared object and as a Microsoft Windows dynamic link library. Figure 3 shows how the system connects to EnergyPlus. In the same way that EnergyPlus reads in the building configuration and weather data from the IDF file and the EPW file, No-MASS reads in data from an XML file called NoMassConfig.xml. This file contains information relating to the occupants that is used to build and attribute the agent population, facilitating the subsequent processing of an agent activity profile that is used to calculate the probability of an activity taking place at each timestep, as well as the bedroom and office that agent will belong to. This allows No-MASS to assign an agent to a zone for when they are in an office or to a bedroom when their activity is sleeping. As new models are integrated into No-MASS, the configuration file will need extending to include the inputs of the new models.

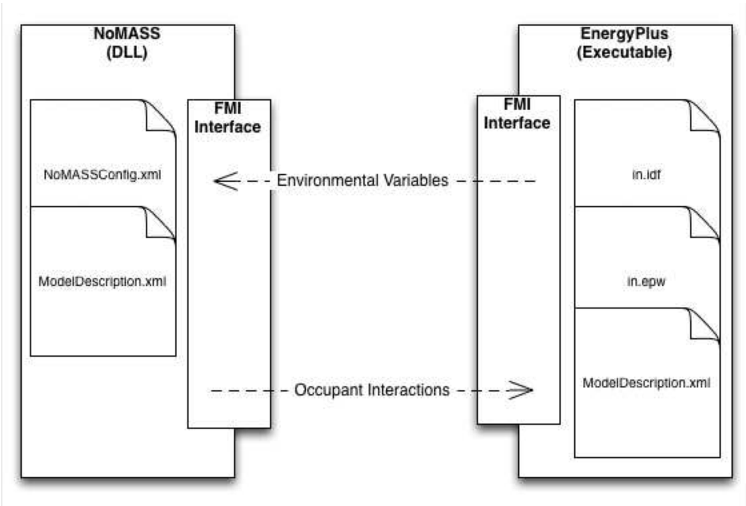

Figure 3. No-MASS Data Flow Diagram

In principle No-MASS could be readily adapted to also read Hong et al's 2015b obXML, should this be further developed in the future to be No-MASS compatible.

4. Case study

To demonstrate the application of No-MASS and its coupling with EnergyPlus (Version 8.4) we examine two different buildings in two locations. A hypothetical house and a shoe box office are simulated in Geneva, Switzerland and in the more temperate location of Nottingham, UK. Results from No-MASS are compared to the results arising from standard deterministic schedules and rules for the relevant house/ office typology (or template) used by the DesignBuilder interface. The layouts of the buildings are shown in Figure 4.

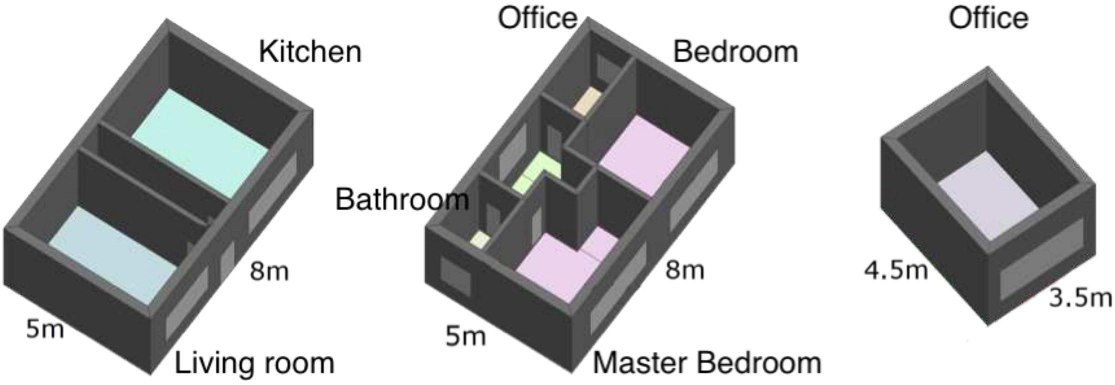

Figure 4. Residential ground floor (left), Residential 1st floor (middle), Office (Right)

Details such as heating set-points, glazing ratios, etc. are given in Tables 2 and 3. For simplicity, both buildings adopt the same constructions as in Table 4. The weather files are taken from DesignBuilder giving the locations Geneva, Switzerland ($+46°25', 6°13'$) and a location about 40 miles from Nottingham, UK ($+53°28', -1°0'$) called Finningley. To help judge the utility of No-MASS we also simulate our use cases based on deterministic representations of occupants. To this end our offices are assumed to be occupied according to the following fractional schedule during the weekdays: [0.0] 00:00 until 07:00, [0.25] until 08:00, [0.5] until 09:00, [1.0] until 12:00, [0.75] until 14:00, [1.0] until 17:00, [0.5] until 18:00, [0.25] until 19:00, [0.0] until 24:00. During the weekend offices are assumed to be vacant. Interactions with external shades and lights operate on the same schedule, with the windows being open when occupants are present and the indoor temperature exceeds 24° C. In Nottingham we consider only heating demand, whereas in Geneva we also consider cooling demand.

Zone	Area $[m^2]$	Volume $[m^3]$	Gross Wall Area$[m^2]$	Glazing ratio%	Lighting $[W/m^2]$	Setpoint Temp$[c]$
Livingroom	13	46	36	7	7.5	21
Halldownstairs	4	15	6	0	5	20
Kitchen	15	52	39	8	15	18
Bathroom	3	10	12	11	7	18
Hall	4	19	10	0	5	18
Residential Office	3	12	13	10	5	22
Second bedroom	9	34	22	15	5	18
Master bedroom	10	37	24	16	5	18
Attic	37	26	7	0	0	-
Total	101	255	172	68	5	-

Table 2. Residential Building Zone Details

Zone	Area $[m^2]$	Volume $[m^3]$	Gross Wall Area$[m^2]$	Glazing ratio%	Lighting $[W/m^2]$	Setpoint Temp$[c]$
Office	11	39	47	6	20	21

Table 3. Non-Residential Building Zone Details

Location	Layer	Thickness (m)	Material
External Wall	Outer	0.1	Brick
External Wall	2	0.07	XPS extruded
External Wall	3	0.1	Concrete Block
External Wall	Inner	0.01	Gypsum Plaster
U-Value			0.37
Internal Partition	Outer	0.02	Gypsum Plaster
Internal Partition	2	0.1	Air Gap
Internal Partition	Inner	0.02	Gypsum Plaster
U-Value			2.86
Ground Floor	Outer	0.13	Urea Formaldehyde Foam
Ground Floor	2	0.1	Cast Concrete
Ground Floor	3	0.07	Floor Screed
Ground Floor	Inner	0.03	Timber Flooring
U-Value			0.26
Floor	Outer	0.10	Cast Concrete
U-Value			4.7
Pitched Roof	Outer	0.02	Clay Tile
Pitched Roof	2	0.02	Air Gap
Pitched Roof	Inner	0.005	Roofing Felt
U-Value			4.97

Table 4. Construction Materials

Repeated simulations help us to understand the likely distribution of the output parameters of interest and thus the corresponding robustness of alternative design proposals. But the extra simulation time needed for replicates can be seen as a weakness, especially with large models. The form of the model and demographics of population are kept the same, the stochastic models are seeded with a different numbers at the start of each simulation thus causing variations in the outputs of the random number generator and this in the choices each agent makes. It is therefore important then to calculate the minimum number of simulations we need to perform to achieve a converged solution, as judged by a cumulative mean convergence graph (Stewart 2004). To this end, the heating demand at each simulation is taken and added to a cumulative mean and plotted, with the results converging on the number of simulation replicates needed (Figure 5). Using a t-test we find that the results do in fact converge at 97 replicates with a 95% confidence interval and at 55 replicates at a 90% confidence interval. Since these cases are rather different from one another, adopting 55 replicates, at which the variance has also stabilised, would appear to be a robust choice for future similar studies.

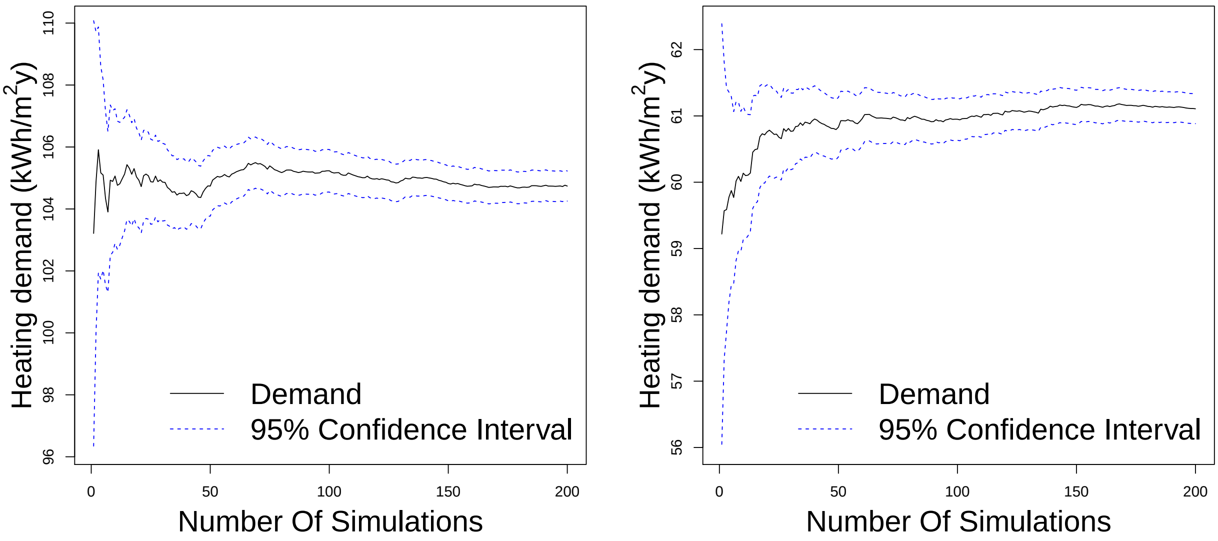

Figure 5. Convergence of mean heating demand: Geneva Office (left) and House (right)

5. Comparison of deterministic simulation and No-MASS

Depending upon the assumptions made in the choice of deterministic rules and schedules, performance results can deviate significantly from those arising from the stochastic representation of people. The predicted median heating demand for our office located in Nottingham obtained using No-MASS was 118.4 kWh/m^2, compared with 93.3 kWh/m^2 when assuming deterministic behaviours. Meanwhile, for Geneva we predict 103.9 kWh/m^2 (No-MASS) and 83.8 kWh/m^2 (deterministic) and 6.3 kWh/m^2 (No-MASS) and 5.6 kWh/m^2 (deterministic) for cooling.

Our predicted energy demands are considerably closer in the case of our house. For the house located in Nottingham for heating we predict 68.5 kWh/m^2 (No-MASS) and 66.1 kWh/m^2 (deterministic), whilst for the Geneva house we predict a demand of 60.4 kWh/m^2 (No-MASS) and 58.3 kWh/m^2 (deterministic) for heating and 2.6 kWh/m^2 (No-MASS) and 4.9 kWh/m^2 (deterministic) for cooling.

In this case study the default deterministic rules and schedules assigned to the office building by DesignBuilder under predict (with respect to that predicted using our empirically derived stochastic models) the heating demand by 15 to 25 kWh/m^2. The use of windows during periods of heating causes the principle increase in demand; as the deterministic rules would not allow this to happen. Relative to the office the house encloses a much larger volume of space, so dampening the effects of occupants' interactions compared to the office, so that interactions per zone cause a smaller difference of approximately 2 kWh/m^2 between the deterministic and stochastic results. This close agreement also suggests that the deterministic representation of occupants' interactions in DesignBuilder is coincidentally close to that predicted using No-MASS, where models are estimated from observed data. No-MASS predicts a lower cooling demand in the house than in the deterministic representation but a marginally higher demand in the office. The difference in both cases is approximately 2 kWh/m^2.

In addition to more reliably estimated (median) energy demands, repeated stochastic simulations enable the likely range of possible energy demands arising from occupant interactions (our type IIIb and type IV errors) to be quantified.

Repeated stochastic simulations enable the likely range of possible energy demands arising from occupant interactions to be quantified. For example, in the case of our office 90% of our predicted heating demand results lie in the range 100 kWh/m^2 to 109 kWh/m^2 (see also Figure 6, in which we also plot the deterministic value as a point for comparison).

In line with the adaptive principle that upon experiencing discomfort people act in ways which tend to restore their comfort, we may assume that in No-MASS our agents' interaction are similarly motivated. Our agents sense their environment, calling stochastic models that predict interactions that are motivated by the agents' (or strictly speaking the population from which these models were derived) desire to restore their comfort. It is interesting to determine whether our agents' interactions have been successful. To this end, we aggregate thermally discomforting stimuli by calculating the degree hours for which a threshold of 25° C has been exceeded, as an indicator of overheating risk (Robinson and Haldi 2008). We predict for the Nottingham office 3% (No-MASS) and 3.5% (deterministic). Predictions for the Geneva office are 15% (No-MASS) and 14% (deterministic), which in both cases are similar. For the house the percentage of time above 25° C are lower for No-MASS compared to the deterministic case. For the UK we predict 0.01% (No-MASS) and 2% (deterministic), whilst for the Geneva house we predict 6% (No-MASS) and 8.5% (deterministic).

The improved performance here in the case of No-MASS suggests that our empirically derived stochastic models better emulate occupants' behaviours (they are more effective) than the assumed deterministic rules.

Breaking the simulations down into monthly box plots (Figure 7) enables us to further understand the variations in building performance arising from occupants' interactions over the course of a year. During January and December the heating demand is higher for the stochastic simulations, as occupants can interact with the windows at a range of temperatures (e.g. to refresh the indoor air). During the summer months the deterministic simulations register no heating demands, whereas the stochastic simulations allow the temperature to drop below the heating setpoint as windows can now be left open over night and so may have inadvertently cooled the interior. This is shown in Figure 8, where during the summer windows can be open for as much as 20% of the month (with the proportion of time that lights are on following the inverse of this trend). Similar monthly box plots for the rooms of the house (Figure 9) demonstrate that windows are proportionately more open during the summer months.

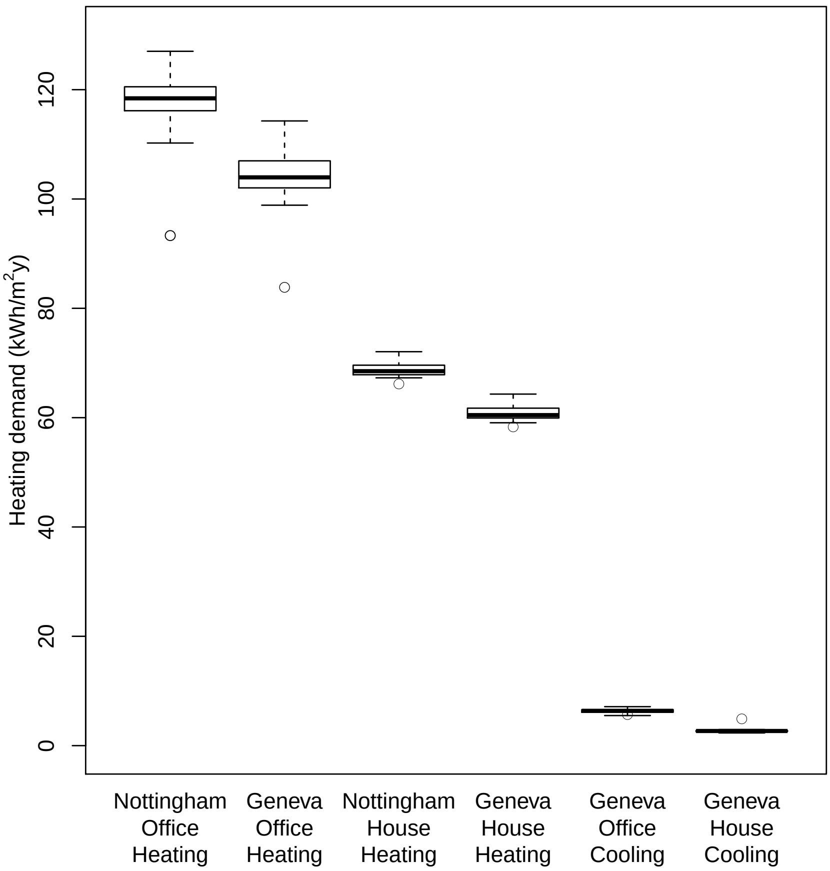

Figure 6. Simulation results for yearly heating demand (Boxplot) No-MASS for 100 replicates, (Circle) Single deterministic simulation

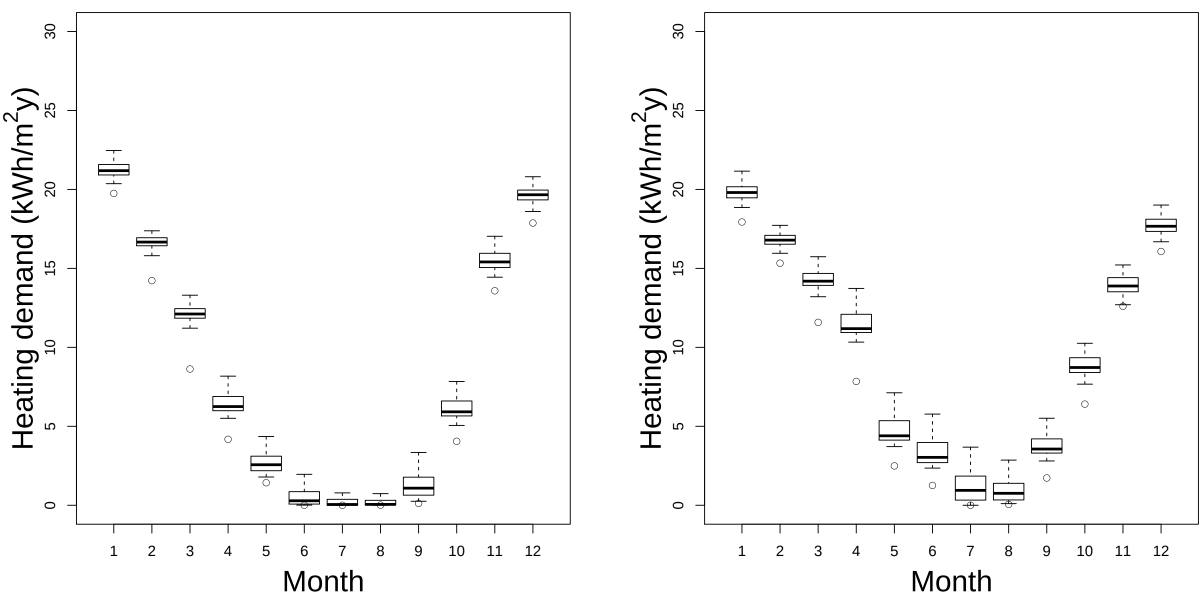

Figure 7. Simulation results for monthly heating demand, (Left) Geneva Office, (Right) Nottingham Office. (Boxplot) Stochastic agent platform 100 replicates, (Circle) Single deterministic simulation

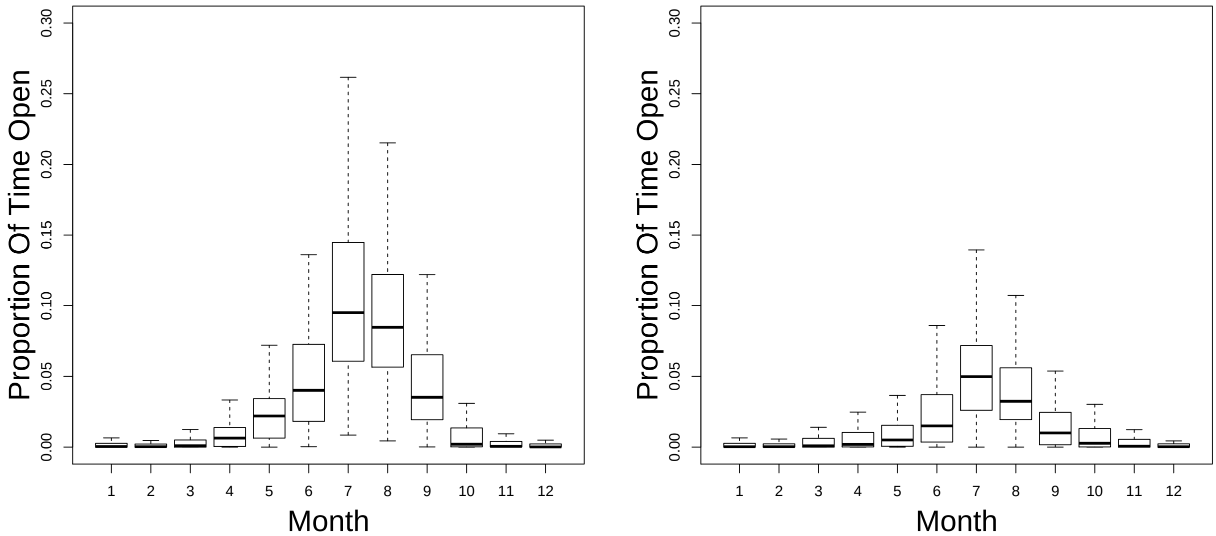

Figure 8. Monthly average window state, Geneva Office (Left), Nottingham Office (Right)

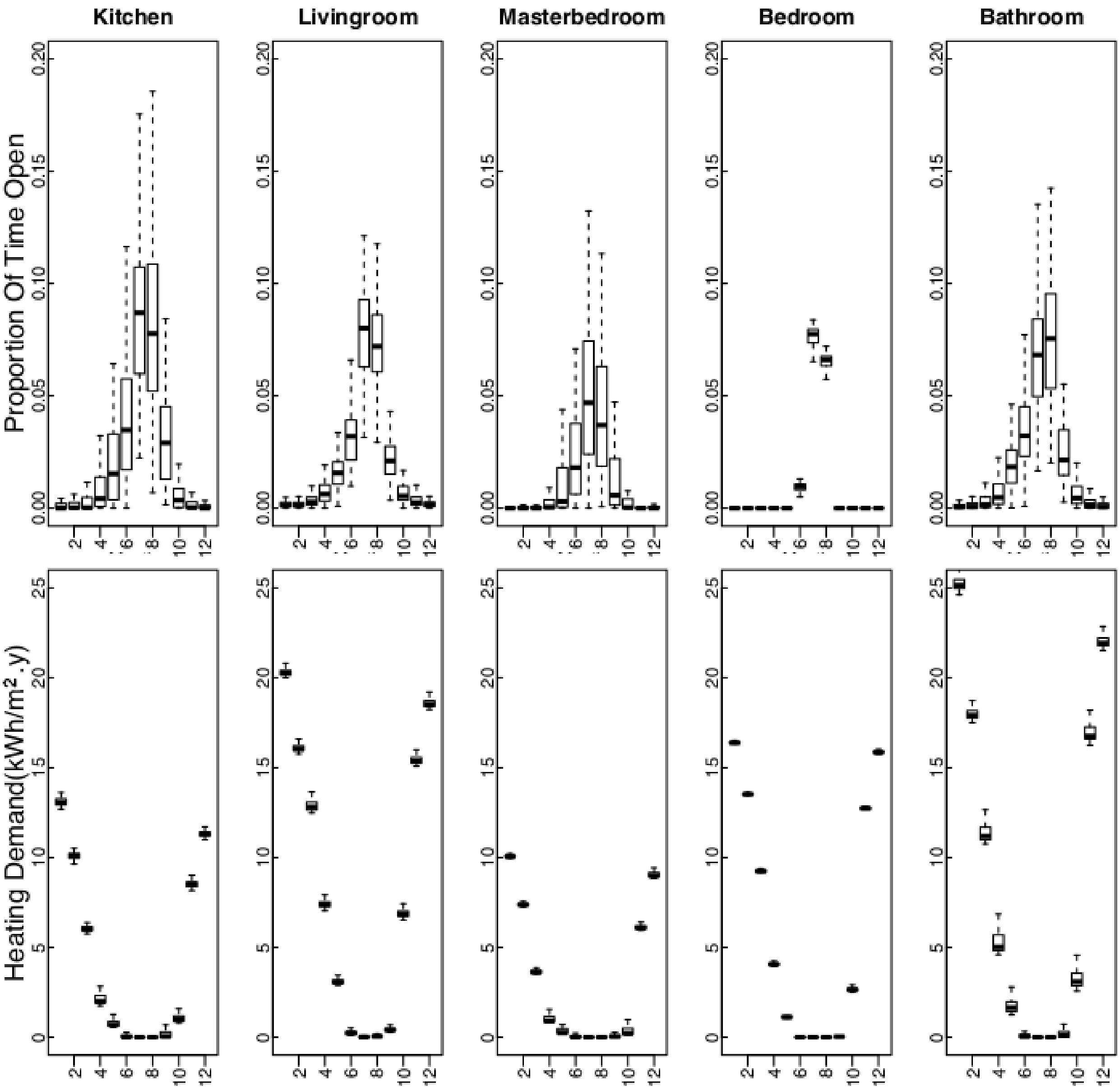

Figure 9. Monthly window and heating usage for the rooms of the Geneva House

6. On the utility of No-MASS and its core behavioural models

Relatively few of the stochastic behavioural models, that have been developed thus far, have been subjected to rigorous and comprehensive validation exercises. Of those that have, the focus has been on the models' ability to reproduce observed behaviours, expressed as discrete states. Through careful parameter selection, the best of these models have retained a parsimonious number of parameters and their coefficients estimated, for the purpose of emulating reality. But these models may be more complicated than they need to be, for the purposes of energy performance prediction or for design decision making support. It may be that for such purposes less complicated forms of model would suffice. Chapman (2017) has studied this issue using No-MASS, firstly to determine whether our stochastic models are useful (have a significant impact on building performance) and then whether these models really are parsimonious, as their authors claim them to be; for the purpose of building performance prediction. This was achieved by comparing predictions from 100 replicates with and without a model or with and without a parameter of a model, and performing a t-test to determine whether the two datasets are significantly different from one another. For all use cases (house, office, Geneva, Nottingham) the models (p-value < 0.05) were found to be useful; but that in the case of window openings both the rain and presence parameter can be removed. This simplifies somewhat the form of the model needed for building simulation purposes.

7. Future developments

This is the first of three papers focussing on the development and application of No-MASS. This first paper is a straightforward introduction to No-MASS; a proof-of-concept for this new software integration technology. The first of the two companions (Chapman, Siebers, and Robinson 2017) to this paper extends No-MASS to the modelling of social interactions amongst diverse members of a building population and the enrichment of our capabilities to model phenomena that are important but for which data is scarce. In this we employ two techniques: i) Belief-Desire-Intention rules for relatively simple habitual behaviours, such as the closing of curtains whilst preparing for bed or the opening of curtains and then of windows upon awakening, and ii) machine learning techniques for more complex behaviours, such as time-varying choices to regulate heating systems. The second companion paper (Sancho-Tomás et al. 2017) addresses the extension of the No-MASS framework to simulate (device-to-device) interactions between electrical demand, storage and supply devices and the machine learning of strategies to maximise rewards (e.g. to minimise cost or maximise some other measure of utility). Finally, we demonstrate how these two agent "world views" can be combined to simulate occupant-to-device and vice-versa interactions, for example to simulate occupants modifying their use of energy-related services in response to tariff forecasts or social norms. These extensions to No-MASS could in the future be further enriched through the modelling of long absences (due to vacations, illness or business trips); the probabilistic generation of household compositions given the house type, location and size; the use of cold and hot water, given the underlying activities; the prediction of comfort and overheating risk, accounting for feedback from the specific adaptive behavioural actions that have been exercised. In addition to extending the scope of No-MASS it would also be highly desirable to compare performance predictions from its application to the results from high quality field surveys of whole building performance. This ensemble validation would usefully be conducted with a focus on Passivhaus buildings (as in Blight and Coley (2013)), as the stringent constraints imposed by the Passivhaus standard minimise Type II errors in performance prediction; so that predicted deviations should arise mainly from stochastic weather and occupant influences.

8. Conclusions

In this paper we have introduced the Nottingham Multi-Agent Stochastic Simulation platform (No-MASS) for coupling stochastic modelling of occupants' behaviours with dynamic building simulation programs; its applications and forthcoming features. Coupled with EnergyPlus two test cases were studied, with the range of results being compared to deterministic representations. We have shown through these applications (a single occupied office building and a house occupied by two adults who do not have children) that No-MASS provides a convenient, comprehensive and rigorous basis for representing occupants' stochastic behaviours in EnergyPlus (and other software using FMI); providing designers with means to evaluate the performance of their designs in response to the range of expected behaviours and thus to evaluate the robustness of their design solutions that is not possible using current simplistic deterministic representations.

In terms of the usefulness of the models integrated into No-MASS and their composition we have found that each of the window, lighting and shading models can significantly effect the simulation results, but that the window model within No-MASS can be simplified by removing the rain presence and duration of absence from a room at departure. This simplifies the calculations taking place, and the processing of inputs to No-MASS.

Using No-MASS in conjunction with EnergyPlus to perform a single simulation of the house described in this paper increases the simulation time by 50% relative to EnergyPlus simulating independently in conjunction with deterministic occupancy representations; but this relative increase varies depending on the choice of occupant behaviour models used and the number of occupants to be simulated. Simulating replicates carries a further computational penalty in proportion to the number of replicates, but this can be handled through hardware acceleration. We would argue that this manageably small cost is considerably more than offset by the additional information provided to evaluate the robustness of design solutions, given the likely distribution of predicted outcomes that replicated simulations provides.

The lack of variance between repeated simulations in this paper is due to a combination of the following factors: (i) the moderately performing buildings are located in temperate climates in which shading has a modest impact and window use is curtailed to some extent by the systems, (ii) in the residential case, the relative moderate impacts of occupants behaviours (and metabolic heat gains) in individual rooms is dampened at the whole house level, as results are normalised over the entire house footprint, (iii) exclusion of models of heating (indeed HVAC) system settings, hot water use, electrical appliances, (iv) exclusion of explicit modelling of behavioural diversity. More comprehensive models of diverse populations accommodated in buildings of higher performance located in more extreme climates would lead to considerably greater variance.

We show in a companion to this paper that we can readily change input coefficients for each model, allowing us to test multiple occupant use cases. This can be done automatically at each simulation iteration, enabling users to more fully explore the robustness of their design to uncertain future populations of occupants and the diversity in behaviours amongst members with similar characteristics.

We demonstrate in that paper how BDI rules and machine learning techniques can be employed to more comprehensively simulate agents' behaviour and how a social interaction framework can be employed to emulate negotiated decision making between agents, achieved through a vote casting process. Finally, in a second companion paper we show how No-MASS can simulate populations within multiple buildings and the modelling of interactions between different typologies (demand, storage and supply) of electrical devices and indeed the interactions between appliances and occupants within a smart grid context; resolving device to device interactions through a contract negotiation system and occupant to device interactions through BDI rules.

To improve the accessibility of No-MASS, the source code will be released at no-mass.io; and a prototype of No-MASS has already been integrated into the DesignBuilder graphical user interface to EnergyPlus. This will allow users to quickly set up their stochastic occupancy representations for future simulations with No-MASS, and enable them to take advantage of the simulation manager that allows for repeated simulations, either locally or in the cloud.

References

Andersen, Rune Vinther, Bjarne Olesen, and Jørn Toftum. 2007. "Simulation of the Effects of Occupant Behaviour on Indoor Climate and Energy Consumption." In *Proceedings of Clima 2007,* .

Andrews, Clinton J., Daniel Yi, Uta Krogmann, Jennifer A. Senick, and Richard E. Wener. 2011. "Designing buildings for real occupants: An agent-based approach." *IEEE Transactions on Systems, Man, and Cybernetics* 41 (6): 1077–1091.

Axelrod, Robert M. 1997. *The complexity of cooperation: Agent-based models of competition and collaboration.* Princeton University Press.

Axtell, Robert. 2000. "Why agents?: on the varied motivations for agent computing in the social sciences." *Center on Social and Economic Dynamics Washington, DC* .

Balmer, Michael, KW Axhausen, and Kai Nagel. 2006. "Agent-based demand-modeling framework for large-scale microsimulations." *Transportation Research Record: Journal of the Transportation Research Board* 4: 1–17.

Blight, Thomas S., and David A. Coley. 2013. "Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings." *Energy and Buildings* 66: 183–192.

Bonabeau, Eric. 2002. "Agent-based modeling: methods and techniques for simulating human systems.." In *Proceedings of the National Academy of Sciences of the United States of America,* Vol. 997280–7.

Bonte, Mathieu, Françoise Thellier, and Bérangère Lartigue. 2014. "Impact of occupant's actions on energy building performance and thermal sensation." *Energy and Buildings* 76: 219–227.

Bourgeois, Denis, Christoph Reinhart, and Iain Macdonald. 2006. "Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control." *Energy and Buildings* 38 (7): 814–823.

Bratman, Michael. 1987. *Intentions, Plans, and Practical Reason.* Harvard University Press.

Chapman, Jacob. 2017. "The University of Nottingham Multi-Agent Stochastic Simulation of Occupants in Buildings." Ph.D. thesis. The University of Nottingham.

Chapman, Jacob, Peer-olaf Siebers, and Darren Robinson. 2017. "Data Scarce Behavioural Modelling and the Representation of Social Interactions." *Unpublished manuscript* 1–48.

Chen, X, and F B Zhan. 2006. "Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies." *Journal of the Operational Research Society* 59 (1): 25–33.

D'Inverno, Mark, David Kinny, Michael Luck, and Michael Wooldridge. 1998. "A Formal Specification of dMARS." *Proceeding of International Workshop on Agent Theories, Architectures, and Languages* 155–176.

Epstein, Joshua M, and Robert Axtell. 1996. *Growing artificial societies: social science from the bottom up.* Brookings Institution Press.

Gill, Zachary M., Michael J. Tierney, Ian M. Pegg, and Neil Allan. 2010. "Low-energy dwellings: the contribution of behaviours to actual performance." *Building Research & Information* 38 (5): 491–508.

Gimblett, H Randy. 2002. *Integrating geographic information systems and agent-based modeling techniques for simulating social and ecological processes.* Santa Fe Institute studies in the sciences of complexity. Oxford University Press.

Gunay, H. Burak, William O'Brien, and Ian Beausoleil-Morrison. 2016. "Implementation and comparison of existing occupant behaviour models in EnergyPlus." *Journal of Building Performance Simulation* 9 (6): 567–588.

Haldi, Frédéric, and Darren Robinson. 2009. "Interactions with window openings by office occupants." *Building and Environment* 44 (12): 2378–2395.

Haldi, Frédéric, and Darren Robinson. 2010. "Adaptive actions on shading devices in response to local visual stimuli." *Journal of Building Performance Simulation* 3 (2): 135–153.

Haldi, Frédéric, and Darren Robinson. 2011a. "Modelling occupants' personal characteristics for thermal comfort prediction.." *International journal of biometeorology* 55 (5): 681–94.

Haldi, Frédéric, and Darren Robinson. 2011b. "The impact of occupants' behaviour on building energy demand." *Journal of Building Performance Simulation* 4 (4): 323–338.

Hong, Tianzhen, Simona D'Oca, William J N Turner, and Sarah C. Taylor-Lange. 2015a. "An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework." *Building and Environment* 1–14.

Hong, Tianzhen, Simona D'Oca, William J N Turner, Sarah C. Taylor-Lange, Yixing Chen, and Stefano P. Corgnati. 2015b. "An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema." *Building and Environment* 94: 196–205.

Hong, Tianzhen, Hongsan Sun, Yixing Chen, Sarah C. Taylor-Lange, and Da Yan. 2016. "An occupant behavior modeling tool for co-simulation." *Energy and Buildings* 117: 272–281.

ISO. 2005. *ISO 7730: Ergonomics of the thermal environment Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.* Vol. 3.

Jaboob, Said. 2015. "Stochastic Modelling of Occupants' Activities and Related Behaviours." Ph.D. thesis. The University of Nottingham.

Janssen, MA, and Elinor Ostrom. 2006. "Empirically based, agent-based models." *Ecology and Society* 11 (2).

Kashif, Ayesha. 2014. "Modélisation du comportement humain réactif et délibératif avec une approche multi-agent pour la gestion énergétique dans le bâtiment." Ph.D. thesis. Université Grenoble Alpes.

Langevin, Jared, Jin Wen, and Patrick L Gurian. 2014. "Including occupants in building performance simulation: integration of an agent-based occupant behavior algorithm with EnergyPlus.." In *Proceedings of Building Simulation Conference,* .

Liao, Chenda, Yashen Lin, and Prabir Barooah. 2012. "Agent-based and graphical modelling of building occupancy." *Journal of Building Performance Simulation* 5 (1): 5–25.

Maier, T., M. Krzaczek, and J. Tejchman. 2009. "Comparison of physical performances of the ventilation systems in low-energy residential houses." *Energy and Buildings* 41 (3): 337–353.

Nagel, Kai, RJ Beckman, and CL Barrett. 1999. "TRANSIMS for urban planning." In *Proceedings of Computers in Urban Planning and Urban Management,* .

Nouidui, TS, Michael Wetter, and Wangda Zuo. 2013. "Functional Mock-Up Unit Import in EnergyPlus For Co-Simulation." In *Proceedings of International Building Performance Simulation Association,* .

Page, J., D. Robinson, N. Morel, and J.-L. Scartezzini. 2008. "A generalised stochastic model for the simulation of occupant presence." *Energy and Buildings* 40 (2): 83–98.

Pigg, Scott, Mark Eilers, and John Reed. 1996. "Behavioral aspects of lighting and occupancy sensors in private offices: A case study of a university office building." In *Proceedings of ACEEE Summer Study,* 161–170.

Rao, Anand S, and Michael P Georgeff. 1995. "BDI agents: From theory to practice.." In *Proceedings of ICMAS95,* 312–319.

Reinhart, CF. 2004. "Lightswitch-2002: a model for manual and automated control of electric lighting and blinds." *Solar Energy* 77 (1): 15–28.

Robinson, Darren, and Frédéric Haldi. 2008. "Model to predict overheating risk based on an electrical capacitor analogy." *Energy and Buildings* 40 (7): 1240–1245.

Robinson, Darren, Urs Wilke, and Frédéric Haldi. 2011. "Multi Agent Simulation Of Occupants' Presence And Behaviour." In *Proceedings of building simulation,* .

Roetzel, A, A Tsangrassoulis, U Dietrich, and S Busching. 2011. "Context dependency of comfort and energy performance in mixed mode offices." *Journal of Building Performance Simulation* 4 (4): 303–322.

Sancho-Tomás, A., J. Chapman, M. Sumner, and D. Robinson. 2017. "On the generalisation of multi-agent stochastic simulation to study electrical demand response strategies." *IEEE Transactions on Sustainable Energy (in preparation)* .

Schweiker, Marcel, Frédéric Haldi, Masanori Shukuya, and Darren Robinson. 2012. "Verification of stochastic models of window opening behaviour for residential buildings." *Journal of Building Performance Simulation* 5 (1): 55–74.

Siebers, Peer-Olaf, and Uwe Aickelin. 2011. "A first approach on modelling staff proactiveness in retail simulation models.." *The Journal Of Artificial Societies And Social Simulation* 14 (2): 1–25.

Stewart, Robinson. 2004. *Simulation: the practice of model development and use.* John Wiley & Sons.

Vorger, Eric. 2014. "Etude de l'influence du comportement des habitants sur la performance énergétique du bâtiment." Ph.D. thesis. Ecole Nationale Superieure des Mines de Paris.

Wooldridge, Michael, and Nicholas R Jennings. 1995. "Intelligent agents: Theory and practice." *The knowledge engineering review* 10 (02): 115–152.

Zhang, Tao, Peer-Olaf Siebers, and Uwe Aickelin. 2011. "Modelling electricity consumption in office buildings: An agent based approach." *Energy and Buildings* 43 (10): 2882–2892.

Appendix A. EP Source code changes

EnergyPlus differences for allowing shading interactions.

```
--- EnergyPlus/src/EnergyPlus/DaylightingManager.cc
+++ EnergyPlusNoMass/src/EnergyPlus/DaylightingManager.cc
@@ -5744,7 +5745,10 @@
     }
+
+    if (SurfaceWindow(IWin).ShadingFractionEMSOn){
```

```
+     VTRatio = VTRatio * SurfaceWindow(IWin).ShadingFractionEMSValue;
+    }

--- EnergyPlus/src/EnergyPlus/SolarShading.cc
+++ EnergyPlusNoMass/src/EnergyPlus/SolarShading.cc
@@ -5180,6 +5197,16 @@
      CosInc = CosIncAng( TimeStep, HourOfDay, SurfNum2 );
      SunLitFract = SunlitFrac( TimeStep, HourOfDay, SurfNum2 );

+     //! Set trans to shading fraction
+     //! EMS Actuator Point: override setting if ems flag on
+     if (SurfaceWindow(SurfNum).ShadingFractionEMSOn){
+      SunLitFract = SunLitFract -
+            ( 1 - SurfaceWindow(SurfNum).ShadingFractionEMSValue);
+      if(SunLitFract < 0.0){
+       SunLitFract = 0.0;
+      }
+     }
+

@@ -9534,6 +9563,89 @@

+ voidComputeWinShadeAbsorpFactorsFor(int SurfNum)
+ {
+  int WinShadeCtrlNum; // Window shading control number
+
+  int ConstrNumSh; // Window construction number with shade
+  int TotLay; // Total layers in a construction
+  int MatNumSh; // Shade layer material number
+  Real64 AbsorpEff;
+  // Effective absorptance of isolated shade layer (fraction of
+  //  of incident radiation remaining after reflected portion is
+  //  removed that is absorbed
+
+  if ( Surface( SurfNum ).Class == SurfaceClass_Window
+         && Surface( SurfNum ).WindowShadingControlPtr > 0 ) {
+   WinShadeCtrlNum = Surface( SurfNum ).WindowShadingControlPtr;
+   if ( WindowShadingControl( WinShadeCtrlNum ).ShadingType
+                == WSC_ST_InteriorShade
+      || WindowShadingControl( WinShadeCtrlNum ).ShadingType
+                == WSC_ST_ExteriorShade
+      || WindowShadingControl( WinShadeCtrlNum ).ShadingType
+                == WSC_ST_BetweenGlassShade ) {
+    ConstrNumSh = Surface( SurfNum ).ShadedConstruction;
+    TotLay = Construct( ConstrNumSh ).TotLayers;
+    if ( WindowShadingControl( WinShadeCtrlNum ).ShadingType
+                 == WSC_ST_InteriorShade ) {
+     MatNumSh = Construct( ConstrNumSh ).LayerPoint( TotLay );
+    } else if ( WindowShadingControl( WinShadeCtrlNum ).ShadingType
+                 == WSC_ST_ExteriorShade ) {
+     MatNumSh = Construct( ConstrNumSh ).LayerPoint( 1 );
+    } else if ( WindowShadingControl( WinShadeCtrlNum ).ShadingType
```

```
+                      == WSC_ST_BetweenGlassShade ) {
+       if ( Construct( ConstrNumSh ).TotGlassLayers == 2 ) {
+        MatNumSh = Construct( ConstrNumSh ).LayerPoint( 3 );
+       } else {
+        MatNumSh = Construct( ConstrNumSh ).LayerPoint( 5 );
+       }
+     }
+     //! Set trans to shading fraction
+     //! EMS Actuator Point: override setting if ems flag on
+     if (SurfaceWindow(SurfNum).ShadingFractionEMSOn){
+      Material(MatNumSh).Trans =
+             SurfaceWindow(SurfNum).ShadingFractionEMSValue;
+     }
+
+     AbsorpEff = Material( MatNumSh ).AbsorpSolar /
+                          ( Material( MatNumSh ).AbsorpSolar
+        + Material( MatNumSh ).Trans + 0.0001 );
+     AbsorpEff = min( max( AbsorpEff, 0.0001 ), 0.999 );
+     SurfaceWindow( SurfNum ).ShadeAbsFacFace( 1 ) =
+         ( 1.0 - std::exp( 0.5 * std::log( 1.0 - AbsorpEff ) ) ) / AbsorpEff;
+     SurfaceWindow( SurfNum ).ShadeAbsFacFace( 2 ) =
+             1.0 - SurfaceWindow( SurfNum ).ShadeAbsFacFace( 1 );
+   }
+  }
+
+ }


--- EnergyPlus/src/EnergyPlus/WindowManager.cc
+++ EnergyPlusNoMass/src/EnergyPlus/WindowManager.cc
@@ -2886,6 +2890,9 @@

    if ( ShadeFlag == IntShadeOn || ShadeFlag == ExtShadeOn
      || ShadeFlag == IntBlindOn || ShadeFlag == ExtBlindOn
      || ShadeFlag == BGShadeOn || ShadeFlag == BGBlindOn
      || ShadeFlag == ExtScreenOn ) {
     nglfacep = nglface + 2;
+
+    EnergyPlus::SolarShading::ComputeWinShadeAbsorpFactorsFor(SurfNum);
+
     ShadeAbsFac1 = SurfaceWindow( SurfNum ).ShadeAbsFacFace( 1 );
     ShadeAbsFac2 = SurfaceWindow( SurfNum ).ShadeAbsFacFace( 2 );
     AbsRadShadeFace( 1 ) = ( SurfaceWindow( SurfNum ).ExtBeamAbsByShade +
      SurfaceWindow( SurfNum ).ExtDiffAbsByShade ) * ShadeAbsFac1 +
      ( SurfaceWindow( SurfNum ).IntBeamAbsByShade +
      SurfaceWindow( SurfNum ).IntSWAbsByShade ) * ShadeAbsFac2;
```