COUPLING MULTI-AGENT STOCHASTIC SIMULATION OF OCCUPANTS WITH BUILDING SIMULATION

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ABSTRACT

One of the principle causes for deviations between predicted and simulated performance of buildings relates to the stochastic nature of their occupants: their presence, activities whilst present, activity-dependent behaviours and the consequent implications for their perceived comfort. A growing research community is active in the development and validation of stochastic models addressing these issues; and considerable progress has been made. But one key outstanding challenge relates to the integration of these emerging prototype models with building simulation in a coherent and generalizable way; meaning that emerging models can be integrated with a range of building simulation software. One promising approach is to integrate stochastic occupancy models within a multi agent simulation (MAS) platform, which communicates directly with building simulation software. This paper describes one such example.

INTRODUCTION

Deviations between the predicted and simulated performance of buildings have lead to the development of models addressing the stochastic nature of occupants behaviours: their presence, activities whilst present, activity-dependent behaviours and the consequent implications for their perceived comfort - see Robinson et al (2011) for a review of progress.

To capitalise on the value of these models they should be integrated with building performance simulation software, such as EnergyPlus or ESP-r. Achieving this in a coherent and generalised way is important if these models are to gain widespread use in an industry which continues to use outdated methods to support building design.

But we are not starting from scratch here. Several attempts have been employed in the past to integrate behavioural models with building performance simulation software. These range from hard coded integration in the case of lighting behaviour models in Reinhart's (2004) lightswitch2002 algorithm and Haldi and Robinson's (2011) integration of window and blind models into CitySim, to Bourgeois et al's (2006) integration of lighting and blind models with ESP-r via their SHOCC platform. Although these efforts have usefully demonstrated the impact of stochastic behaviours (and models of them) on building performance, they lack generality. The approaches adopted are software specific and do not support more complex features such as: the definition of archetypes and archetypal behaviours, interactions between members of a population and behaviours that are conditional on other behaviours having already been exercised or indeed on proximity of the member of the population to the behavioural mechanism (e.g. the window).

With the objective of addressing these and other issues our approach is to use Multi-agent simulation (MAS); to combine stochastic models into a single package that can be used to support building performance simulation using a range of software.

Multi-agent simulation is a tool that has developed in the social sciences field to effectively model human interaction (Bonabeau, 2002; Zhang, Siebers, & Aickelin, 2011). Agents are implemented as objects in software, each agent has rules and behaviours making them excellent at modelling group and individual interactions (Axtell, 2000).

Agent based simulation in the social sciences has typically been used to study behaviours that emerge from bottom up interactions, allowing the creator to make judgements to what has caused them. It is important that the results have a high degree of certainty and therefore that agents' rules and behaviours are grounded with data based on reality (Gimblett, 2002). In recent years there has thus been a move from models based on social theoretical rules and behaviours, to those derived from observation (Janssen & Ostrom, 2006). By using stochastic models of occupant behaviour previously developed it is possible to predict agent behaviours based on solid empirical evidence.

To this end, models of occupants' activities (Jaboob and Robinson, 2014), metabolic heat gains, use of windows (Haldi & Robinson, 2009) and shading devices (Haldi & Robinson, 2010a) have been integrated within a bespoke MAS framework that parses agents' characteristics to the EnergyPlus simulation program, which in turn parses environmental parameters to our MAS platform, to impact on future behaviours.

We describe this new framework (from population generation, through parameter assignment to simulation (pre and runtime)), demonstrate its utility through a case study of a residential building and discuss modelling capabilities that will be integrated in the future.

COMBINING AGENTS WITH BUILDING PERFORMANCE SIMULATION

Our evolving MAS platform is coded in C++ and is currently designed to interface with EnergyPlus, as its source code is freely available and it is comprehensively documented. EnergyPlus has been developed to allow for coupling with other software to extend its functionality.

In our case this means that we do not need to modify the source code directly. Instead we simply override its ability to interface with the building control virtual test bed (BCVTB). This allows our agent platform to define input/output variable schedules via the EnergyPlus configuration files. Environmental conditions are retrieved where needed, as inputs, for the prediction of actions an agent may perform. The consequences of these actions are then set back in EnergyPlus at the end of the time step.

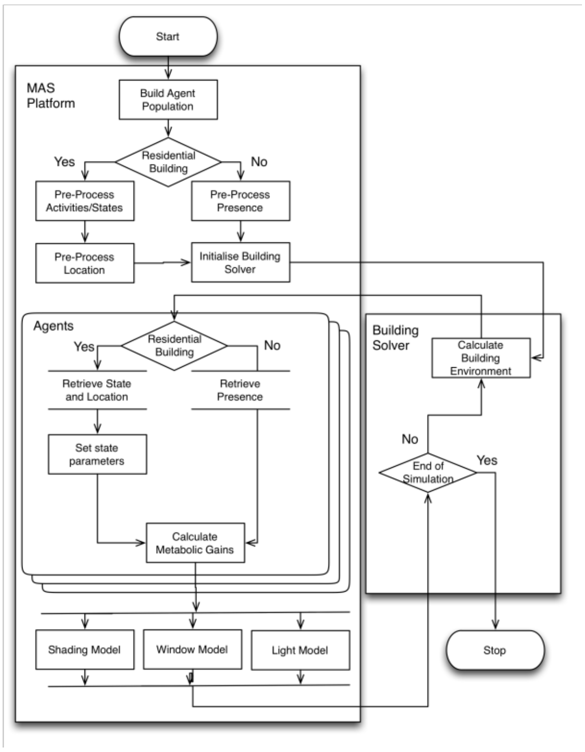

Figure 1 MAS Platform Flow Chart

The MAS platform follows the process in Figure 1. First an agent population is produced, at present our agents are assumed for simplicity to be adults that act independently, but whose activity choices may be influenced by household composition in the case of homes (e.g. couples may have different activity profiles than single adults living alone). A number of pre-processes are then executed. For residential buildings we model the activities that an agent may perform at each timestep and the locations they perform them in. These are stored for later use. In the case of non residential buildings, a separate presence model is used to calculate if an agent is present or not at each time step. Once complete EnergyPlus is called to simulate the building's energy flows. At the end of each timestep, our MAS platform is called using the modified BCVTB interface. This parses the environmental conditions that are needed to predict our agents' behaviours. Each agent is called independently. For residential buildings they retrieve the pre-processed state and activity for the present timestep and use these to set their location and to calculate their metabolic gains. In non residential buildings only the pre-processed presence is retrieved to calculate metabolic gains. Next our agents' interactions with shading, windows and lighting are predicted. 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. This process continues until the end of the simulation time.

Activity model

The activity model (Jaboob and Robinson, 2014) predicts the time-dependent probability that one of a set of ten 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. These activities are modelled as a Bernoulli process using multinomial logistic regression:

$$P(x,t) = \frac{\exp(A_j(x))}{\sum_{j=1}^{N} \exp(A_j(x))}, j = 1, \ldots, \mathrm{N} \quad (1)$$

and $$\mathrm{A_j(x)} = \alpha_j + \sum_{k=1}^{n} \beta_{jk} x_{jk} \quad (2)$$

where N corresponds to the total number of activities and n is the number of predictors x, each associated with a slope coefficient β, and α is the intercept. As the probabilities are only dependant on time it is possible to generate a matrix 10 by 24 giving the probability of performing each activity at a given hour.

Models can also be fit to subpopulations of the time use survey dataset from which they're derived, to give probabilities that depend say on age, employment status, season or day of the week.

At present our MAS platform offers a choice of three submodels depending on the type of individual; adult with children, adult without children or retired adult (we have not yet fit a submodel for children's activities). This model is pre-processed, assigning a state to each timestep within the simulation. This is achieved by drawing a random number for each timestep for each agent. Where that number falls within the vector 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 for the simulation of non-residential buildings for which the corresponding time use survey date is not available.

Table 1
Agent states with corresponding locations and values

STATE	LOCATION	CLO	METABOLIC RATE (W/M2)
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

Agent States

During a simulation our (residential) agents are assigned one of ten activity-dependent states. A state machine is then used to modify the values of certain state-dependent parameters: Table 1. In future research we plan to expand on these and give different values depending on the agent archetype e.g. retired, adult without children. These values are taken from ISO 7730.

In the case of the more constrained environments of non-residential buildings we set metabolic rate to 116 and Clo to 1.

Presence and Location

We have two methods for calculating presence within a building. We can choose which to use depending on the type of building. For the simulation of non-residential buildings a presence model (Page et al., 2008) predicts when an occupant is present within an office, based on an inhomogenous Markov chain, using a mobility parameter μ and a time-dependent profile of the probability of presence P(t) as input.

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. These are deduced by calculating the transition probability at each time step, either from absent to present:

$$T_{01}(t) = \frac{\mu-1}{\mu+1} \cdot P(t) + P(t+1) \qquad (3)$$

Or present to present:

$$T_{11} = \frac{P(t)-1}{P(t)} \cdot \left[\frac{\mu-1}{\mu+1} \cdot P(t) + P(t+1)\right] + \frac{P(t+1)}{P(t)} \qquad (4)$$

Where the constant mobility parameter $\mu = 0.11$. The other two transitions, present to absent and absent to absent are simply $T_{10} = 1 - T_{11}$ and $T_{00} = 1 - T_{01}$.

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 they are in the bedroom. This may not hold true for occupants with the profile retired in which case if they are asleep during the day they may be asleep in the living room. Thus we may in the future need archetype-dependent assignment probabilities.

To allocate agents to a zone within EnergyPlus we define an external schedule of occupancy for each zone in EnergyPlus's configuration file. EnergyPlus then assumes that a value for each schedule will be received by its external interface at each time step.

Metabolic gains

Metabolic gains are calculated using Fanger's PMV model, as described in the algorithm described in ISO 7730 and based on the standard physical (air temperature, radiance 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 m/s, the physical parameters are supplied by EnergyPlus, whereas the state-dependent personal parameters are as defined in table 1 (external work is 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 it by the number of present occupants to determine the total metabolic gains for all occupants.

Window Actions

We use the model of Haldi and Robinson (2009) to predict interactions with windows. This 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 windows stays open using a Weibull distribution. At each time step transition probabilities in window opening state, from i to j (i, j= 0,1) are calculated using logistic models of the form:

$$P_{ij}(x_1, \dots, x_n) = \frac{\exp(\alpha + \sum_{k=1}^{n} \beta_\kappa x_\kappa)}{1 + \exp(\alpha + \sum_{k=1}^{n} \beta_\kappa x_\kappa)} \qquad (5)$$

The predictors x, which include indoor, outdoor and daily mean outdoor temperature as well as the occurrence of rain, are supplied by EnergyPlus. The agent side supplies the occupants' presence as well as the future presence and past absence durations. The parametric Weibull distribution of window opening survival time has shape log(1/ α) = 0.871 and scale:

$$\lambda = 1/\exp(a + b\theta_{out}) \qquad (6)$$

where a = 2.213, b = 0.1727 and θ_{out} is outdoor temperature supplied by EnergyPlus.

At a given time-step we determine whether a zone is unoccupied. If so, the window opening status is unchanged; otherwise five further cases are considered:

1) If the occupant arrives and window is closed we draw a random number.

1a) If this is greater than probability for opening we keep window closed.

1b) If the random number allows opening we calculate a duration from the Weibull distribution. If this duration is less, then for each time-step we keep the window closed, if greater, we set the window to open.

2) If the occupant arrives and the window is open we draw a random number from our Weibull distribution and follow the same steps as in case 1b.

3) For intermediate presence a random number is drawn from a uniform distribution and if this is greater than the probability for opening, we keep the window closed. Otherwise, a random number is drawn from the Weibull distribution and step 1b is implemented.

4) If there is intermediate presence and the window is open, we decrement the opening duration. If this becomes less than a time-step we set window to closed, otherwise it remains open.

5) If occupants vacate the zone, we calculate the probability of either an opening or closing depending on current state. A random number is drawn, if this is within the probability of performing the action, the action is performed; otherwise state is left in the current state.

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 we will include predictions of opening proportion).

External Shading Actions

The shading action model (Haldi & Robinson, 2010b) predicts lowering and raising probabilities, which are also based on Markov chains. The first step in this model is to determine the probability with which a raising or lowering action will take place:

$$P_{act}(E_{in}, B_L) = \frac{\exp(a+b_{in}E_{in}+b_L B_L)}{1+\exp(a+b_{in}E_{in}+b_L B_L)} \quad (7)$$

Where Ein is the indoor illuminance supplied by EnergyPlus, at a suitable daylight reference point within the zone. BL is the unshaded fraction at the previous time-step, a and bL are parameters taken from Haldi & Robinson, (2010b).

We then predict if the blind is fully raised or closed:

$$P_{full\ act}(E_{gl,hor}, B_L) = \frac{\exp(a+b_{out}E_{gl,hor}+b_L B_L)}{1+\exp(a+b_{out}E_{gl,hor}+b_L B_L)} \quad (8)$$

With Egl,hor as the outdoor global horizontal illuminance, also supplied from EnergyPlus. If the blinds are only partially raised or lowered, their fractions are drawn from a Weibull distribution:

$$f(\Delta B) = \lambda\alpha(\lambda\Delta B)^{\alpha-1}\exp(-(\lambda\Delta B)^{\alpha}) \quad (9)$$

with α=1.708 and

$$\lambda = \frac{1}{\exp(-2.294+1.522B_{L,init})} \quad (10)$$

For the blind calculation, we again take an aggregate view of the agent population. If there is an arrival in the zone, we calculate whether the external blind will be lowered. If so, we calculate the shading fraction (full or partial). If not, we calculate whether a raising action will occur and the corresponding new shaded 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 opening fraction in EnergyPlus, defined as the shading control schedule.

Lighting

The prediction of lights within the MAS Platform is achieved with the lightswitch2002 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. The probabilities are calculated as:

$$P = a + c/(1 + \exp[-b(\log 10\,(E) - m)]) \quad (11)$$

where for arrival a = -.0175, b = 4.0835, c = 1.0361, m = 1.8223 and while present a = 0.0027, b = 0.017, c = -64.19 and m = 2.41. When all agents vacate the zone we predict if the lights will be turned off, as a function of the duration of their absence, determined by our presence model as a pre process. The probability of turning the lights off on departure is set for a duration of absence below 30 mins, 1 hour, 2 hours, 4 hours and 12 hours to 0.08, 0.31, 0.38, 0.60 and 0.96 respectively. Any time over 12 hours and the lights are assumed to be turned off (Pigg 1995).

The consequent lighting status (on-off) is set within EnergyPlus at each timestep as a lighting schedule for each zone within the building.

CASE STUDY

To demonstrate the application of this new MAS framework, coupled with EnergyPlus, we examine two simple case studies: a hypothetical house and a shoe box office. In this we simulate 50 replicates using our MAS framework and compare the results with those arising from standard deterministic schedules and rules for the relevant house/office typology (or template) used by the design builder interface. All simulations are annual.

The layout of the residential building and the non-residential building are depicted in Figure 2. To keep things simple they both have the design properties in Table 2 and construction material properties in Table 3. They are located in Nottingham with the weather file taken from the Design Builder software giving the location to be Finningly, UK (+53°28', -1°0').

Table 2
U Values

LOCATION	U-VALUE (W/M2.K)
External wall	0.37
Internal Partition	2.86
Pitched Roof	4.97
Floor / Attic Floor	0.26

This study focuses on the energy required to heat the building (so that cooling is not activated), using Design Builder's default set point schedules (see tabel 4). We set the infiltration rate to 0.7(ac/h) for all zones, except the attic where we use 1(ac/h).

With the multi-agent platform we need to define the agents that will occupy the building and their activity-dependent states and corresponding properties (see above). The simulation is performed according to the flow diagram in figure 1.

RESULTS

For the residential building the MAS predicts a median annual heating energy demand of 59.0kWh/m2, as compared with 68.7kWh/m2, in the case of deterministic people simulations; an increase of 16%. For the non-residential building the corresponding annual heating energy demands are 62.4kWh/m2 and 91.0kWh/m2 respectively: an increase of 45%.

The density plots of watts show similar trends between the MAS platform and the deterministic simulation, with a peak towards 0 watts, due to summer months having no heating demand (figure 5). In both cases the MAS platform the densities at the zero are much higher than the deterministic results. Breaking the results into monthly box plots (Figures 3 & 4), the average output is consistently lower for the multi agent simulation for both buildings. The results from the house have less variance over the replicates than that of the office. The greatest contribution to variance between results is the window model. Windows are seldom used within the house (figure 6), the window model lacks two key influences humidity and air quality, resulting in artificially low opening probabilities in the winter. The blinds, though used, have a weak impact on the building's heat balance; presumably because the solar gain is small compared to the overall heat demands.

FUTURE WORK

Our immediate next steps are to consolidate the existing modelling capability. First, the activity model should be adapted to support the modelling of a wider range of subpopulations and procedures to assign the relevant archetypal household composition; perhaps based on economic factors such as job, education level and salary earned. These are likely to change the agents' activity profiles and associated behaviours.

On a related note, the ePad group at Nottingham is currently developing models of electrical appliance ownership and usage (the former also depending upon household composition and related economic factors). This model will enable us to more faithfully predict electrical energy demands and the corresponding implications on heating and cooling demands

With the basic energy modelling capability complete, we will proceed to acquire data on residential energy use, to compare predicted with observed energy performance. We will also conduct a comprehensive analysis of the sensitivity of predicted outcomes of changes to model parameters and uncertainties in the inputs to them.

Looking further to the future, we will integrate procedures to represent interactions between agents and responses to stimuli destined to bring about behavioural change; in particular with respect to more frugal energy usage.

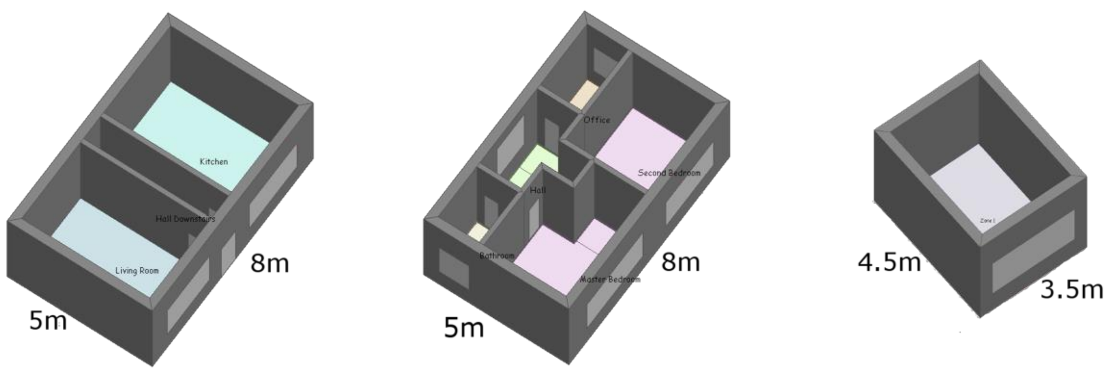

Figure 2 (left) Residential ground floor (middle) Residential 1st floor (Right) Office - Not To Scale

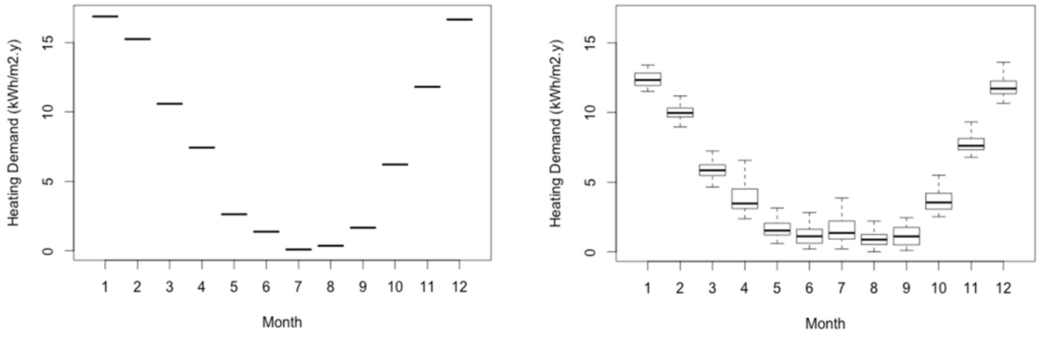

Figure 3 Office monthly heating demand box plots (left) Single deterministic (right) MAS Platform 50 replicates

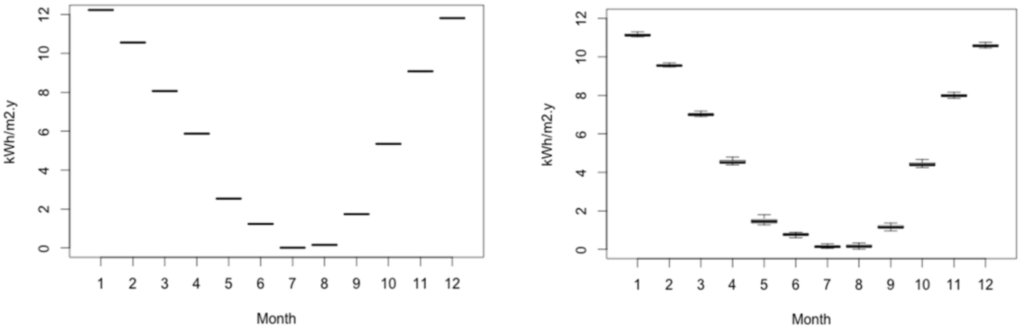

Figure 4 House monthly heating demand box plots (left) Single deterministic (right) MAS Platform 50 replicates

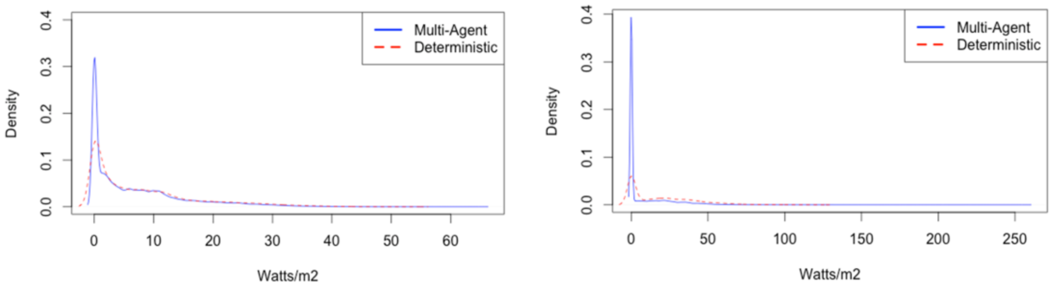

Figure 5 Heating demand density plots (left) house (right) office

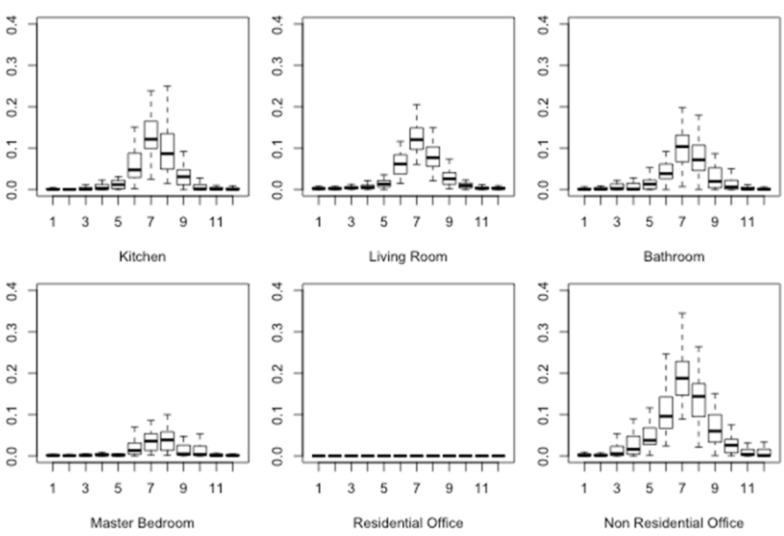

Figure 6 Probability of window open in each zone for each month

Table 3
Construction Materials

LOCATION	LAYER	THICKNESS (M)	MATERIAL	LOCATION	LAYER	THICKNESS (M)	MATERIAL
External Wall	Outer	0.1	Brick	Internal Partition	Outer	0.02	Gypsum Plaster
External Wall	2	0.07	XPS extruded	Internal Partition	2	0.1	Air Gap
External Wall	3	0.1	Concrete Block	Internal Partition	Inner	0.02	Gypsum Plaster
External Wall	Inner	0.01	Gypsum Plaster	Floor	Outer	0.025	External Rendering
Ground Floor	Outer	0.13	Urea Formaldehyde Foam	Floor	2	0.14	MW Stone Wool (Rolls)
Ground Floor	2	0.1	Cast Concrete	Floor	Inner	0.005	Timber Flooring
Ground Floor	3	0.07	Floor Screed	Pitched Roof	Outer	0.02	Clay Tile
Ground Floor	Inner	0.03	Timber Flooring	Pitched Roof	2	0.02	Air Gap
				Pitched Roof	Inner	0.005	Roofing Felt

Table 4
Zone Details

	AREA [M2]	VOLUME [M3]	GROSS WALL AREA [M2]	GLAZING RATIO %	LIGHTING [W/M2]	SETPOINT TEMP [C]
LIVINGROOM	13	46	36	7	7.5	21
HALLDOWNSTAIRS	4	15	6	0	5	20
KITCHEN	15	52	39	8	15	20
BATHROOM	3	10	12	11	7	20
HALL	4	19	10	0	5	20
RESIDENTIAL OFFICE	3	12	13	10	5	20
SECONDBEDROOM	9	34	22	15	5	20
MASTERBEDROOM	10	37	24	16	5	20
ATTIC	37	26	7	0	0	-
Total	101	255	172	68	5	
NON RESIDENTIAL OFFICE	11	39	47	6	20	22

CONCLUSION

The Purpose of this paper was to outline a framework in which multi-agent simulation is used to integrate stochastic models of people coupled with a building performance simulation environment such as EnergyPlus. We suggest that the stochastic simulation of occupants' presence, activities and behaviours provides for a coherent and rigorous basis for representing occupancy in building simulation, to reduce the gap between observation and prediction.

The deviation between predicted median indoor temperature and heating energy are considerable. It might be argued this is in part because we are not comparing like with like: the deterministic rules are schedules do not derive from the probabilistic models. They do however represent current practice and the stochastic models are based on observed behaviours in real buildings and have been carefully cross validated. It would seem that the scale of this deviation is cause for concern and supports the urgent need to provide access to stochastic models to the building simulation user community. We suggest that a coherent, general and extensible way of achieving this is through MAS of the like presented in this paper.

At present, our platform models presence, activities, location, activity-dependent metabolic gains and interactions with windows, blinds and lights. In the future this platform will be extended to model water usage, electrical appliance usage, and heating/cooling set point interaction as well as interactions amongst members of the agent population.

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