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Coupling stochastic occupant models to building performance simulation using the discrete event system specification formalism

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When applying occupant models to building performance simulation (BPS), it is common practice to use a discrete-time approach requiring fixed time steps. Consequently, a simulated occupant's decisions do not increase in frequency in response to rapid changes in environmental conditions. Furthermore, as illustrated in this study through the analysis of a discrete-time EnergyPlus simulation, changing the time step between simulation runs may have a dramatic effect on BPS predictions. It is therefore necessary to adhere to a prescribed time step, which may complicate the synchronization of events when models of different domains are coupled. The main contribution of this study is an investigation of the viability of employing the discrete event system specification (DEVS) formalism to represent occupant behaviour without fixed and prescribed time steps. Results indicate that using an adaptive time advancement scheme, the DEVS formalism permits realistic patterns of decision-making while facilitating the coupling of stochastic occupant models with thermal and heating, ventilation and air-conditioning models.

Keywords: occupant behaviour; stochastic occupant model; discrete event system specification; adaptive time stepping; building performance simulation; manual control of occupant

1. Introduction

Approximately 40% of the total energy produced in North America is consumed by residential and commercial buildings (DOE 2012). It is reported by NRCan (2010) that nearly 60% of the total energy consumption of buildings in Canada can be attributed to space heating and cooling. Building performance simulation (BPS) is a powerful analysis tool for predicting buildings' energy performance and thermal comfort. It represents significant potential for optimizing design such that substantial energy and operating cost savings can be achieved with little, if any, additional capital cost. Clarke (2012) estimated these savings to be as high as 50–75% in new buildings and 30% in existing buildings relative to 2000 levels; however only a marginal change in building energy-use statistics was reported in the last decade (NRCan 2010).

1.1. Research potential

BPS, despite the aforementioned potential for significant improvements in energy use and indoor environment, has often been undermined with predictions that do not fully represent actual performance (Cole and Brown 2009; Hopfe 2009). Some of these discrepancies can be attributed to deviations from standard weather data (Hong, Chang, and Lin 2013), modelling and simulation simplifications (Macdonald 2002), occupancy profiles (Page et al. 2008; Wang, Yan, and Jiang 2011; Hong and Lin 2013), unanticipated control behaviour, and material/workmanship-related uncertainties. However, the uncertainty introduced by occupant behaviours are undeniable (Bourgeois, Reinhart, and Macdonald 2005; Hoes et al. 2009; Tanimoto et al. 2013). At the whole building scale, occupants' impact on building energy-use accounts for about an uncertainty of 20% (Parys, Saelens, and Hens 2011) and the energy use in identical units, particularly residential units, occupied with different occupants can vary by as much as 200–300% (Lutzenhiser, Hackett, and Schutz 1987; Lutzenhiser 1993). Occupants often adapt their environment (e.g. by opening a window, lowering a blind, switching-on lights) and/or adapt to their environment (e.g. by taking-off a layer of clothing, drinking a hot/cold beverage) to maintain their comfort (Baker and Standeven 1996; Nicol 2001; Rijal et al. 2007). These adaptive behaviours, aside from their impact on comfort, often have significant impacts on energy use. Therefore, a major task for building designers is to foresee these occupant behaviours and to adapt their designs accordingly. For example, a concrete floor may be covered by a carpet or hardwood flooring if an occupant finds the sensation of

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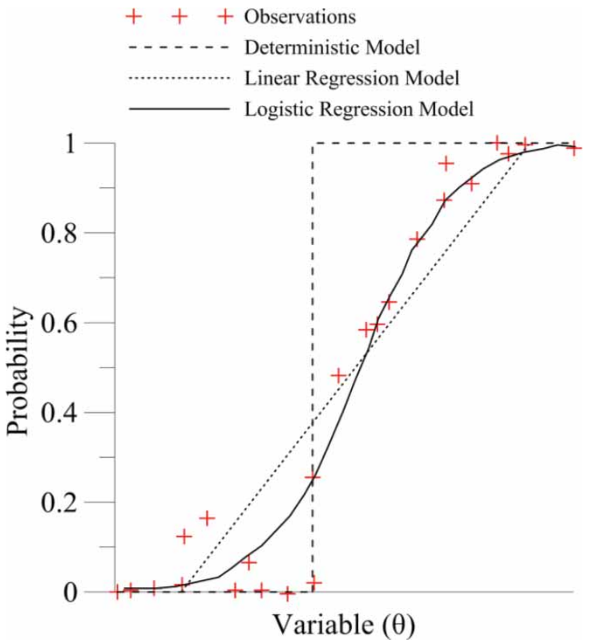

Figure 1. Generic univariate deterministic, linear regression, and logistic regression occupant models representing the probability of undertaking an adaptive behaviour or observing an adaptive state at a particular position.

cold feet too uncomfortable. Similarly, blinds may be left closed by an occupant to avoid excessive glare in a house designed to benefit from solar gains (Gunay, O'Brien, and Beausoleil-Morrison 2013). Failure to consider these simple alterations can lead to inaccurate or misleading BPS predictions and ultimately poorer performing buildings.

1.2. *Background on occupant behaviour models and simulation approaches*

Recognizing the significance of adaptive occupant behaviours, numerous researchers (Lee and Selkowitz 1994; Newsham 1994; Goller 1998; Reinhart and Voss 2003; Reinhart 2004; Inkarojrit 2005; Rijal et al. 2007; Yun and Steemers 2007; Herkel, Knapp, and Pfafferott 2008; Inkarojrit 2008; Haldi and Robinson 2009; Dutton and Shao 2010; O'Brien et al. 2010b; Zhang and Barrett 2012b) carried out observational studies (e.g. time-lapse photography or sensory data logging) to reveal the stimuli (e.g. indoor temperature, transmitted solar radiation) that lead to a particular adaptive behaviour (e.g. opening a window). These observations on the states (e.g. window open/closed), once plotted with respect to the monitored variables (e.g. indoor temperature) resulted in data scatter, as shown in Figure 1. Early researchers (Newsham 1994; Lee and Selkowitz 1994; Goller 1998) and most of the current practitioners used deterministic models to predict the adaptive occupant behaviours. These models are simple enough to be easily incorporated in the BPS-based design process and design recommendations such as ASHRAE (2010). For example, in these models the probability of an occupant being uncomfortable below the defined threshold value is zero and the probability becomes one just after the predictor variable or variables reach the threshold value, as shown in Figure 1. A visual comparison between the data scatter and the probability curve, which is a step function, shows that a deterministic model cannot represent the observed adaptive occupant behaviour shown in Figure 1. Nicol (2001) explained that occupants' adaptive behaviours, despite being clearly influenced by the physical conditions, are governed by a stochastic rather than a precise relationship. Stochastic models estimate an adaptive behaviour by assuming a probabilistic relationship with the predictor variable or variables. Although some of the researchers (Warren and Parkins 1984; Inoue et al. 1988; Foster and Oreszczyn 2001; Inkarojrit and Paliaga 2004) employed linear-response models (e.g. linear or polynomial regression), these failed to predict the upper and the lower bounds of the observations as shown in Figure 1. Generalized linear models (e.g. logistic regression or probit) cover such cases by letting response variables have non-normal distributions. In generalized linear models, a linking function (e.g. logit function) of the response variable is a linear function of the predictor variables. Currently numerous researchers (Nicol 2001; Clarke, Macdonald, and Nicol 2006; Rijal et al. 2007; Haldi and Robinson 2008, 2009, 2010, 2011a; Inkarojrit 2008; Rijal et al. 2008; Zhang and Barrett 2012a, 2012b) accept that logistic or probit regression models are appropriate for estimating the probability of an adaptive occupant behaviour with respect to predictor variables. To apply these stochastic models, researchers (Fritsch et al. 1990; Reinhart 2004; Pfafferott and Herkel 2007; Haldi and Robinson 2008, 2009; Rijal et al. 2008; Hoes et al. 2009; Parys, Saelens, and Hens 2011; Zhang and Barrett 2012a, 2012b; Smires et al. 2012) sought algorithms and formalisms to simulate occupant models dynamically with the building and heating, ventilation and air-conditioning (HVAC) domains. In the reviewed literature, models for adaptive occupant behaviours were typically simulated as random processes, in particular Bernoulli or Markov processes (Fritsch et al. 1990; Reinhart 2004; Pfafferott and Herkel 2007; Rijal et al. 2008; Haldi and Robinson 2009; Hoes et al. 2009; Haldi 2010; Parys, Saelens, and Hens 2011; Zhang and Barrett 2012a, 2012b; Smires et al. 2012). A Bernoulli process is a memoryless process represented as a sequence of independent binary random variables such that current state has no impact on future state. Occupant behaviour models simulated as a Bernoulli process provides the probability of finding a state in a particular position (e.g. 60% of the windows will be open at 27°C) rather than the probability of a state transition (e.g. there is a 60% chance of opening the windows at 27°C). By contrast, a Markov process is a random process, given that the present state is specified, its past has no influence on the future (Papoulis 2002). Occupant behaviour models simulated as Markov

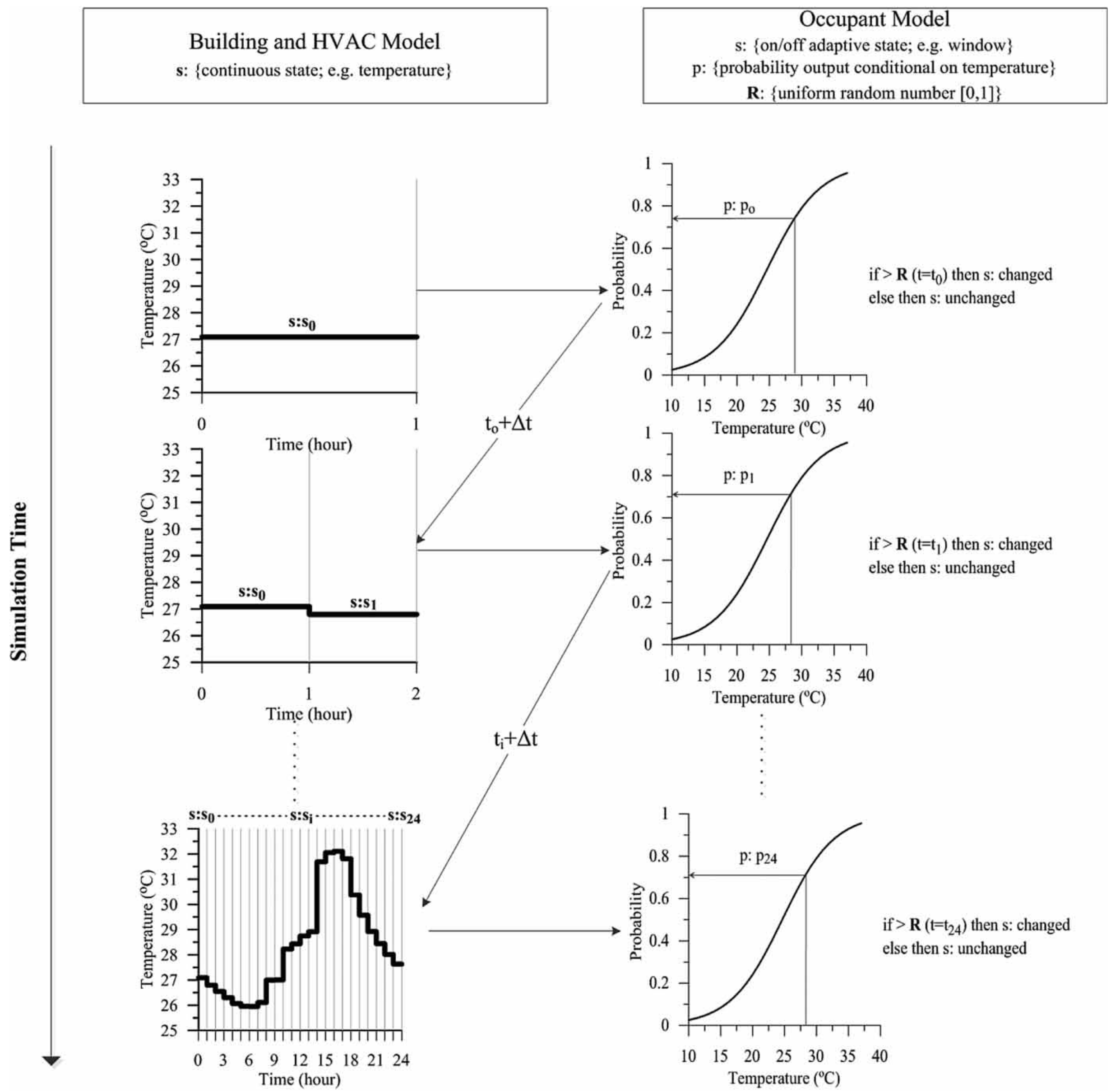

Figure 2. Discrete-time simulation algorithm with a behavioural occupant model.

processes provide the probability of state transitions rather than the probability of finding a state in a particular position.

To integrate these simulation approaches in conventional BPS tools in which time advance in fixed time steps, these random processes were typically employed as discrete-time random processes. A simple and generic example of a discrete-time Markov process representing the simulation of a generic occupant behaviour model in tandem with a Building/HVAC model simulation output is illustrated as a flowchart in Figure 2. The HVAC and building model simulations perform calculations which output predictor variables such as indoor temperature. The occupant model estimates the probability that a particular behaviour will be undertaken or not, as shown in Figure 2. However, it is worth noting that it does not predict the time at which the active adaptive state (e.g. open window) will be reversed. In the meantime, a pseudo-random number is generated and compared with the probability that is estimated by the model. If the estimated probability exceeds the random number, the occupant undertakes the behaviour (e.g. opens the window). This is received as a message by the building model and time advances to the next time step. Haldi (2010) reported that these discrete-time approaches (Bernoulli and Markov processes) alone cannot truly simulate the dynamic realization of adaptive occupant behaviours and developed a hybrid approach: state transitions were predicted as Markov processes, while a continuous-time approach was employed to estimate the time to reversal of the adaptive state (Haldi and Robinson 2011b). For example, blinds closing behaviour can be realized as a Markov process and the duration blinds remained closed (i.e. the following instant of decision-making) can be estimated through a survival analysis. This was a notable recognition of the importance of determining the *instants of decision-making* (instants at which the Markovian state transitions occur) in occupant behaviour simulation via a continuous simulation approach.

1.3. Motivation

In traditional BPS tools (e.g. EnergyPlus), time advances in fixed time steps. These discrete-time simulations are well suited for continuous problems (e.g. heat transfer) that can be defined with an approximation of a partial differential equation (PDE). In other words, sampling the continuous field variable (e.g. temperature) at fixed time steps would be a reasonable approximation, if the time steps are short enough. However, occupant actions are discrete events that take place at irregular time instances. Using a discrete-time approach for a discrete-event problem is to assume that all events (e.g. window opening) will take place at these discrete-time instants (Robinson 2004). Haldi and Robinson (2009) and Parys, Saelens, and Hens (2011) acknowledged this limitation and stated that fixed time steps may cause a possible loss of information, redundant calculations, and most importantly, time-step-size dependent state transition predictions of the adaptive state which limits the applicability to cases with a prescribed time step. Thus, the discrete-time approach requires a stochastic occupant behaviour model to have a time step that is both *fixed*, meaning that it does not change during a simulation run, and *prescribed*, meaning that it must not change between runs or experiments. The issues related to the use of fixed and prescribed time steps can be summarized as follows. (1) Fixing the time step implies the frequency of an occupant's instants of decision-making remains constant; it is logical that these instants should increase in frequency during periods in which environmental conditions are rapidly changing. (2) More complex models may require occupants to respond immediately to prominent stimuli such as the activation of artificial lights, the opening of a nearby window, or the sounding of an alarm; with a discrete-time simulation, these responses must be postponed should the stimulus occur between time steps. (3) When coupling models for BPS, it is sometimes desirable to synchronize events occurring in different models; this becomes more difficult when a model's time step may not be altered. (4) Different simulation-based design applications require different levels of execution speed and temporal resolution; the use of prescribed time steps makes it more difficult to adjust the trade-off between speed and accuracy to suit a particular application. (5) Should a modeller choose to alter the time step of a stochastic discrete-time occupant simulation, the consequence may be a dramatic change in the BPS predictions.

Here, the adoption of a modular and continuous simulation formalism, namely the discrete event system specification (DEVS), is proposed as a potential solution. With DEVS, it is common practice to quantize state changes (e.g. 1°C change in temperature or 100 lx change in workplane illuminance) rather than quantizing the time elapsed in each state. As these quantized state changes can be applied to the predictor variables of occupant models, the time elapsed between decisions becomes a variable quantity that can be compared with observations. The decision-making mechanism of the occupants can be portrayed as 'It is getting warm in here, should I open a window?' instead of 'It has been 30 min since my last decision, should I open a window?'. In this way, continuous-time Markov Chains can be used to predict not only the probability of state transitions, but also the instants of decision-making.

1.4. Document structure

Section 2 provides a brief insight about the application of the DEVS formalism by comparing it with the discrete-time approach. In Section 3, adaptive occupant models used in the current study are presented by discussing their limitations and assumptions. In Section 4, the dependency of stochastic occupant behaviour models on the time-step-size, if simulated with a discrete-time procedure, is demonstrated through a sensitivity analysis on a generic coupled-building energy model. EnergyPlus v.7.2 is used to model a simple mixed-mode building (single-zone office space with an operable window) and a simple HVAC system (packaged terminal air conditioner); and the energy management system (EMS) application of EnergyPlus v.7.2 is used to build the stochastic occupant behaviour model. In Section 5, the viability of the DEVS formalism to improve the aforementioned drawbacks of the discrete-time random processes is investigated. A coupled-DEVS building energy model, which is composed of the building, HVAC, and occupant submodels, is established using a DEVS-based simulation prototype (Autodesk DesignDEVS v.0.4.1). To illustrate the modularity of the DEVS formalism, a building submodel, an HVAC system submodel, and a stochastic occupant submodel were developed independently as atomic models. These submodels were then linked with each other by defining the input/output relationships to demonstrate the overall response of the coupled-DEVS building energy model. In Section 6, the results of the current study are discussed, limitations/challenges are assessed and acknowledged by comparing them with the existing literature; concluding results are summarized and future work recommendations are developed. Supplementary results for the verification of DesignDEVS Building/HVAC models and for the verification of the time-step-size sensitivity in more detailed occupant models are provided in the appendix.

2. Discrete event system specification

The DEVS is a formalism for describing simulation models in a continuous and modular fashion (Zeigler, Praehofer, and Kim 2000). Although it has not yet been adopted by the building science community, it has been widely used in many other fields for the design, analysis, and implementation of complex systems. This section briefly outlines the application of the DEVS formalism by comparing it with the discrete-time approach. Detailed information about the theory of DEVS can be found elsewhere (Wainer 2010; Zeigler, Praehofer, and Kim 2000).

A DEVS model is either an atomic model or a coupled model. Figure 3(b) illustrates the simulation procedure of an atomic DEVS model. Simulation starts with the initial time (t_o) and state (s_o). In BPS, state can be, for example, a temperature array defined for all nodal points. Subsequently, the internal transition function (δ_{int}) computes the new state at the scheduled internal transition time (t_{int}). For example, an internal transition function in a building physics model may compute the time at which a presumed temperature change (i.e. discrete event) will occur and update the temperature array at that time instant. A major difference between the DEVS and discrete-time approaches is that time advances in a sequence of discrete events rather than a sequence of fixed time steps, as shown in Figure 3. For example, in EnergyPlus the state marches through time by recalculating model equations at each time step (DOE 2011). The model equations (e.g. energy balance) are typically solved with an approximation such that state and parameter properties remain constant in a given time step. In the discrete event approach this approximation prevails such that state and parameter properties remain constant in a given event step. In the following time or event step, the state and parameters are updated in accordance with the model equations. It should be noted that model equations in BPS are non-linear such that the parameters evolve in time as a function of the state in the solution domain and on the convective and radiative boundaries. Therefore, large time spacings between events should be avoided in discrete-time simulations (Ceylan and Meyers 1980). For example, the EnergyPlus adaptive time stepping algorithm for plant size simulation acknowledged this and introduced an upper limit (15 min) for the time-step-size (DOE 2011). The external transition function (δ_{ext}) defines how inputs from other models affect the state at an external transition time (t_{ext}). For example, if an occupant opens a window at t_{ext}, the external transition function (δ_{ext}) invokes the time advance function (*ta*) and determines the physical impact of opening the window on the heat transfer problem in the building model. If t_{ext} is earlier than t_{int}, time advances to t_{ext}. Otherwise, time advances to t_{int}. In other words, if occupant chooses to open the window at t_{ext} before the scheduled event time (t_{int}) – which may happen if, for example, if the adaptive behaviour is modelled as a survival model – the time advance function (*ta*) handles the discrepancy between t_{int} and t_{ext} and determines the time-span of the new state. Another major difference between the DEVS and the discrete-time approach is the separation of the physical

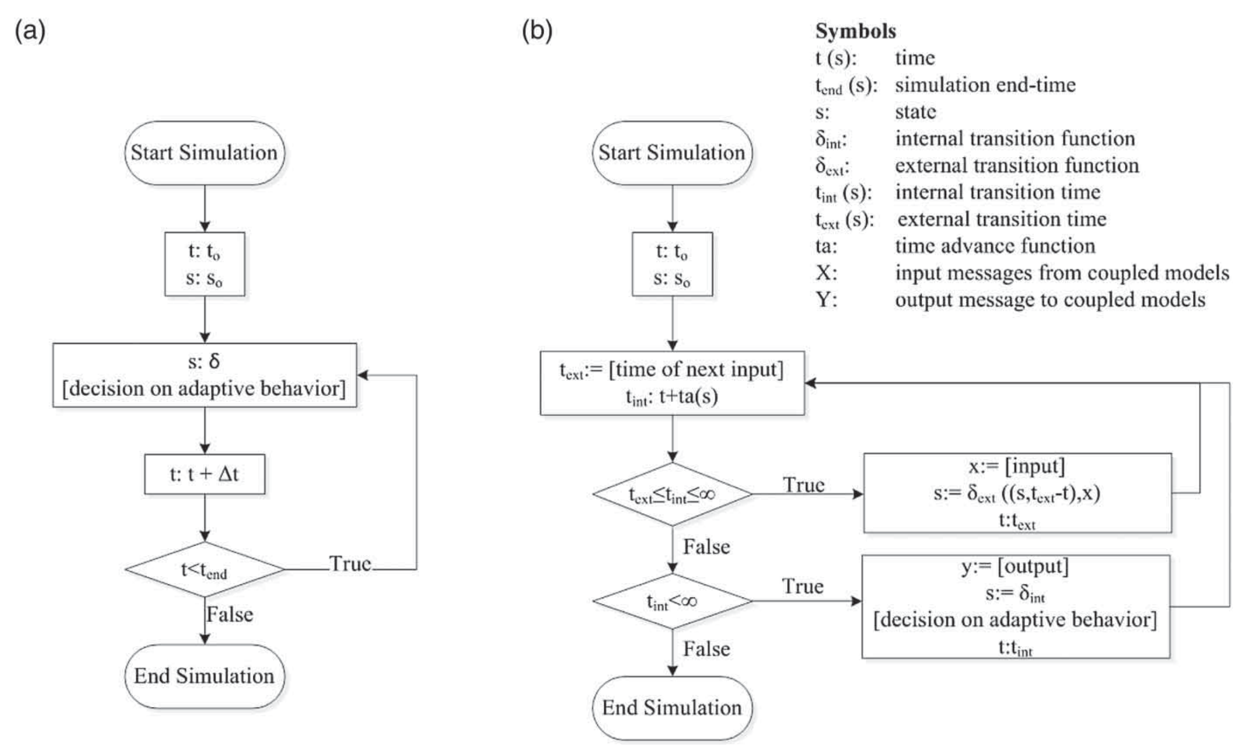

Figure 3. (a) Discrete time and (b) DEVS simulation procedure.

model (i.e. state transition functions) and simulator code (i.e. time advancement). The δ_{ext} and t_{ext} which supports the coupling of smaller models, does not exist in discrete-time formalism. This makes DEVS a modular formalism. The time advance function and the external and internal transition functions are the key elements of indivisible, or atomic, DEVS models.

The other type of DEVS model is the coupled model, which links submodels of either type; i.e. both atomic and coupled models. For example, the temperature calculated in a building model can be used to calculate the window opening probability; and the occupant's window opening behaviour can be used to update the airflow network in the building model. In this way continuous (e.g. building and HVAC) and discrete (e.g. occupant control) state systems of BPS can be coupled using the DEVS formalism at discrete events. Continuous state system simulations in DEVS can be achieved with the quantization of state variables, instead of time discretization, described by differential equations (Cellier and Kofman 2006). In the context of BPS, this approach can be adopted by discretizing temperature changes (e.g. 0.5°C or 1°C) as discrete events. This way, the occupant's decision-making process can be isolated from the time-step-size selection, i.e. an occupant may decide whether to undertake an adaptive behaviour or not when a physical stimulus is changed rather than restraining decision-making instants to fixed time steps.

3. Occupant model

The occupant model developed for this study is a set of decision-making processes related to the way an occupant satisfies his/her thermal comfort. It involves actions to adapt both personal (clothing, drinking) and environmental (windows, blinds, and HVAC) characteristics. The occupant model is based on logistic regression models with model coefficients taken from Haldi and Robinson (2008). Although this previous work was later refined, it serves as a reasonable basis for comparing discrete-time and discrete-event simulation approaches. It is worth noting that this comparison, independent of the details of the model, is the focus of the current paper.

The occupant model receives inputs such as the operative temperature (average of the indoor air temperature and the mean radiant floor temperature), indoor luminance, and occupant' schedule and outputs control decisions about the blind state, clothing state, drinks state, lights state, window state, and HVAC state, as shown in Figure 4. Given social restrictions in office environments, daily clothing level adaptations are modelled as a binary state of ±0.1 clo. This can be achieved by minor adjustments such as shortening sleeves or opening collars (Haldi and Robinson 2011a). Based on a simple steady-state heat balance calculation for a human body weight of 70 kg and a surface area (BSA) of 1.8 m^2 with 100 W of metabolic energy generation (MEG) rate, the clothing level change is assumed to provide

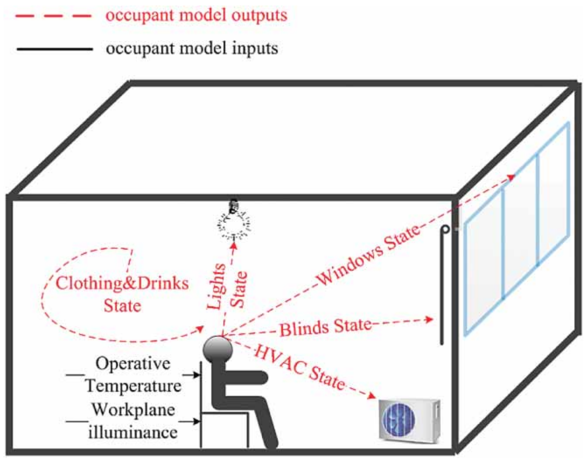

Figure 4. Inputs/outputs to the occupant model.

an additional 0.9°C (ΔT_{cloth}) tolerance. Drinking cold drinks are assumed to provide an incremental tolerance of 0.3°C (ΔT_{drinks}) as reported in Haldi and Robinson (2008). The effects of personal adaptive behaviours (e.g. drinks or clothing) are incorporated in the environmental adaptive behaviours (e.g. blinds, windows, and thermostat) such that the operative temperature is reduced by ΔT_{cloth} and ΔT_{drinks}. These additive tolerances (ΔT_{cloth} and ΔT_{drinks}) are in line with the adaptive increments concept suggested by Baker and Standeven (1996).

The flowchart shown in Figure 5 shows the decision-making process of the occupant. The probability of state transitions (P) are estimated using uniformly distributed pseudo-random numbers (R). The random number generator is seeded to ensure repeatability between simulation runs. If P exceeds R, the occupant undertakes the corresponding adaptive behaviour. In the decision-making sequence shown in Figure 5, the occupant first decides about personal adaptive behaviours. This way, their immediate impact on the perceived thermal comfort can be reflected in the succeeding behaviours. For example, the operative temperature sensed by the occupant (i.e. input in the logistic regression model) is reduced by ΔT_{cloth} after the clothing adaptation and by ΔT_{drinks} after the drinking adaptation. This indirectly reduces the probability of undertaking environmental adaptive behaviours (e.g. window opening). If the window opening probability (P_{win}) exceedes the corresponding random variable (R_{win}), the window state (S_{win}) is changed to 'true'. If the probability of blind lowering (P_{blinds}) exceeds the random variable (R_{blinds}), the blind state (S_{blind}) is changed to 'true'. The light use decision (S_{light}) is undertaken when the indoor daylight (E_{dl}) falls below 300 l× or when the blinds are closed. Lights are assumed to turn off automatically, if the workplane illuminance rises above 300 l×. The blinds are assumed to block the airflow substantially, therefore the window was closed when the blinds were closed. The HVAC system is assumed to be manually controlled by the occupant. If the probability of HVAC

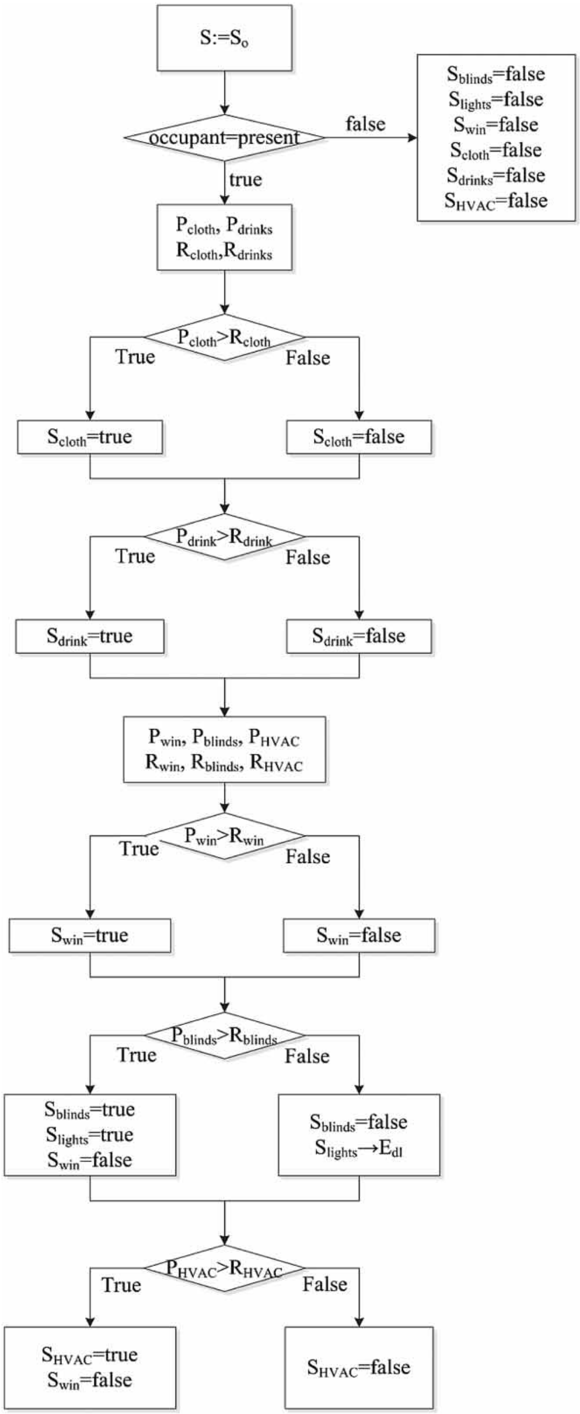

Figure 5. Decision-making process of occupants.

unit-on (P_{HVAC}) exceed the random number (R_{HVAC}), the HVAC unit state (S_{HVAC}) changes to 'true'. Concurrently, the occupant closes the window, once the HVAC unit is switched-on.

The probability of undertaking these adaptive behaviours (P) is calculated using logistic regression models (Figure 6) with parameter coefficients taken from Haldi

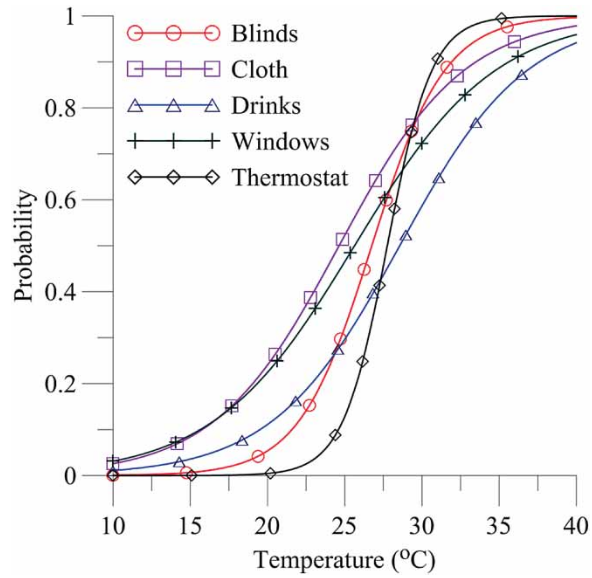

Figure 6. Stochastic adaptive behaviour models taken from Haldi and Robinson (2008).

and Robinson (2008). It should be noted that these parameter coefficients were not designed to be incorporated in BPS. In the future, these regression coefficients can be replaced with studies and analyses intended for calibrating simulation models such as those presented in Haldi and Robinson (2009) for occupant control on windows, in Haldi and Robinson (2010) for occupant control on shading devices, in Haldi and Robinson (2011a) clothing level adjustments or in Reinhart (2004) for occupant control of lighting. To this end, supplementary results are presented in the appendix by employing Haldi and Robinson (2009) for occupant use of windows only. However, Haldi and Robinson (2008), to the best of authors' knowledge, remains as the only study covering multiple adaptive behaviours in one paper.

Another assumption made in the occupant model is that the occupant decides any adaptive action in the flowchart (Figure 5) regardless of his/her previous decision. In other words, at the instants of decision-making all adaptive behaviours are simulated independently with only two exceptions: (1) an occupant, if turning on the HVAC unit, does not open the window, (2) an occupant, if opening the window, does not close the blinds. However, it should be noted that the order in which adaptive behaviours are undertaken can impact simulation results significantly. In line with this, Andersen (2009) reported that the order of the manual control sequence (e.g. thermostat → window → blinds → lights) may be responsible for up to 3.3-fold variation in the energy use predictions. However, it still remains unclear whether or not the order in which the occupants undertake adaptive behaviours can be stated in a statistically coherent way.

It should be noted that the number of occupants responsible for an adaptive action can also impact the overall likelihood of its realization (Herkel, Knapp, and Pfafferott 2008; Haldi and Robinson 2009). For example, Haldi and Robinson (2009) observed a slight variation in the window opening behaviour in offices with one or two occupants. This was confirmed by similar observations by Herkel, Knapp, and Pfafferott (2008) in two or three person offices while studying manual blinds control and by Moore, Carter, and Slater (2003) in one to nine person offices while studying light switching. However, this complexity introduced due to social dynamics between occupants is neglected in the current study.

It is worth noting that this occupant model can be used to predict the probability of undertaking an adaptive behaviour; however the instances at which these discrete-time random processes, representing the decision-making sequence of the occupants (Figure 5), will be called by the BPS tools are not inherently available. The challenge in simulating these adaptive behaviour models in BPS is to find a scheme that is capable of predicting the instants of decision-making (i.e. the instants at which these discrete-time random processes are to be called by the BPS tools) and probability of the behaviour realization together.

4. Sensitivity of discrete-time solvers to the time-step-size dependency

To demonstrate the influence of time-step-size alterations on the BPS predictions with an example, a simplified thermal model for a generic office space in Ottawa, Canada was established in EnergyPlus v.7.2. The office was modelled with a west-facing exterior window area of 7.8 m^2 and an opaque wall area of 4.6 m^2. The floor and ceiling concrete slabs were taken as 15.9 m^2 area and 0.2 m thick. The room air space was assumed to be separated from the floor slab with a carpet and from the ceiling slab with ceiling tiles. All other surfaces were taken as adiabatic due to symmetry boundaries shared with rest of the building. EnergyPlus' conduction transfer function solution algorithm was used to solve for the combined heat and mass transfer problem specified for the analysis domain. Windows were simply modelled with the solar heat gain coefficient of 0.58 and U-factor of 2.6. Infiltration rate was taken as 0.1 ach. A simple HVAC system (i.e. a packaged terminal air conditioner) of 3 kW cooling coil capacity was included in the model. The HVAC system was able to modulate proportionally such that the cooling coil operates at full capacity once the system variable (i.e. control point) was 6°C above the setpoint. It was assumed that the office space was occupied full-time by four people from 8 am to 4 pm. Each occupant was assumed with 100 W of metabolic heat generation rate. Of this, 30% was taken as radiative and 70% was assumed as convective heat gains. Mechanical ventilation was set to 10$\dot{L}$/s-person during the occupied period. All control decisions (i.e. blinds, lights, windows, HVAC setpoint) were made as defined in the occupant model. The EMS application in EnergyPlus v.7.2 was used as the intermediary between the physical model (i.e. building and HVAC) and control model (i.e. occupant). It sensed variables from the physical model such as operative temperature; and based on the control decisions as defined in the occupant model actuated the physical model components. For example, window opening was modelled with an increase in the airflow rate due to wind and stack driven single-sided ventilation (CIBSE 1997). To this end, the wind schedules at the height of the opening were exported as output files and used in the EMS application to revise the airflow rate accordingly. Light switch-on was assumed to cause 210 W (6 × 32T8 light bulbs) increase in heat gains. Half of this was taken as convective and the other half was taken as radiative. Internal roller blinds were defined as perfect diffusers with optical properties that were independent of angle of incidence; i.e. solar transmittance of 0.1 and reflectance of 0.75.

The operative temperature, cooling load, and adaptive states of identical occupant and building models were simulated at different time steps. The results are presented in Figure 7. In the figure, active adaptive states stand for open windows, closed blinds, reduced clothing levels (shortened sleeves or open collars), cold beverage use; while passive adaptive states stand for closed windows, open blinds, unchanged clothing (sleeves and collar at default positions) and beverage drinking at neutral temperature. Building and HVAC models communicate with the occupant model only at simulation time steps; i.e. the events were forced to take place at fixed time steps. This caused simulations with longer time steps to have more stagnant adaptive states; e.g. windows remain open longer periods. For example, for the simulation with one hour time steps, the window was opened only one time, as shown in Figure 7(e). The frequency of window openings increased from one per day for 1 h time steps to 103 per day for 1 min time steps. Similarly, blind use frequency increased from four per day for 1 h time steps to 214 per day for 1 min time steps. As illustrated in Figure 8, the frequencies of simulated adaptive behaviours resembled a power-law distribution. However, the total duration that states remained active (e.g. open window, lowered blind), showed significant variation with the time-step-size. For example, the duration that clothing state was active (e.g. opened collar or shortened sleeve) changed from 5 h for 1 h time steps to 9 h for 3 min time steps. Likewise, the duration that windows remained open changed from 0.75 h for 15 min time steps to 2 h for 30 min time steps. As a consequence of the time-step-size dependency of simulated adaptive behaviours, the total cooling energy input was estimated at 4.5 kWh/day for 30 min time steps and 6.3 kWh/day for 1 min time steps. The peak cooling load was estimated at 1 kW at 4:00 pmfor 1 h time steps and 0.85 kW at 2:40 pm for 4 min time steps. Similarly, the varying frequency of occupant behaviours for different discrete-time steps resulted in discernible operative temperature distributions, as shown in Figure 7. More importantly, identical occupant models, even if they were in good agreement with the observed behaviour, generated

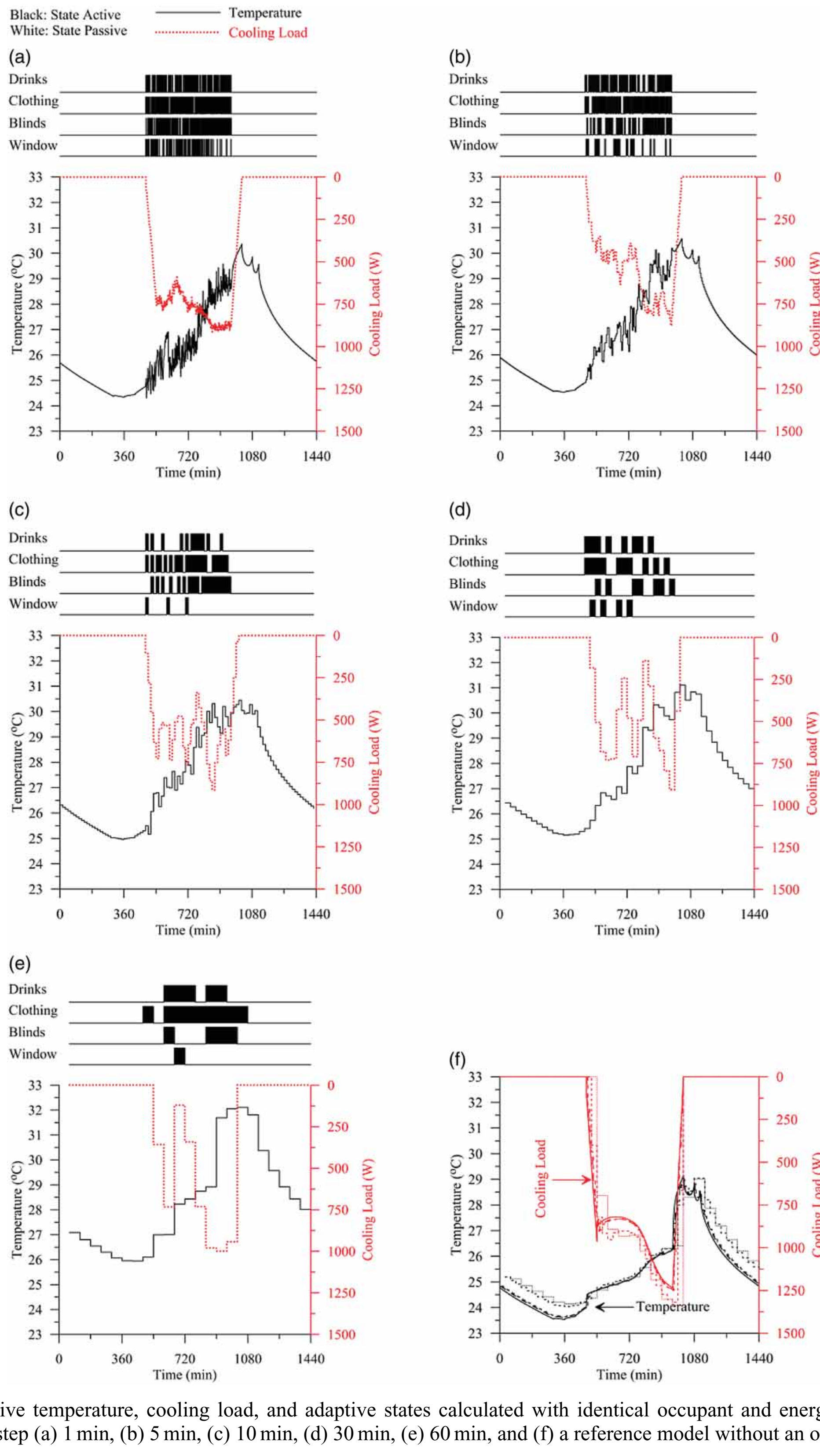

Figure 7. Operative temperature, cooling load, and adaptive states calculated with identical occupant and energy models that were simulated at time-step (a) 1 min, (b) 5 min, (c) 10 min, (d) 30 min, (e) 60 min, and (f) a reference model without an occupant model.

inconsistent results once simulated using varying fixed time steps. A reference model was also simulated by removing the occupant model and defining a fixed setpoint with the identical HVAC system. Figure 7(f) shows cooling load and temperature response in absence of the occupant model from time steps of 1, 5, 15, 30, 60 min. Results indicate

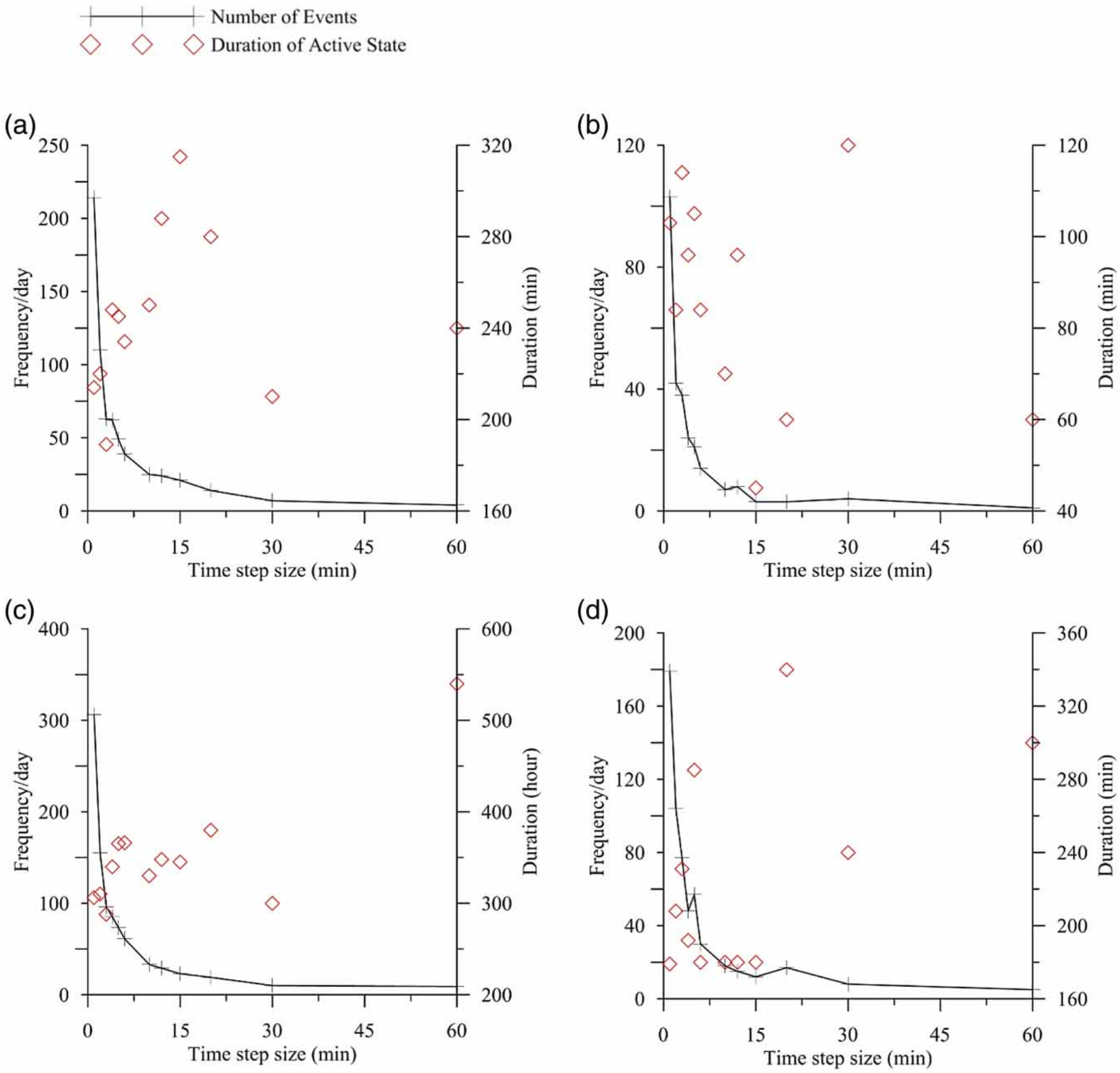

Figure 8. Change in number of simulated events (e.g. window openings or blinds closings) and duration of states remain active (e.g. open windows or lowered blinds) with the time-step-size (a) blinds, (b) windows, (c) clothing, and (d) drinks.

that the time step selection represents a negligible impact in comparison to its effect once the stochastic occupant model was present. This indicates that a change in the time-step-size alteration can account for dramatic changes in the predicted outcomes of the adaptive states and BPS.

Many studies (Nicol and Humphreys 2007; Rijal et al. 2007, 2008; Haldi and Robinson 2008, 2009, 2010, 2011a) also acknowledged the time-step-size dependency of Markov Chain discrete-time simulations and suggested two complimentary methodologies to be able to simulate stochastic occupant models; i.e. the deadband incorporated models (Nicol and Humphreys 2007; Rijal et al. 2007, 2008) and the survival models (Haldi and Robinson 2009, 2010, 2011a).

Deadbands are controls terminology suggesting that the controller does not produce a signal for a particular range of process variable. Deadband models assume that an event (i.e. change in state) does not take place for a specified range of predictor variable. For example, Rijal et al. (2007) suggested to shift cumulative probability distribution curves ±2 K from the original logistic regression curve such that window opening/closing probabilities would always be 4 K apart from each other. It was reported that a deadband must be introduced to occupant models otherwise its effect would have resulted in instability, similar to the fluctuations seen in smaller time steps (Figure 7(a)–(c)). In other words, the deadband concept may be applied to tackle the problems associated with the discrete-time simulation algorithm rather than modelling a certain observed phenomenon. In fact, Rijal et al. (2007) acknowledged that the deadband concept was approximate and required revisions. Moreover, deadbands are not appropriate to be used in

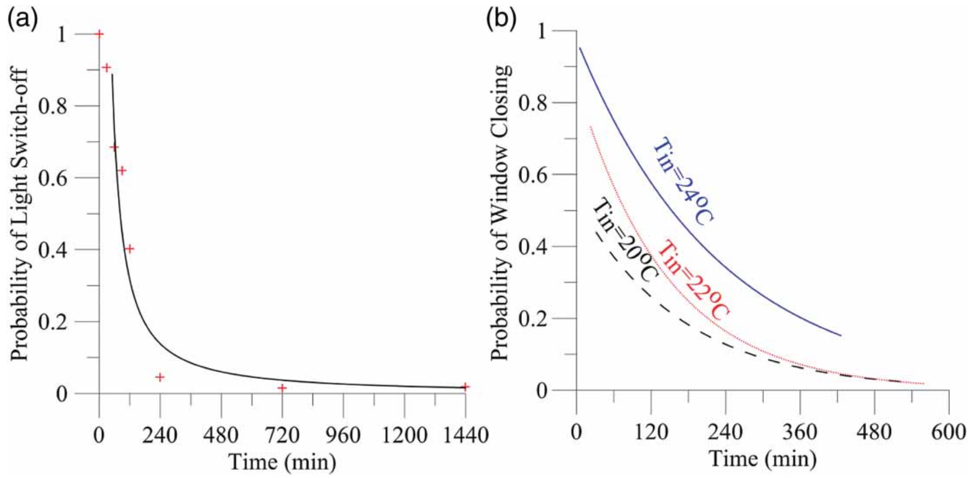

Figure 9. (a) Light switch off survival model predicted from a data scatter taken from Reinhart and Voss (2003) and (b) a window closing survival model taken from Haldi and Robinson (2009).

this context as they restrain the modeller such that the window closing action can only be defined with the identical set of predictors (e.g. temperature) as the window opening action. This contradicts Haldi and Robinson (2009) and Rijal et al. (2008) that suggest window opening action to be modelled as a function of the indoor variables, while the window closing action to be modelled with the outdoor and indoor variables. Similarly, blinds are lowered for glare or solar radiation protection (Reinhart and Voss 2003; Reinhart 2004); but they are raised to maintain the view to the outside or to get more daylight (Veitch, Hine, and Gifford 1993; Veitch and Gifford 1996). Therefore, deadbands introduced to behavioural models, despite providing numerical stability, are limited due to the assumption that the reversal of adaptive behaviours can be described with the same set of predictor variables as the adaptive behaviour.

Survival analysis is a method to analyse the timing of events. It was originally used to model the survival time to the death, however it was later adopted by the various engineering disciplines to study failure times. Haldi and Robinson (2009) applied the technique to estimate the duration windows remain open. To demonstrate this technique, a crude survival model is built using the light switch-off observations presented in Reinhart and Voss (2003), as shown in Figure 9(a). As the time after departure elapses, the probability of the lights remaining switched-on decreases. The survival models were also extracted from Haldi and Robinson (2009) which are shown in Figure 9(b). The probability that windows remain open decreases as the time elapses. However, the survival analysis resulted in different curves at different indoor temperatures. In that case, Haldi (2010) recommended to interrupt the simulation and to change the survival curve, if the predictor variable changes before the calculated survival-time. This was noted as the first formal effort to predict the instants of decision-making in occupant behaviour simulation in BPS. However, the practical challenge here was to acquire observations enough to establish survival curves for every possible predictor variable range. This questions the practicality of survival models to be able to predict the adaptive behaviours. Survival analysis can be useful to describe events in which the stimulating factors are weak. For example, the two weak motivations for the manual light switch-off action are workspace brightness (which is usually controlled with the blinds) and the presumption that artificial light is not healthy (Veitch, Hine, and Gifford 1993; Veitch and Gifford 1996). Therefore, light switch-off probability can solely be described with the time elapsed using the survival analysis. However, if there are significant time-varying stimuli to reverse an adaptive behaviour, such as indoor temperature causing window closing, survival analysis may not be as appropriate. In fact, in those cases, with strong time-varying stimuli for the reversal of an adaptive state (e.g. closing a window), reversal of an adaptive state can itself be treated as an adaptive behaviour. For example, window closing behaviour can be explained with the ambient noise, thermal discomfort, or draftiness and can be represented as a Markov Process. However, doing so would again result in with the same limitations related with discrete-time approach; leading to inaccurate adaptive state predictions.

5. DEVS building energy model and simulation

DEVS, by quantizing the state variables, provides an adaptive time advancement scheme. Thus, the modeller does not choose a time-step-size in BPS. This section demonstrates the viability of the DEVS formalism to improve the aforementioned limitations associated with the use of fixed and prescribed time steps by providing an example application. To be able to demonstrate the process of time-step-size adaptation in a more transparent manner using explicit equations, a simplified thermal network model was formed to represent the physical model (i.e. building and HVAC) instead of using a packaged BPS tool (e.g. EnergyPlus).

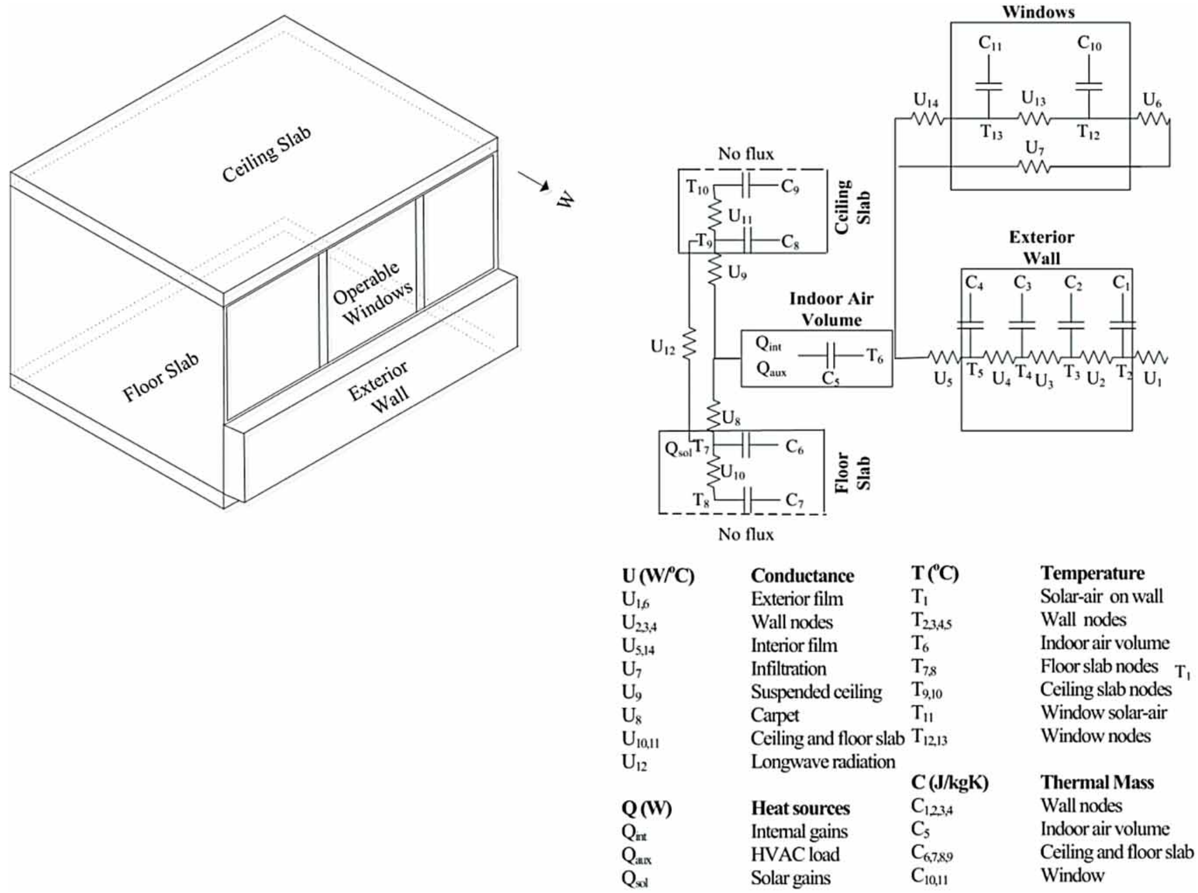

Figure 10. (a) Analysis domain and (b) thermal network model.

5.1. *Building model*

The thermal network model was formed for the previously described generic west-facing office with the identical geometry and constructions as the discrete-time model, as shown in Figure 10. This thermal network model was used to solve for the first-order approximation of the heat conduction equation. In a thermal network model, a building is represented as an electrical network. Thermal masses, which include both indoor air volumes and physical elements like walls, windows, and slabs, become nodal points in the network. They are each assumed to have a uniform temperature in the same way that nodal points in an electrical network are each associated with a single voltage level. Adjacent thermal masses may be linked by a time-dependent thermal resistance – the reciprocal of thermal conductance – through which heat flows like current in an electrical network (Clarke 2012). A thermal network model consists of lumped thermal mass (J/°C), lumped conductance elements (W/°C), and heat sources (W). Detailed information about thermal network models can be found elsewhere (Athienitis 1994).

Figure 11 shows the parameters used in the simplified thermal network model which represents the building model and the input/output relationships of these parameters. The coupled-building model consists of two submodels: (1) *environmental load generator* transforms the weather data to environmental loads, (2) *building model* receives control decisions or loads from the occupant model, the HVAC model and the *environmental load generator* through its external transition function. Subsequently, *building model* calculates the temperature at each of the nodes and outputs the air temperature of zone and mean radiant temperature. The building model, in absence of the occupant model and the HVAC model, revealed the passive building response, as shown in Figure 11.

All control decisions (i.e. blinds, lights, windows, and HVAC setpoint) were made as defined by the occupant model. A DEVS-based simulation prototype (Autodesk DesignDEVS v.0.4.1) was used to sustain the communication between the physical model (i.e. building and HVAC) and control model (i.e. occupant). It inputted variables from the physical model such as air and mean radiant temperatures and actuated the physical model components based on the control decisions defined in the occupant model. For example, window opening was modelled with an increase in the airflow rate due to wind and stack driven single-sided ventilation (CIBSE 1997). Similarly, light switch-on was assumed to cause 210 W (6×32T8 light bulbs) increase in

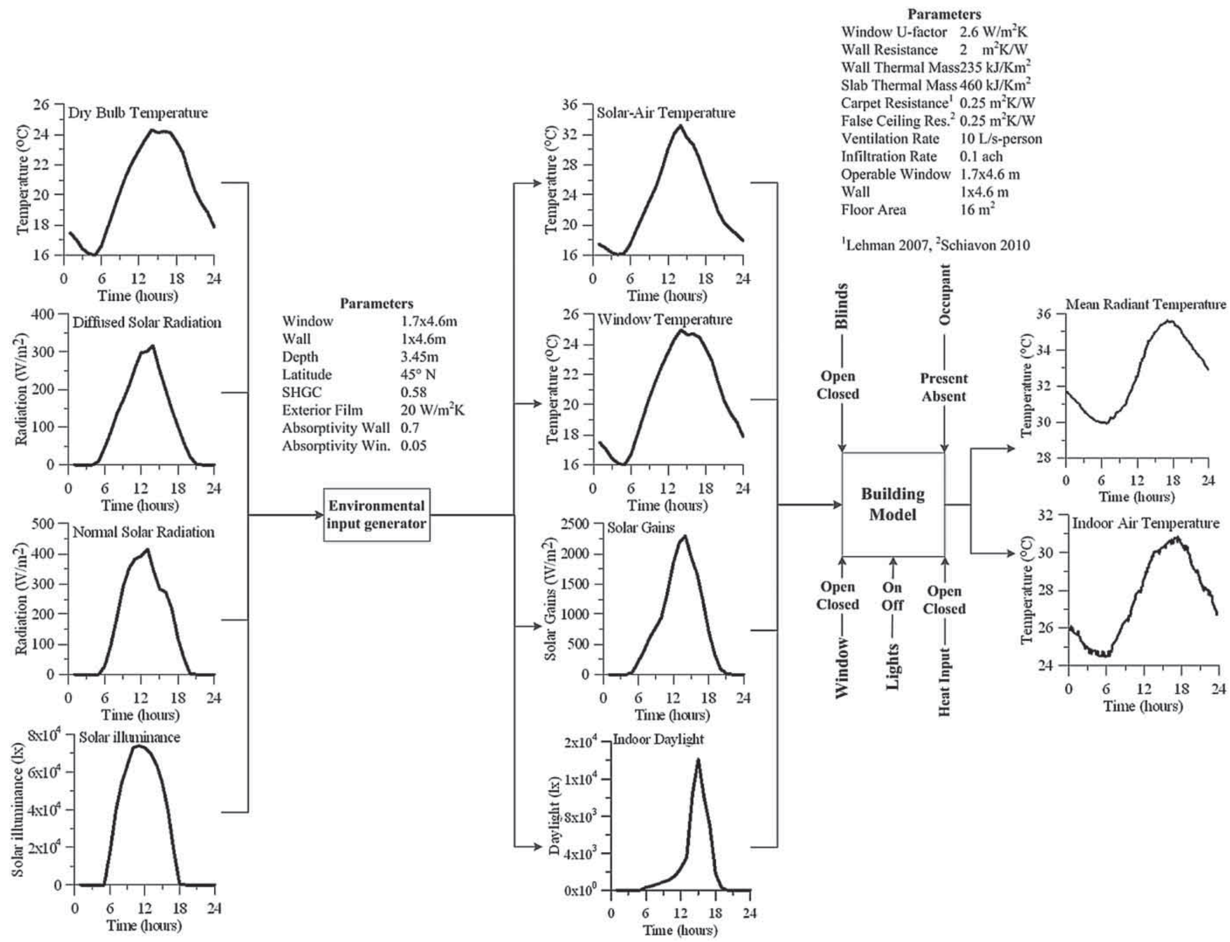

Figure 11. Parametric input/output relationships to the building model.

heat gains. Internal roller blinds were defined as perfect diffusers with optical properties that were independent of angle of incidence; i.e. solar transmittance of 0.1 and reflectance of 0.75.

An explicit central finite difference formulation was used to solve for the thermal network model explicitly as follows:

$$T_{m,t+\Delta t} = T_{m,t} + \overbrace{\left[(1/C_m)\left(\sum_{i=1} U_{im,t}(T_{i,t} - T_{m,t}) + Q_{m,t}\right)\right]}^{\Delta T_{m,t}} \Delta t, \tag{1}$$

where the conductance U (W/°C), the temperature T (°C), thermal mass C (J) and the heat source Q (W) at a given time (t) were used to determine the heat flow in the thermal network model. The time-step Δt (s) was then used to determine temperature variations ΔT (°C) due to the heat flow in the thermal network model. The subscripts m and t denotes for the spatial and temporal labels for the nodal point to be solved. The subscript i represents other nodal points that exchange heat with node m. The summation of $\Delta T_{m,t}$ and $T_{m,t}$ are then used to determine the temperature in the next time-step $T_{m,t+\Delta t}$.

5.2. Time-step-size adaptation

While discrete-time solvers use fixed time steps, discrete event solvers may vary the time-step according to how fast a system is changing state. As mentioned, the quantization of state variables is one way to determine Δt (Cellier and Kofman 2006). The building model presented here determines an adaptive Δt by limiting the temperature change per time-step for all thermal masses. Therefore, during the simulation, when abrupt temperature changes are expected due to occurrences such as opening the window or turning the HVAC unit on, the model chooses smaller $\Delta t's$, but during unoccupied periods of the simulation such as night time, the model chooses larger $\Delta t's$. The internal time advancement in the building model is carried out as follows:

$$\Delta t = \min\left(\min_m \left(\frac{\Delta T}{\left|\begin{array}{c}(1/C_m)\left(\sum_{i=1} U_{im,t}\right.\\ \left.(T_{i,t} - T_{m,t}) + Q_{m,t}\right)\end{array}\right|}\right); \ 15 \text{ min}\right), \tag{2}$$

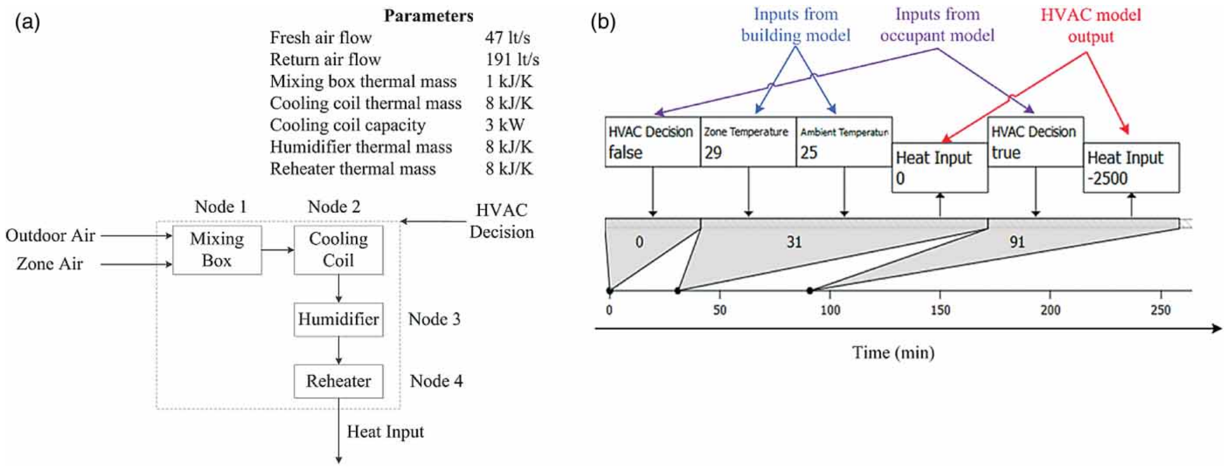

Figure 12. (a) Parametric input/output relationships to the HVAC systems model and (b) an unit test on the HVAC systems model.

where ΔT (°C) is the maximum temperature change (e.g. 0.5°C change in temperature at any of the nodal points). The function determines the scheduled time advance so that a ΔT change can happen at any of the nodal points. It should be noted that Δt is a real number and its variation depends on the physics of the problem. This internal scheduling can be interrupted with an external input being received at anytime or if the next scheduled event is more than 15 min away from the current state. For example, if the occupant opens the window; the time advance stops, the model is modified accordingly with the change in physics, and then proceeds. The limitation on the maximum time-step-size was chosen based on the adaptive-time-step solver for HVAC plant models of EnergyPlus to limit truncation error in the field variable of the continuous domain. The choice of maximum time-step-size did not affect the occupant model such that it was not invoked, if the predictor variable was not changed at the event-step-size.

5.3. HVAC model

A simple quasi-steady-state model of a packaged terminal air conditioner was formed using a set of mass and energy balance equations at each component. The HVAC systems model was composed of a mixing box, a cooling coil, a humidifier, and a reheater, as shown in Figure 12(a) (Clarke 2012). The cooling coil capacity was determined based on a sizing run in EnergyPlus. The fresh air portion of the ventilation was selected as per ASHRAE (2010) recommendations. The return air mixing rate was selected to meet 13°C at the diffuser (Sugarman 2005) when the cooling coil was operated at full capacity. For simplicity, each component was represented as a single node. At the mixing box the return air (indoor air volume temperature) (80%) and the outdoor air (20%) was mixed prior to entering the cooling coil (Sugarman 2005). Then, the cooling coil extracted the heat from the ventilation air. The humidifier and reheater components maintained the humidity of ventilation air. The conditioned ventilation air was then supplied to the zone. Each component in the HVAC systems model introduced a thermal inertia that lagged the output of the model. The HVAC systems model needed to receive input messages (HVAC decision, outdoor, and indoor air temperatures) to invoke its internal transition function that solves for the output message (heat input). To demonstrate this input/output relationship of the atomic model before coupling with other models, a few input messages were left on the HVAC systems simulation time grid, as shown in Figure 12(b). Input messages (i.e. HVAC decision, zone temperature, ambient temperature) were denoted with arrows pointing downwards and the output message (i.e. heat input) was denoted with arrows pointing upwards. The event times (e.g. input message arrival time) were specified within the triangle-shaped objects that represent the states at different periods of the simulation. Initially, HVAC decision (input) state was defined as false, thus the heat input to the zone (output) is 0. The indoor and outdoor air temperatures were defined at time = 31 min. Once the HVAC decision state was informed as an input message to change 'true', the internal state transition function was invoked and solved for the heat input as follows:

$$\text{Energy balance}\begin{cases}\dot{m}_o c_{\text{air}}(T_o - T_1) + \dot{m}_r c_{\text{air}}(T_r - T_1) \\ = T_1 C_1 \Delta t, \\ \dot{m}_2 c_{\text{air}}(T_1 - T_2) + Q_2 = T_2 C_2 \Delta t, \\ \dot{m}_3 c_{\text{air}}(T_2 - T_3) = T_3 C_3 \Delta t, \\ \dot{m}_4 c_{\text{air}}(T_3 - T_4) = T_4 C_4 \Delta t, \end{cases} \tag{3}$$

$$\underbrace{\text{Mass balance}\ \{\dot{m}_2 = \dot{m}_3 = \dot{m}_4 = \dot{m}_o + \dot{m}_r,}_{Q_{\text{input}} = (T_4 - T_z)\dot{m}_4 c_{\text{air}}}$$

where m_i (kg/s) represented mass flow rate between the component nodes, m_o (kg/s) and m_r (kg/s) were the outdoor and return air flow rates, c_{air} (J/kg-K) was the specific heat of air, Q_2 (W) was the capacity of the cooling coil, Q_{input}

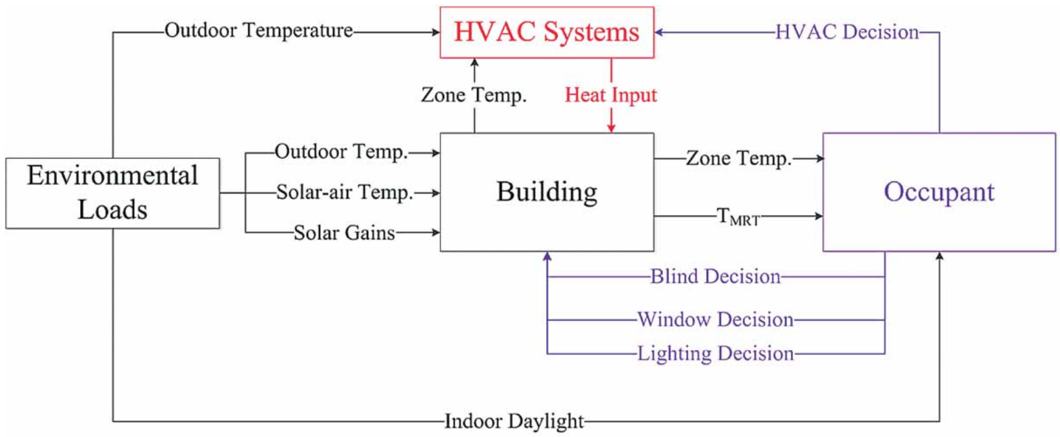

Figure 13. Coupled-DEVS building energy model.

(W) was the heat input rate to the zone and C_i (J/K) was the thermal mass of the component nodes. Q_2 (W) was modulated proportionally such that the cooling coil operated at its full capacity once the difference between the setpoint and the control point was 6°C.

5.4. *Coupled-DEVS building energy model*

Three domains of the building energy simulation problem (i.e. building, HVAC systems, and occupant models) have been separately modelled. A coupled-DEVS building energy model was formed as shown in Figure 13. Figure 14 summarizes the DEVS simulation process with an event-step-size of 0.5°C. This event-step-size value (0.5°C), despite having an approximate meaning based on ASHRAE (2010) to account for about an ±0.25 PMV deviation, has no observational basis. It was assumed that ±0.25 PMV is a large enough thermal comfort variation which can lead to a decision-making about an adaptive behaviour. Here, it was intended to demonstrate that an event-step, unlike a time-step, can attain an observational basis. This way, occupant's instants of decision-making increase in frequency during periods in which environmental conditions are rapidly changing. Also, event-driven advancement in simulation ensures that occupant responses for stimuli need not be postponed until the following time-step. This may be particularly important for reactions against instantaneous stimuli (e.g. light switch-on).

First, the building and HVAC models calculated that temperature would reduce by 0.5°C at $t = 0.58$ h. Then, the occupant model decided whether or not this new state caused discomfort. Thus, the occupant undertook control decisions at $t = 0.58$ h. If the occupant decided to turn the air-conditioning on, the HVAC model computed the heat input rate to the zone. The building model again predicted the time of next event and updated the temperature array. Time marched to $t = 1.38$ h, where the occupant model again decided whether this new state required an adaptive behaviour or not. This way the time evolved in simulation, where adaptive behaviours were predicted at state transitions. It should be noted that the building and HVAC models did not march from $t = 0$ to $t = 0.58$ h or from $t = 0.58$ h to $t = 1.38$ h at once. To limit the truncation error imposed by the finite difference method, a maximum time-step-size of 15 min was introduced for the building and HVAC models. In other words, if the time-step-size calculated in Equation (2) was larger than 15 min, the building and HVAC models advanced internally by 15 min. However, the occupant model was not invoked if the temperature change since the last occupant decision instant does not exceed the event-step-size. If the time-step-size calculated in Equation (2) was smaller than 15 min, the building and HVAC models advanced to a new state.

Figure 15 shows the operative temperature, cooling load, and adaptive states calculated using the DEVS building energy model and simulation. The peak cooling load was estimated at 0.51 kW at 3:42 pm. The total cooling load was estimated at 2.3 kWh/day. For the day, the blinds remained closed for 84 min, the windows remained open for 374 min, the clothing state was remained active for 292 min, and the drink state remained active for 327 min. As opposed to the frequent changes observed in the discrete-time simulation, all adaptive behaviours were undertaken two to four times and remained active for a relatively longer period of times. This is in line with observational studies on adaptive behaviours (Reinhart and Voss 2003; Inkarojrit and Paliaga 2004; O'Brien et al. 2010a; O'Brien, Kapsis, and Athienitis 2013) suggesting that adaptive behaviours were rarely applied more than a few times a day.

6. Discussion and conclusions

Simulation of building physics (e.g. building and HVAC systems) and control (e.g. occupant) models has been drawing attention from various researchers (Wetter 2009, 2011; Nghiem 2013). It should be noted that the building physics models involve a continuous problem (i.e. state variables such as temperature are differentiable) whereas control

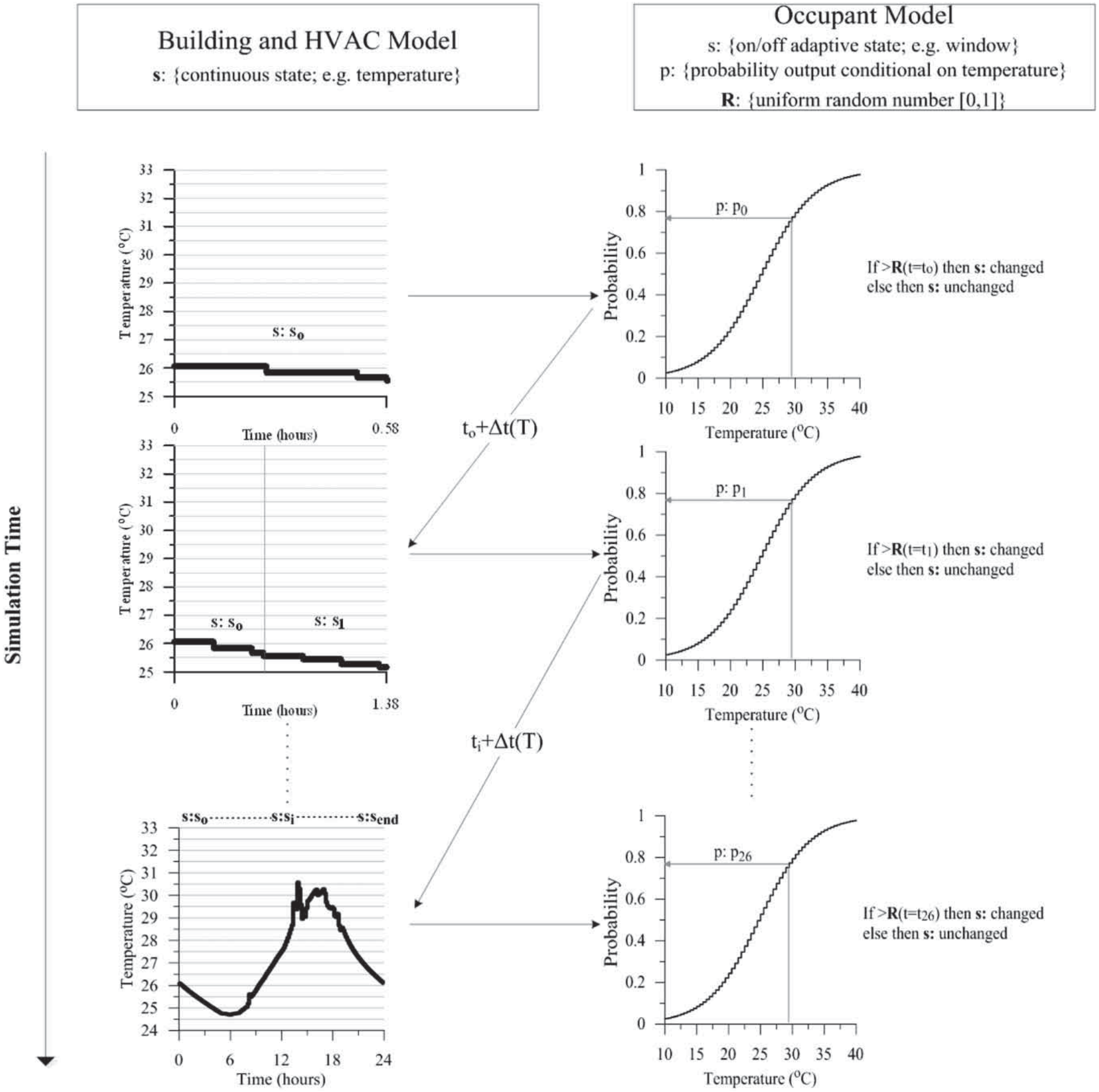

Figure 14. DEVS simulation algorithm with a behavioural occupant model.

models involve a discrete problem (i.e. state variable such as blind position are not differentiable). Despite this substantial difference, the prevalent use of the discrete-time simulation approach in BPS leads to the simulation of occupant behaviour models as discrete-time random processes. However, these discrete-time random processes require the use of fixed and prescribed time steps. In the current paper, the following problems associated with the use of fixed and prescribed time steps in occupant behaviour simulation are noted and the viability of the DEVS formalism to provide a potential improvement for these problems is discussed:

(1) When coupling models for BPS, it is sometimes desirable to synchronize events occurring in different models; this becomes more difficult when a model's time step may not be altered. Also, different simulation-based design applications require different levels of execution speed and temporal resolution; the use of prescribed time steps makes it more difficult to adjust the trade-off between speed and accuracy to suit a particular application. Due to these difficulties, the modeller may choose to alter the time step of a stochastic discrete-time occupant simulation; however, it is shown in Section 4 that the consequence may be a dramatic change in the BPS predictions and in the predicted outcomes of adaptive states. However, it is worth noting that this time-step-size sensitivity represents a problem particularly for BPS models with stochastic control inputs. For example, in the stochastic occupant models shown in Figure 5, even at lower temperatures, the probability of adaptive behaviours is non-zero. Moreover, these probabilities are sensitive to

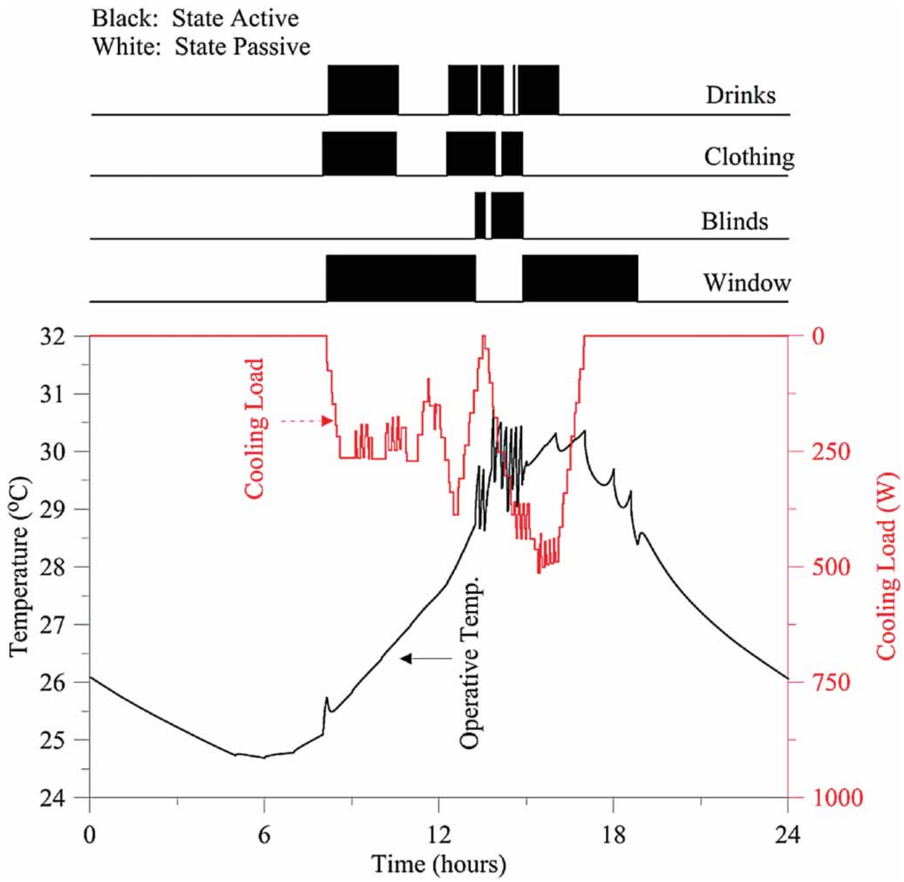

Figure 15. Operative temperature, cooling load, and adaptive states calculated that was simulated using the DEVS building energy model.

the predictor variable at the instant of decision-making. Therefore, simulation of stochastic occupant behaviour models requires the prediction of the *instants of decision-making* along with the probabilities of state transition. On the other hand, this challenge is not relevant for deterministic control models, such as a predefined setpoint controller. A deterministic control model, as shown in Figure 1, is a step function. The probability of a state transition is zero below the setpoint and one above the setpoint. Therefore, a deterministic occupant model would not suffer from poor predictions of *decision-making instants*. Because, even if the occupant makes a decision about undertaking an adaptive behaviour once in every minute, the likelihood of realizing it will be zero for all instants below setpoint and one for all instants above setpoint. This was illustrated in Figure 7(f) by replacing the stochastic occupant control model with a fixed setpoint controlled HVAC unit.

(2) More complex models may require occupants to respond immediately to prominent stimuli such as the activation of artificial lights, the opening of a nearby window, or the sounding of an alarm; with a discrete-time simulation, these responses must be postponed should the stimulus occur between time steps. It is shown here that DEVS, being a continuous formalism, does not require occupant responses to be postponed until the next time step. This can become particularly important for actions responding to instantaneous stimuli (i.e. light switch-on).

(3) Fixing the time step implies that frequency of an occupant's instants of decision-making remains constant; it is logical that these instants should increase in frequency during periods in which environmental conditions are rapidly changing. It is shown here that DEVS, being an event-driven formalism, inherently accommodates this such that frequent occurrences of events can be associated with rapid change in the stimulating variables. In DEVS, time progresses at discrete events, which were defined as a 0.5°C variation in the temperature in this particular simulation. However, it should be noted these discrete events could also be defined with non-thermal stimuli such as the change in CO_2 level or workplane illuminance. Therefore, the probability of state transitions was not affected by the time discretization; instead it was affected by the event discretization. It should be noted that both time and event discretization introduce truncation error and observational bias. However, observational bias introduced by the event discretization can be reduced, since event discretization can attain observational basis to a predictor variable; e.g. how large a temperature change typically results in a window opening. Time discretization can be prone to larger errors, since it cannot attain observational basis to a predictor

variable. This can be illustrated within the following explicit finite difference formulation:

$$T_{m,t+\Delta t} = T_{m,t} + \left[\frac{1}{C_m}\left(\sum_{i=1} U_{im,t}(T_{i,t} - T_{m,t}) + Q_{m,t}\right)\right]\Delta t(T), \quad (4)$$

where – unlike the finite difference formulation shown in Equation (1) – $U_{im,t}$ (W/K) and $Q_{m,t}$ (W) are random variables; e.g. change in infiltration conductance after window opening. The probability of state transition in time is represented with univariate logistic regression models, as shown in Figure 6. It should be noted that these models were developed as a function of the predictor variable temperature; which is also the state variable in the heat transfer problem. More importantly, although these occupant models (Figure 6) do not depend on the time-step, the randomness transformed to the temperature in the following time-step $T_{m,t+\Delta t}$ becomes a function of the time-step-size (Bendat and Piersol 2011). Therefore, the DEVS simulation scheme, by suggesting an adaptive time advancement as a function of the predictor variable $\Delta t(T)$ as shown in Equation (4), can better represent the occupant behaviours in BPS. It is worth noting that there is a computationally less efficient way of using the adaptive time advancement for stochastic occupant behaviour models in conventional BPS tools. A small time-step (e.g. 1 min) in building and HVAC systems can be selected to acquire an almost continuous solution in these domains. In that case, the stochastic occupant model can be invoked only when a related continuous value changes by at least some predefined interval. The control interfaces for typical BPS tools (e.g. EMS application for EnergyPlus) provides default calling points such as *before time step before predictor*; implicitly leading occupant models to be simulated as discrete-time random processes. Developers of these BPS tools can enrich their calling points in these control interfaces to support such discrete-event-based interactions with stochastic occupant models.

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Appendix

Building model verification/calibration

Prior to the current study, a verification study was performed on deterministic passive and active discrete-time models built in Matlab, and EnergyPlus, and on discrete event models built in DesignDEVS. Figure A1 shows the results of a passive building simulation using each tool. DesignDEVS and Matlab solves for the thermal network model. DesignDEVS quantizes temperature steps of 0.5°C to move forward in time; while Matlab and EnergyPlus uses 1 minute time steps to handle the time advance. The results of the DEVS model are in line with the EnergyPlus and Matlab models. This shows that parameters and the logical structure of the model implemented correctly in the building submodel; and DEVS conforms to the traditional discrete-time model in absence of the stochastic control inputs.

HVAC Model verification/calibration

Figure A2 shows the response of the coupled active building response where a constant cooling setpoint is assigned at 25°C for the occupied period (i.e. work hours) and setback after the occupied period. DEVS results indicate that both the temperature and the cooling load are parallel with the discrete-time models built in Matlab and EnergyPlus. This indicates that the parameters and the logical structure of the DEVS coupled-building energy model were implemented correctly.

Verification of time-step-size sensitivity of discrete-time random processes

To verify the time-step-size sensitivity of discrete-time random processes with more rigorous adaptive behaviour models; the Markov Chain window use model of Haldi and Robinson (2009) was adopted based on the coefficient parameters summarized in Haldi and Robinson (2011b). These models, unlike the univariate logistic regression models used in the current study, were multivariate models with explanatory variables of indoor and outdoor temperatures, occurrence of rain (0 or 1), previous absence (0 or 1) or ongoing presence (min) or next absence (0 or 1). This way, these models accommodate the state of presence as arrival, during presence, and departure to update the probability of state transitions. The equations representing these logistic regression models are as follows:

Window opening at arrival:

$$P_{01} = \frac{\mathrm{e}^{-13.88+0.312T_{\text{in}}+0.0433T_{\text{out}}+1.862\text{ fabs}-0.45\text{ frain}}}{1+\mathrm{e}^{-13.88+0.312T_{\text{in}}+0.0433T_{\text{out}}+1.862\text{ fabs}-0.45\text{ frain}}}.$$

Window opening during presence:

$$P_{01} = \frac{\mathrm{e}^{-12.23+0.281T_{\text{in}}+0.0271T_{\text{out}}-8.78\times10^{-4}t_{\text{pres}}-0.336\text{ frain}}}{1+\mathrm{e}^{-12.23+0.281T_{\text{in}}+0.0271T_{\text{out}}-8.78\times10^{-4}t_{\text{pres}}-0.336\text{ frain}}}.$$

Window opening at departure:

$$P_{01} = \frac{\mathrm{e}^{-8.75+0.1371T_{\text{out}}+0.84\text{ fabs}+0.83\text{ frain}}}{1+\mathrm{e}^{-8.75+0.1371T_{\text{out}}+0.84\text{ fabs}+0.83\text{ frain}}}.$$

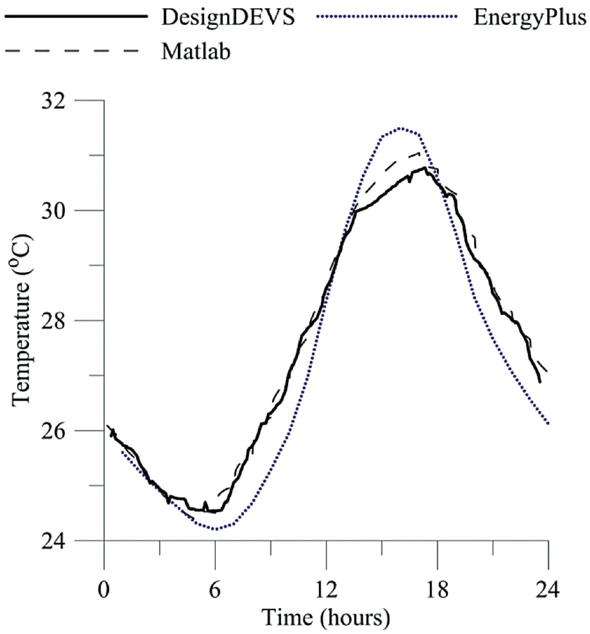

Figure A1. Verification/Calibration of the DesignDEVS Building Model with EnergyPlus and discrete time Matlab models.

Window closing at arrival:

$$P_{10} = \frac{e^{3.97-0.286T_{in}-0.0505T_{out}}}{1+e^{3.97-0.286T_{in}-0.0505T_{out}}}.$$

Window closing during presence:

$$P_{10} = \frac{e^{-1.64-0.0481T_{in}-0.0779T_{out}-1.62\times10^{-3}t_{pres}}}{1+e^{-1.64-0.0481T_{in}-0.0779T_{out}-1.62\times10^{-3}t_{pres}}}.$$

Window closing at departure: (5)

$$P_{10} = \frac{e^{-8.54+0.213T_{in}-0.0911T_{out}+1.614\text{ fabs}-0.923\text{ frain}}}{1+e^{-8.54+0.213T_{in}-0.0911T_{out}+1.614\text{ fabs}-0.923\text{ frain}}},$$

where T_{in} (°C) is indoor temperature, T_{out} (°C) is outdoor temperature, f_{abs} (0 or 1) is arrival or departure, t_{pres} (min) is the duration of presence, and f_{rain} is the binary rain indicator. Using these models, five day long simulations were repeated with identical

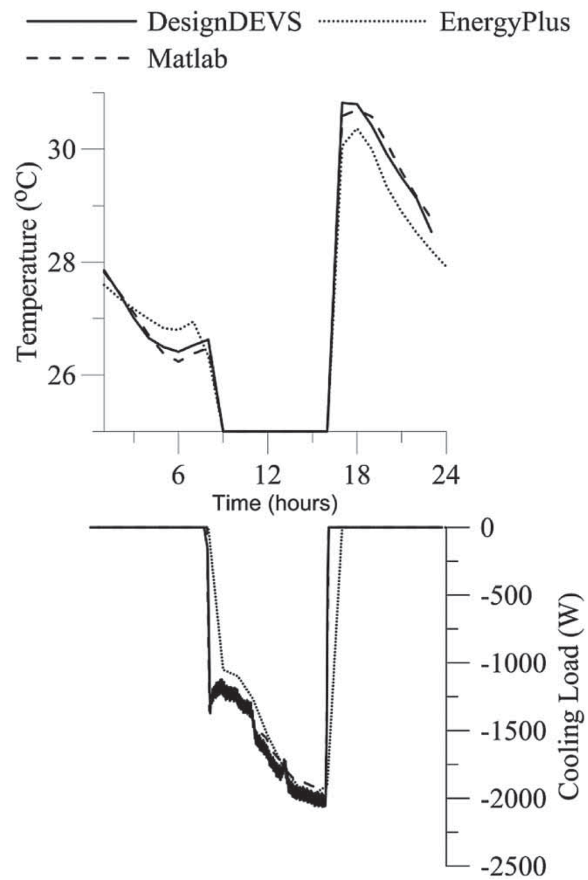

Figure A2. Verification/Calibration of the DesignDEVS Building and HVAC Models with EnergyPlus and discrete time Matlab models.

Building and HVAC models. Occupants' only manual control decision was opening or closing the window. Results shown in Figure A3 suggest that the problem of time-step-size sensitive predictions of adaptive states remains even if more realistic occupant behaviour models are employed. Therefore, this limitation is related with the predictions of instants of decision-making (i.e. instants at which occupant models be invoked by the BPS tool). As Haldi (2010) demonstrated, this problem can be overcome with an hybrid approach combining discrete-time Markov Chains with survival analysis; instead, here, continuous-time Markov Chains were suggested as a potential solution.

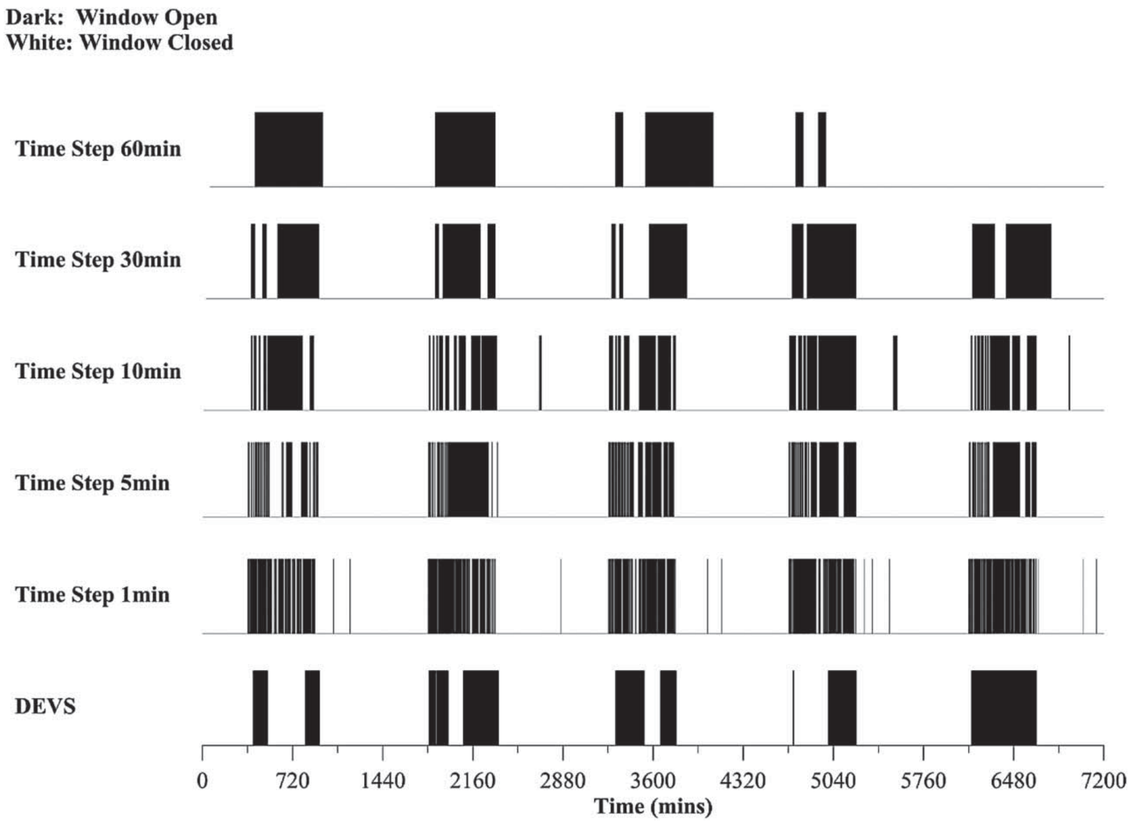

Figure A3. Verification of time-step-size sensitive adaptive state predictions with multivariate Markov Chain occupant model for window opening taken from Haldi and Robinson (2009).