Development of Discrete Event System Specification (DEVS) Building Performance Models for Building Energy Design

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Abstract

The discrete event system specification (DEVS) is a formalism for describing simulation models in a modular fashion. In this study, it is exploited by forming submodels that allow different professions involved in the building design process to work independently to create an integrated model. These submodels are the *building*, the *HVAC system*, and the *occupant*. In this study, a coupled DEVS building energy model of a generic office space is presented to demonstrate the viability of the DEVS formalism for BPS based design. Results indicate that the DEVS formalism is a promising way to improve poor interoperability between models of different domains involved in building performance simulations.

1. INTRODUCTION

Approximately 40% of the total energy produced in North America is consumed by residential and commercial buildings (DOE 2009). More importantly, it is reported by NRCan (2006) 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 design 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 (2001) estimated these savings as high as 50-75% in new buildings and 30% in existing buildings relative to 2000 levels; however, NRCan (2006) reported that the change in energy use per unit area is stable between 2000 and 2005. This indicates that conventional BPS based design techniques have not yet been adapted efficiently by the building industry to the integrated design process.

Integrated design, a process by which all building design team members (architects, mechanical engineers, civil engineers, electrical engineers, consultants, etc.) work together and share a common data model, is very uncommon. Instead, the same data is manually input by multiple designers, leading to redundant work, a slower design process, and possibly errors. The cost of poor interoperability between designers and software has been conservatively estimated at $15.8-billion annually (Gallaher et al. 2004).

The Discrete Event System Specification (DEVS) formalizes the description of simulation models in such a way as to provide benefits in the areas of collaboration and software development, which together, provide scalability. First, models are completely independent of the simulator. That is, a generic DEVS simulator can be created without any knowledge of the domain being simulated. Consequently, models do not contain any simulation management functionality and so, are typically much simpler to program. Second, models may be composed in a hierarchical manner without knowing whether the submodels are themselves compositions. For example, a building energy model may be composed of a building model, an HVAC model, and an occupant model. Each of the submodels may be initially created as simple atomic models but may be refined later to include submodels without affecting the rest of the simulation. Finally, models with no explicit references to one another can be coupled to communicate via input and output messages. Detailed information about the theory and application of DEVS can be found elsewhere (Zeigler et al. 2000, Wainer 2009).

It is the ability to couple independently developed models that makes DEVS a promising option for supporting collaboration between experts of different domains. For example, state-of-the-art building performance models require a background in math and physics for heat transfer, expertise in mechanical engineering for heating, ventilation, and air-conditioning (HVAC) systems, and the use of statistics and psychology for occupant behavior. Using DEVS, the idea is that various teams can each focus on developing a model in a single domain that addresses both the scalability issues of whole building simulation and the practical needs of designers. By combining these submodels, the resulting coupled model may capture interactions between domains such as the effect of an HVAC system on indoor temperatures, the effect of temperature on occupant comfort, and the effect of an occupant's actions on windows, shades, and thermostat set-points.

Building and HVAC system simulations involve the simultaneous solutions of systems with varying time constants ranging from seconds to hours for continuous differential equations. Therefore, solvers that impose a common time step for all submodels introduce considerable redundancy for domains associated with relatively large time constants. Cellier and Kofman (2006) explained a new way of approximating differential equations by replacing time discretization by quantization of the state variables. Moreover, modeling of the occupant involves stochastic decision making processes such as opening the windows, changing the clothing level, adjusting the blinds, drinking a hot/cold beverage and/or changing the thermostat setpoint. Incorporation of such adaptive behavior into conventional BPS tools designed to solve continuous differential equations is rare and restricted to predefined time periods due to the way time advancement is handled. For example, Rijal et al. (2007) demonstrated window opening behavior in ESP-r using Humphrey's window opening algorithm in 1 hour time steps. In reality, the occupant undertakes such adaptive measures at random time intervals rather than fixed multiples of given time steps.

DEVS inherently supports the variable time steps needed for the alternative numerical integration techniques and stochastic behavior described above. A DEVS model's time delay is recalculated after every state transition regardless of whether these delays vary or remain fixed. State transitions are described by an *external transition* function for cases in which the model receives an input message, or by an *internal transition* function for cases in which the model generates an output message. The *time advance* function gives the delay before an internal transition occurs. The delay is recalculated if an input triggers an external transition before the original delay elapses. Understanding external and internal transition functions as well as the time advance function is the key to understanding indivisible, or atomic, DEVS models. The other type of DEVS model is the coupled model, which links submodels of either type.

This paper presents a DEVS building energy model of a generic office space to demonstrate the viability of the DEVS formalism for BPS-based design. A DEVS-based simulation prototype (Autodesk DesignDEVS v.0.4.1) was used in this study. To illustrate the actual workflow of each design group, a *building submodel*, a *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.

2. BUILDING MODEL

A thermal network model of the north facing office shown in Figure 1 is established. This thermal network model is 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 1986). A thermal network model consists of lumped thermal mass (J/^{o}C), lumped conductance elements (W/^{o}C), and heat sources (W). Detailed information about thermal network models can be found elsewhere (Athienitis 2000).

A central finite difference formulation is used to solve for the thermal network model explicitly as follows:

$$\left\{T_{i+\Delta t}\right\} = \overbrace{\left(\left[U_i\right]_{nxn}\left\{T_i\right\}_{nx1} + \left\{Q_i\right\}_{nx1}\right)\Delta t./\left\{C\right\}_{nx1}}^{\Delta T_i} + \left\{T_i\right\} \qquad [1]$$

where the conductance matrix U_i (W/^{o}C), the temperature array T_i (^{o}C), and the heat source array Q_i (W) at a given time are used to determine the heat flow in the thermal network model. The time step Δt (s) and the thermal mass array (J/kg) are then used to determine temperature variations ΔT_i (^{o}C) due to the heat flow in the thermal network model. The summation of ΔT_i and T_i are then used to determine the temperature in the next time step $T_{i+\Delta t}$.

While discrete time solvers use fixed time steps, discrete event solvers may vary the time step according to how fast the 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 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 a smaller Δt but during tranquil regions of the simulation such as night time, the model chooses a larger Δt. The internal time advancement in the building model is carried out as follows:

$$\Delta t = \Delta T \ \min\left|\left\{C\right\}_{nx1}/\left(\left[U_i\right]_{nxn}\left\{T_i\right\}_{nx1} + \left\{Q_i\right\}_{nx1}\right)\right| \qquad [2]$$

where ΔT (˚C) is the maximum temperature change (e.g. 1˚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. 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 *building model* starts with the transformation of the weather data (i.e. dry-bulb temperature, diffused solar radiation, normal solar radiation, and solar luminance) to the environmental loads (i.e. solar-air temperature, solar gains, window temperature, indoor daylight), as shown in Figure 2. This transformation is achieved using input parameters such as window area, latitude, orientation, daylight factor (Simons and Bean 2001), solar heat gain coefficient (SHGC), and absorptivity. The *building model* receives inputs from (1) the environmental loads (i.e. solar-air temperature, solar gains, window temperature, indoor daylight), (2) the *occupant model* (i.e. blind closing, window opening, light turning, and occupant presence), and (3) the *HVAC system model* (i.e. heat input).

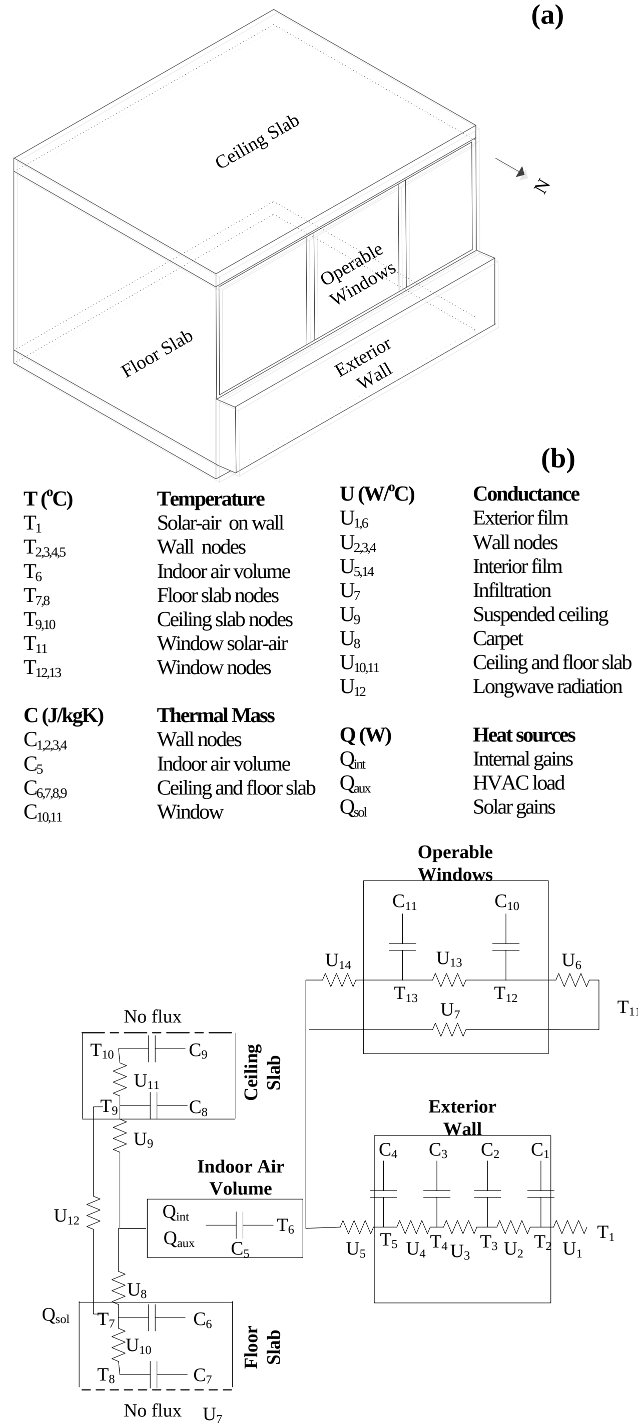

Figure 1: (a) Analysis domain and (b) thermal network model

Subsequently the *building model* calculates the temperature at each of the nodal points and outputs the air temperature of the zone and the mean radiant temperature using the parameters defined in Figure 2. The *building model*, in absence of the *occupant model* and the *HVAC system model*, reveals the passive building response, as shown in Figure 2. It should be noted that both mean radiant temperature and the indoor air temperature are higher than the outdoor temperature. This occurs as the windows are transparent for the shortwave radiation (solar radiation), while opaque for the longwave radiation from building surfaces.

The physical impacts of the occupant adaptive behaviors and the HVAC loads are defined in the *building model*. The primary physical implication of the window opening behavior is the airflow between the indoor and outdoor environment which is adapted as 8 L/s/person from ASHRAE (2009) and CIBSE (2006). This is with 4 occupants ~27 times larger than the air infiltration rate (0.3 ach) assumed in this study. Infiltration conductance in the conductance matrix, U_7 is modified accordingly, if the window is opened. The secondary implication of window opening behavior is that the reflected portion of the shortwave irradiation from the glazing incidents directly on the floor. Moreover, some of the longwave radiation emitted by the slab incident on the window opening leaves the room. This is implemented in the *building model* by changing the solar heat gain coefficient (SHGC) from 0.58 to 1 and by defining a conductance between the ambient air and the slab surface to take into account the radiation emitted from the slab surface through the window opening.

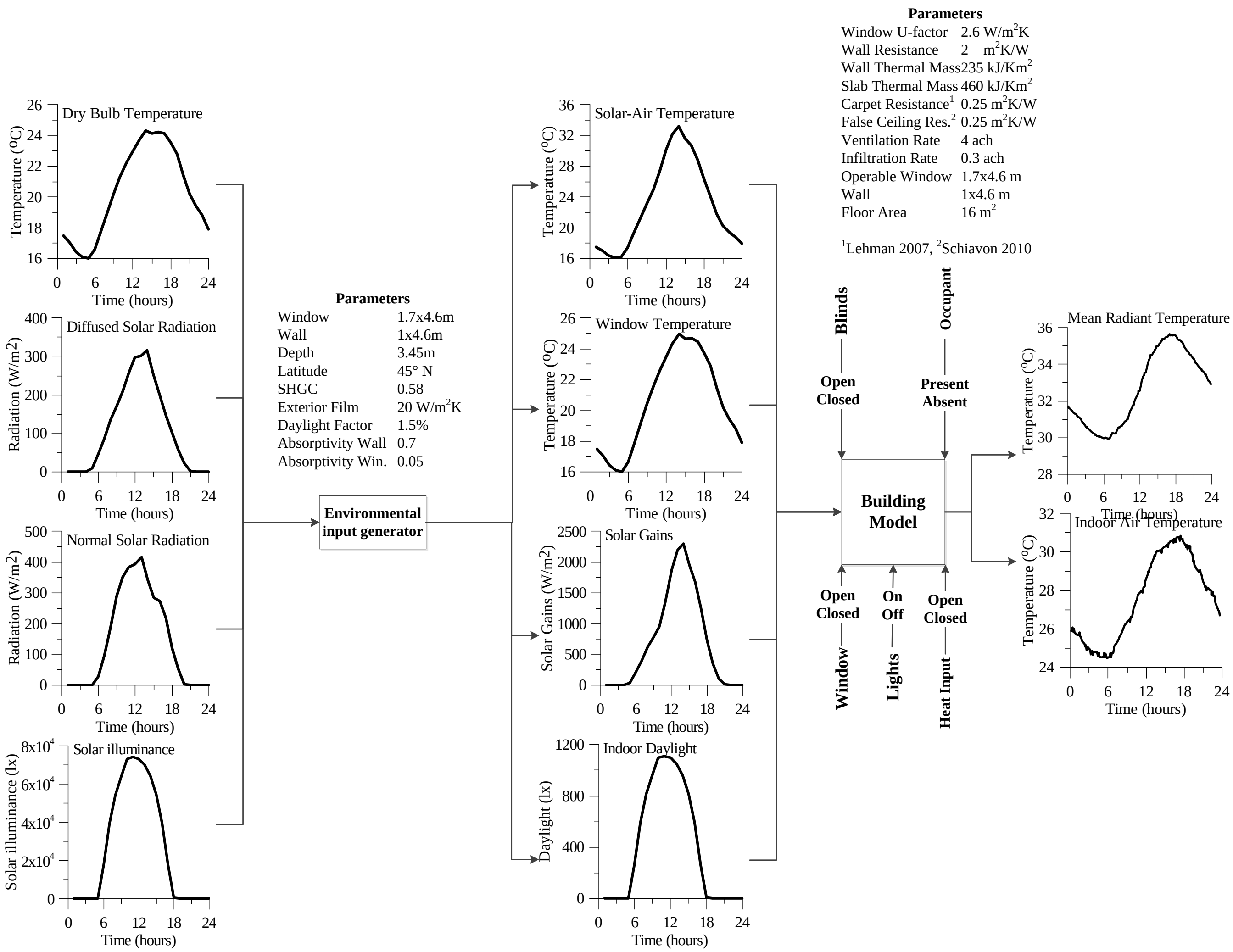

Figure 2: Parametric input/output relationships to the building model

Similarly, the primary physical implication of closing the blinds is reducing the transmitted solar irradiation. The roller blinds are assumed to reduce the transmitted solar irradiation on the slab surface to 10% of the incident solar radiation (Kuhn et al. 2000). The secondary implication of having blinds closed is that 20% of the incident solar energy is absorbed quickly by the blinds and due to its low thermal mass is emitted quickly into the air space (Kuhn et al. 2000).

Physical impacts of the occupant presence and lighting are defined as a heat gain of 100 W/person (ASHRAE 2009) and 32 W/bulb for 3x32T8 light bulbs (DiLouie 1967), respectively. The physical effect of the heat input from the HVAC unit is defined as a conditioned air flow into the air space. This is implemented in *building model* as follows:

$$Q_{aux} = \dot{m}C_{air}(\mathrm{T}_{zone} - \mathrm{T}_{dif}) \qquad [3]$$

where $\dot{m}$ (kg/s) is the mass flow rate of conditioned air through the diffuser, C_{air} (J/kgK) is the specific heat of the air, and T_{zone} (K) and T_{dif} (K) are the air space temperature and the conditioned air temperature by the diffuser, respectively.

3. HVAC SYSTEMS MODEL

A simple model of a packaged air handling unit is formed using a set of mass and energy balance equations at each component. The *HVAC systems model* is composed of a mixing box, a cooling coil, a humidifier, and a reheater, as shown in Figure 3 (Clarke 2001). For simplicity, each component is represented as a single node. At the mixing box the return air (indoor air volume temperature) (80%) and the outdoor air (20%) is mixed prior to entering the cooling coil (Sugarman 2007). Then, the cooling coil extracts the heat from the ventilation air. Humidifier and reheater components maintain the humidity of the ventilation air. The conditioned ventilation air is then supplied to the zone. Each component in the *HVAC systems model* introduces a thermal inertia that lags the output of the model. The *HVAC systems model* needs 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, a few input messages are left on the *HVAC systems* simulation time grid, as shown in Figure 3. Initially HVAC decision (input) state is defined as false, thus the heat input to the zone (output) is 0. The indoor and the outdoor air temperature is defined at time=31 min. Once the HVAC decision state is changed to true, the internal state transition function is invoked and solves for the heat input as follows:

$$\underbrace{\begin{array}{ll}\text{Energy Balance} & \begin{cases}\dot{m}_o c_{air}(\mathrm{T_o}-\mathrm{T_1})+\dot{m}_r c_{air}(\mathrm{T}_r-\mathrm{T_1})=\mathrm{T_1C_1}\Delta\mathrm{t} \\ \dot{m}_2 c_{air}(\mathrm{T_1}-\mathrm{T_2})+\mathrm{Q_2}=\mathrm{T_2C_2}\Delta\mathrm{t} \\ \dot{m}_3 c_{air}(\mathrm{T_2}-\mathrm{T_3})=\mathrm{T_3C_3}\Delta\mathrm{t} \\ \dot{m}_4 c_{air}(\mathrm{T_3}-\mathrm{T_4})=\mathrm{T_4C_4}\Delta\mathrm{t}\end{cases} \\ \text{Mass Balance} & \{\dot{m}_2 = \dot{m}_3 = \dot{m}_4 = \dot{m}_o + \dot{m}_r\end{array}}_{Q_{input} = (T - T_r)\dot{m}_4 c_{air}} \qquad [4]$$

where $\dot{m}_i$ (kg/s) represents mass flow rate between the component nodes, $\dot{m}_o$ (kg/s) and $\dot{m}_r$ (kg/s) are the outdoor and return air flow rates, c_{air} (J/kg-K) is the specific heat of air, Q_2 (W) is the capacity of the cooling coil, Q_{input} (W) is the heat input rate to the zone and C_i (J/K) is the thermal mass of the component nodes. It is evident that the Q_{input} (2.75kW) is different than the cooling coil capacity (i.e. 3kW). This can be explained with the thermal mass induced time lag for the HVAC system to reach its capacity.

Parameters	
Fresh air flow	47 lt/s
Return air flow	191 lt/s
Mixing box thermal mass	1 kJ/K
Cooling coil thermal mass	8 kJ/K
Cooling coil capacity	3 kW
Humidifier thermal mass	8 kJ/K
Reheater thermal mass	8 kJ/K

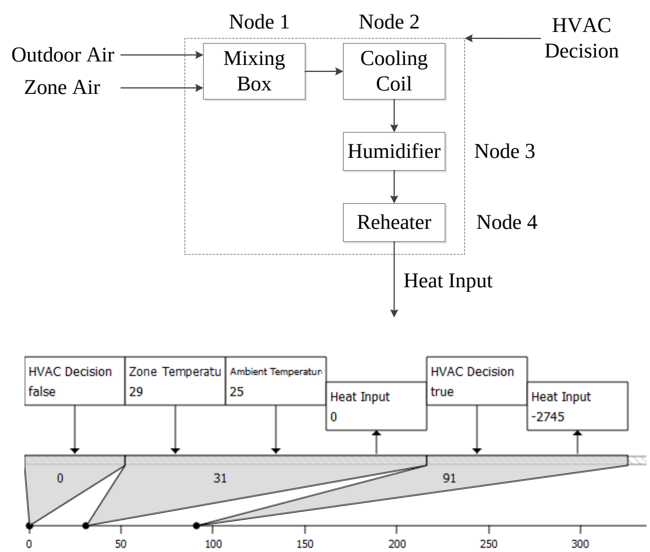

Figure 3: Parametric input/output relationships to the HVAC systems model

4. OCCUPANT MODEL

The *occupant model* is a set of decision making processes related to the way an occupant satisfies his/her thermal comfort. These involve actions to adapt both personal (clothing, drinking) and environmental (windows, blinds, HVAC) characteristics (Haldi and Robinson 2008). This study adapts the experimental results acquired by Haldi and Robinson (2008) to establish the *occupant model*. The model receives inputs such as the operative temperature (average of the indoor air temperature and the mean radiant floor temperature), the indoor luminance, and the occupant's schedule and outputs decisions about the blind state, clothing state, drinks state, lights state, window state, and HVAC state, as shown in Figure 4.

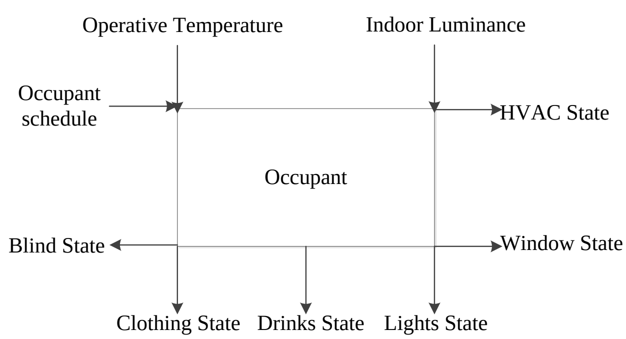

Figure 4: Parametric input/output relationships to the HVAC systems model

The cumulative distribution functions (CDFs) of these decisions are presented in Figure 5.a. The uniform pseudo-random number generator is transformed to a Gaussian probability density function using the Box-Muller algorithm which satisfies these CDFs (Box and Muller 1958). The flowchart shown in Figure 5.b. shows the decision making process of the occupant. For example, whenever an input message indicating a change in the operative temperature (weighted average of the air and the mean radiant surface temperature) is received, a cloth state (S_{cloth}) change temperature (T_{cloth}) is generated with a 24.6℃ mean (μ) and a 6℃ standard deviation (σ). If T_{cloth} exceeds the operative temperature, the occupant reduces his/her clothing level by 0.2 clo or 0.0155 m^2K/W (ASHRAE, 2010). This gives an occupant with 100W of metabolic energy generation an additional 1.5℃ (ΔT_{cloth}) tolerance. If the operative temperature exceeds the window opening temperature (μ=25.6℃ and σ=6℃), the window state (S_{win}) is changed to 'true'. If the operative temperature exceeds the beverage drinking temperature (T_{drink} μ=28.6℃ and σ=6℃), the

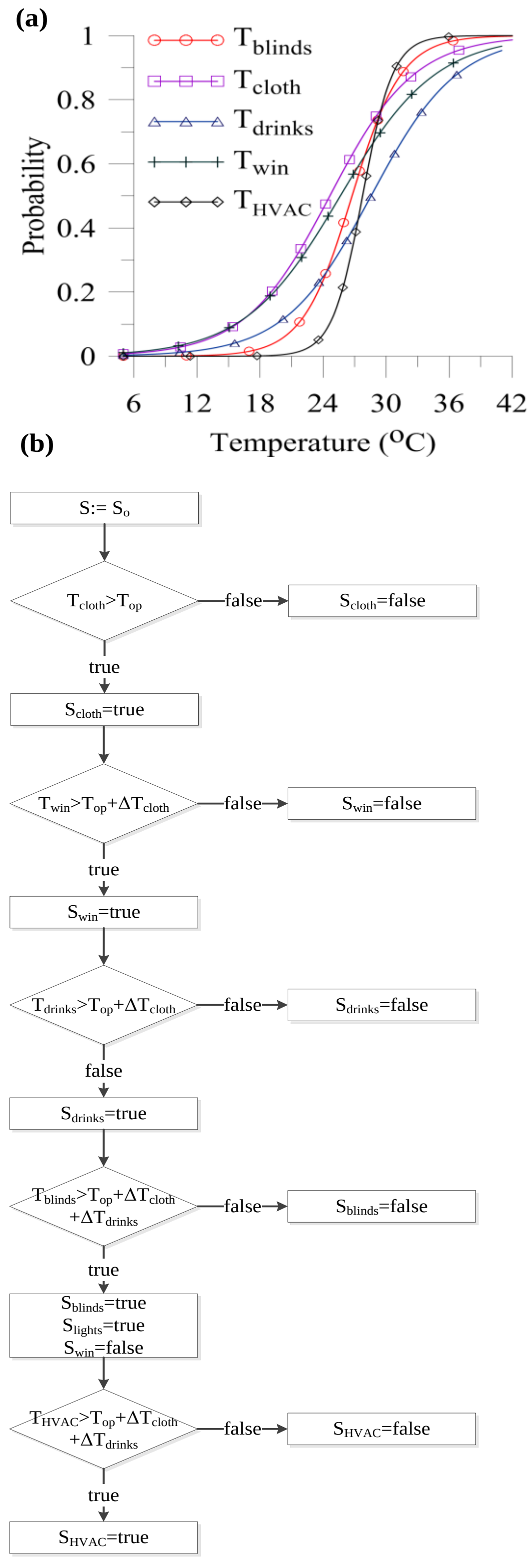

Figure 5: (a) CDFs for decision making temperatures and (b) flow of stochastic adaptive actions undertaken by an occupant

occupant drinks 500mL of a cold beverage at 5℃. This gives the 70kg occupant an additional 0.3℃ (ΔT_{drink}) tolerance. If the operative temperature exceeds the blind closing temperature (μ=26.8℃ and σ=2.5℃), the blind state (S_{blind}) is changed to 'true'. The light use decision (S_{light}) is undertaken when the indoor day light falls less than 300 lx or when the blinds are closed. The blinds are assumed to block the airflow substantially, therefore the window is closed when the blinds are closed. If the occupant, after attempting all available adaptive actions, is not thermally satisfied and the HVAC decision temperature (μ=26.3℃ and σ=1.5℃) is reached; the HVAC unit state (S_{HVAC}) changes to 'true'.

5. DEVS BUILDING ENERGY SIMULATION MODEL

Three domains of the building energy simulation problem (i.e. *building, HVAC systems,* and *occupant models*) have been separately modeled. A coupled DEVS building energy model is formed as shown in Figure 6.

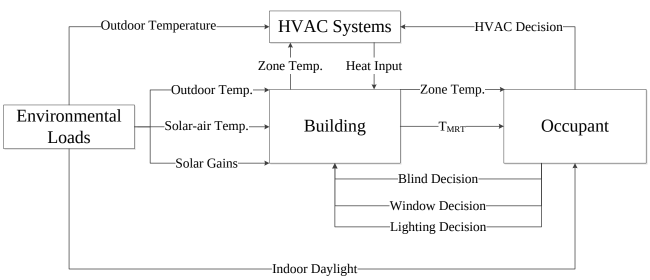

Figure 6: Coupled DEVS building energy model

The simulation of the coupled model starts as the weather data is transformed to the environmental loads such as outdoor temperature, solar-air temperature, and solar gains. These environmental loads are received by the building model and the air and mean radiant temperatures are sensed by the occupant. Subsequently, the occupant, in order to satisfy his comfort, undertakes personal (clothing, drinking) and environmental actions (blinds, window, HVAC). The environmental actions invoke the *building model*, the *HVAC systems model* or the *occupant model* (e.g. closing blind leads to a decision change on the lighting use or HVAC use leads to a decision change on the window state).

Figure 7 shows the operative temperature and cooling loads estimated by 5 repeated simulations of the coupled DEVS building energy model. The steady-periodic temperature data fluctuates between 26℃ and 32℃ where it increases until the occupant begins to adjust his/her personal perception and/or his/her environment. Due to the stochastic nature of the *occupant model*, results of the simulations vary. The temperature and the cooling load data are scattered over a range of a 2-3℃ and 500-1000 W between the simulations, respectively. The design day cooling load is estimated as 11, 11.5, 10, 10, and 14 kWh for the 5 repeated simulations. Thus, the mean cooling load can be estimated as 11.5 kWh with a standard deviation of 1.5 kWh.

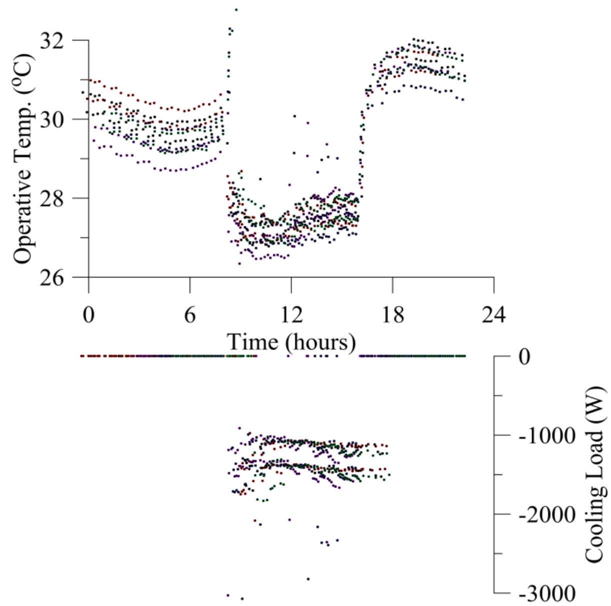

Figure 7: Operative temperature and the cooling load calculated using a coupled DEVS building energy model with repeated 5 simulations

6. DISCUSSION

The major advancement of using the DEVS formalism in *building model* development is that the developers can incorporate the physics of an external output without considering when, why, and how this external event occurs. The developer would rather be concerned with what happens physically, if it occurs. For example, the developer of the *building model* can incorporate the physics of the window opening without being overwhelmed with the processes leading to the window opening action (e.g. adaptive actions undertaken prior to the window opening action or the probability of the window opening behavior). Similarly, the *HVAC systems model* developer is solely concerned with the mechanical component modeling and the developer of the occupant model is just preoccupied with capturing the decion making process behind this adaptive action. In other words, opening the window is not a heat and mass transfer problem for the *occupant model* developer, it is a statistical reflection of a behavioral psychology problem. Thus, DEVS, by introducing modularity can enhance the interoperability of the different professions involved in the integrated design process. However, the modularity may also cause a limitation about performing isolated testing on the submodels. Figure 3 illustrates an isolate testing procedure for the *HVAC systems model* by leaving input messages. The reliability of such submodel testing is restricted by the artificial inputs in absence of other coupled submodels.

Traditional BPS-based design of a real-size building involves the assembly of matrices with a few thousand rows and columns (Clarke 2001). The interaction amongst different domains (i.e. building and HVAC) are sustained at a few overlapping regions, while the occupant decisions are distributed within the solver code. The modularity of the DEVS formalism, rather than challenging the existing building simulation algorithms, suggests a more organized code structure which will make models more flexible, transferable, and reusable. Moreover, degree of freedom of the problem increases as the number of occupants and the number of available adaptive actions that each occupant can undertake increase. This cannot be easily accomodated in traditional BPS tools, as the occupant decisions are distributed within the solver code. The Modelica modeling language, described in the context of BPS by Wetter (2009), addresses many of the same issues as DEVS. It keeps models separate from the simulation process and provides a framework for connecting these models. Modelica, however, features a non-traditional equation-based modeling approach. DEVS does not involve a universal differential equation solver. Multiple solvers, typically implemented by users in imperative code, may be embedded in the submodels.

7. CONCLUSIONS

The modular nature of the DEVS formalism is exploited in this study by forming submodels that allow domain experts to develop simulation techniques independently and later combine their work. These submodels are the *building*, the *HVAC system*, and the *occupant*. The *DEVS building energy* model shows the viability of the formalism in building energy simulation and indicates a promising way to enhance the interoperability amongst different professions involved in the integrated building design process.

Acknowledgements

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