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DISTRIBUTED SIMULATION FRAMEWORK TO ANALYZE THE ENERGY EFFECTS OF ADAPTIVE THERMAL COMFORT BEHAVIOR OF BUILDING OCCUPANTS

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ABSTRACT

People spend most of their time in indoor building environments. Thus, providing a comfortable living environment to the occupants is of extreme importance. Adaptive thermal comfort models developed through many studies suggested that the dynamic thermal based behavior of occupants can be utilized to optimize various energy influencing processes in the building. However, there is little research on how these behavioral patterns can be controlled and influenced using appropriate interventions. In this study, an agent-based model simulating zone-wise thermal comfort level of occupants in an office building is coupled with the energy simulation model through Lightweight Communications and Marshalling (LCM), a distributed computing framework. Case study results demonstrate the LCM framework's ability to communicate between simulation models across various spatially distributed workstations and allow for the quantification of the energy saving potential of various thermal comfort based interventions.

1 INTRODUCTION

People spent around 92% of their time in indoor building environments (Klepeis et al. 2001) and thus, providing comfortable indoor conditions to the building occupants is a top priority to the building owners and the facility managers. Factors such as thermal comfort and indoor air quality (IAQ) are extremely important in deciding the overall comfort level of the occupants (Kim et al. 2015, Yahya et al. 2014, Yun et al. 2012) and these two factors closely relate to the occupants' health. Among these, thermal comfort level is influenced by the effect of various physical quantities related to the environment (for e.g., air temperature, air velocity, humidity level) and interaction with various energy consuming devices such as the building HVAC systems (heating ventilation and air conditioning systems), personnel heaters and fans (Fabbri 2015).

Predicted mean vote (PMV) is used as the most preferred index for measuring the thermal in indoor living environments (Ku et al. 2015, Fabbri 2015). PMV was originally developed by Fanger (1970) by analyzing the comfort levels of occupants in closed climate chambers. Even though this original PMV index works well with climate controlled spaces, its accuracy reduces with naturally ventilated spaces (Yang et al. 2014) and this has resulted in improved versions of the PMV index that can be categorized in general, as adaptive thermal comfort models. These models are based on the adaptive principle, which can be defined as; "If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" (Fabbri 2015, Nicol and Humphreys 2012). Some of the adaptive behavioral patterns analyzed by studies include, but are not limited to, opening or closing the windows, adjusting the window shades, controlling the fan or heater speed, adjusting the thermostat temperature and the lighting appliance use. In general, it has been opined that occupants adjust themselves to achieve thermal comfort and by analyzing the dynamic pattern of a suitable thermal comfort index, building control actions can be optimized by the facility managers. In addition to these efforts, some studies have also quantified the energy saving possibilities of the adaptive behavioral patterns of building occupants (Kim et al. 2015, Daum et al. 2011, Alcala et al. 2005) by controlling and influencing various energy intensive actions.

Appropriate intervention techniques have been proposed as one effective method for influencing occupants' behavioral patterns (Azar and Menassa 2014, 2015, Xu et al. 2014, Staats et al. 2000). However, studying the effects of the interventions in a real building is time intensive and measuring how people adapt their thermal preferences to these interventions is not an easy task. Instead, before applying any intervention in a real building, a tool that can offer insights into effectiveness of various intervention techniques would be an ideal choice and a simulation-based approach can be handy in mimicking this complex system. Hence the main objective of this paper is to create a distributed simulation framework to understand the energy effects of occupants' adaptive thermal behavioral patterns by coupling an occupant behavior simulation model with an energy simulation model using a distributed simulation platform.

2 BACKGROUND AND OBJECTIVES

PMV concept as first proposed by Fanger (1970) takes into account six factors that define the thermal sensation of occupants in a building such as occupant's metabolic rate and clothing insulation, air temperature, mean radiant temperature, air velocity, and humidity. Based on these factors, Fanger developed equations that output a numerical value within -3 to +3 range, which defined the thermal sensation level of a building occupant. A value of '0' for PMV indicates that the occupant has no discomfort, while other values within the above mentioned range indicates increasing levels of discomfort. Olesen (2004) summarized the adaptation of PMV index across various national as well as international codes and among those, ASHRAE standard 55 and ISO 7730 are the most referred standards that provide details on how to measure the PMV levels of building occupants.

The common methodology adopted for developing a thermal comfort based model include collecting relevant data for calculating the PMV index through questionnaires, sensors and building energy management systems and using this data to develop the model. Calvino et al. (2004) used a fuzzy based logic to vary the PMV of occupants from a discomfort zone to a comfort zone by optimizing the speed of the heating fan. This study showed that by controlling the PMV, the HVAC related equipment in the building could be optimized. Haldi and Robinson (2010) collected data on building occupants' comfort parameters through sensors and electronic surveys and found out the probability distribution for the adaptive thermal sensation ranges. Subsequently, this study established the relationship between occupants' actions and its interplay with the thermal sensation levels. The case study results included an adaptive model for the prediction of actions on windows, visual sensation and comfort. Daum et al. (2011) also prepared a probabilistic distribution for the thermal sensation level and an adaptive control model based on collected data and created a model representing the effect of window shade action. Ku et al 2015 developed an inverse PMV model calculating the temperature settings of air conditioners based on fuzzy control logic. Three scenarios were considered and the energy savings were recorded. Kim et al. (2015) suggested alternate aPMV and nPMV models to express the thermal comfort of the building occupants and suggested that adaptive PMVs are better compared to the original PMV model. Adaptive thermal comfort models provide an opportunity for establishing how adaptive behavior of occupants can be used for optimizing building energy intensive systems (for e.g., air conditioner system) thereby achieving possible energy savings. Even though the original PMV or similar comfort indices as suggested by some of these studies are a useful measure to understand the comfort level of occupants, it does not explicitly optimize the energy consumption in buildings (Alcala et al. 2005).

Usually in a climate controlled building, appropriate thermal comfort levels are ensured by controlling the HVAC system. Temperature going below or above the comfortable range can disrupt the building occupant's metabolic rates and hence the comfort levels. Modern HVAC systems do not maintain a uniform temperature throughout the building, and different zones and different rooms in each zone will have slightly varying thermostat settings, mainly because of diverse thermal comfort preferences of people occupying these areas. Proximity of some zones with respect to the outside environment (e.g., perimeter zones compared to core zones) is another reason for non-uniform temperatures throughout a building.

In order to analyze the energy effects of these varying thermal comfort preferences, the ideal way is to perform energy simulation incorporating this dynamic behavior. However, the current energy simulation programs assume fixed heating and cooling schedules for the building and same thermostat set points across different zones. This does not mimic the actual scenario and there is a need for a more realistic way of representing the temperature preferences of the occupants. In addition, inspired by studies that established the energy saving opportunities because of adaptive behavioral patterns, effective ways of controlling this behavioral patterns also could give us insight into optimizing the energy consumption in the building. In order to achieve these two goals, there is a need for a framework that supports seamless integration of adaptive behavior models with energy simulation programs, which is the main motivation of this study.

In summary, the main objectives of this study are:

1. Develop a user friendly framework that couples an adaptive occupant behavior model (OBM) with an energy simulation model (ESM).
2. Analyze and understand the effects of interventions on occupants' adaptive thermal comfort behavior and quantify the possible energy savings.

3 METHODOLOGY

Figure 1 below depicts the overall theme of this ongoing pilot project. Occupants' adaptive behavioral traits that have an effect on the thermal comfort level such as adjusting thermostat to increase/decrease the room temperature, opening or closing windows to control the air flow in and out of the building and turning lights and equipment on or off, adjusting the speed of heaters and fans and adjusting window blinds are coupled with an energy simulation tool. This coupling allows us to understand the effects of aforementioned factors on energy consumption. A coupled system like this could be of use especially to the building facility managers to test the effectiveness of various control and intervention strategies before implementing those in a real building.

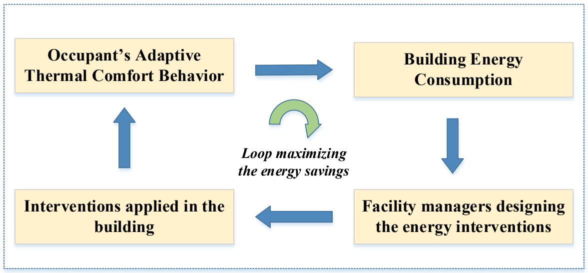

Figure 1: Main theme of this research.

Coupling software programs in the energy domain has been attempted before. Bourgeois et al. (2006) incorporated a sub hourly occupant control model into the energy simulation program to understand the effects on energy consumption. Wetter (2011) proposed Building Controls Virtual Test Bed (BCVTB), a middleware that facilitates the co-simulation between various software programs. From then on, many studies have used the capabilities of BCVTB to create various coupled systems (Zhao et al. 2016, Langevin et al. 2015, Duan et al. 2014, Pang et al. 2012) that proposed energy saving opportunities. Similarly, Menassa et al. 2014 proposed a coupled system using a middleware, High Level Architecture (HLA) for coupling an OBM with an energy simulation program. The main limitation of both BCVTB and HLA framework lies in its complexity involved (Nouidui 2014). An ideal method could be a simple framework that allows the contributing programs to interact (i.e., exchange variables of interest) directly without the presence of a complex middleware. Along these lines, more recently, a framework based on the rules of Functional Mockup Interface (FMI) has been proposed which eliminated the need of a middleware (Nouidui et al. 2014). This framework requires the contributing programs to be converted to a unified format so that each program can exchange data freely among themselves. However this limits the opportunity of coupling a tool which is not supported by FMI rules. In addition, the number and type of variables that can be exchanged in this mechanism is considerably limited, which reduce the flexibility of representing a true dynamic system. This motivates the need of a simple, but effective framework that could be generally applied in creating any coupled system to analyze the interactions between different software programs.

In order to establish such a seamless connection mechanism, the capabilities of Lightweight Communications and Marshaling (LCM), a common tool employed in robotics is explored for this study. LCM eliminates the need of a middleware and allows each connected programs to talk to each other. LCM's major focus is on simplifying the development and debugging of message passing systems and has been widely used in land, underwater and aerial robotics so far (LCM 2015, Huang et al. 2010). Messages can be passed across different systems using LCM's message passing system, which is platform and language independent. LCM uses User Datagram Protocol (UDP) multicasting method (employing a publish-subscribe mechanism) for sending and receiving messages across remotely located workstations (running specific simulation programs; for e.g., OBM, ESM). Each LCM message (for e.g., a text file with the energy simulation results) is transmitted to a UDP multicast group wherein the interested subscriber listens to the specific message. LCM has not been used in the building energy optimization and related domains and hence this study will utilize its simple message-passing feature in achieving the broader objective of coupling multiple software programs. Figure 2 below gives a conceptual outlay of the framework that explains how an OBM and the ESM is interacting with each other.

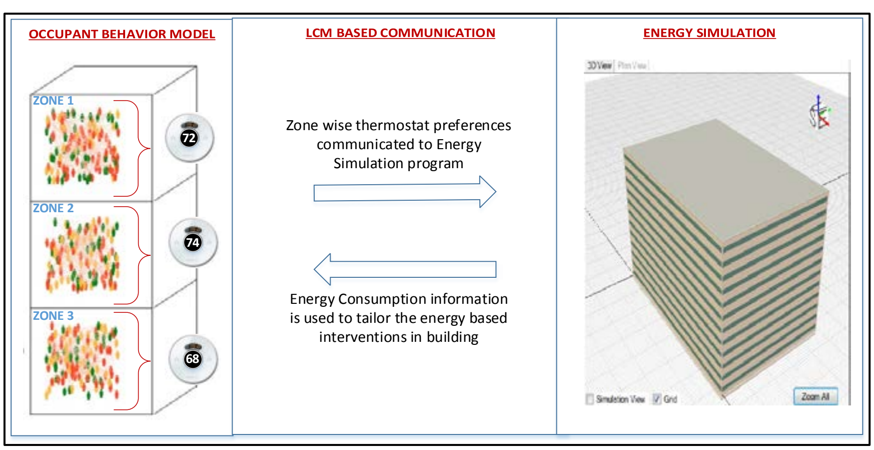

Figure 2: LCM Based communication between OBM and ESM.

The OBM in this study is developed using an agent-based modeling (ABM) concept. This ABM is a direct case study application of the model developed by Azar and Menassa (2013, 2015) that originally simulated the energy use intensity of the building occupants based on the relative agreement principles from the social science domain. In the original study by Azar and Menassa, each occupant had attributes such as energy intensity and variability, which was influenced by peer pressure and energy interventions. In our study, these attributes are replaced by occupants' thermal comfort levels (equivalent to the temperature an occupant wants to be set as the thermostat set point) and variability (the range through which the occupant can increase or decrease this preference). Since the main aim of this study is to understand the effect of this adaptive thermal comfort of occupants on the overall energy consumption and how it can be influenced and controlled, calculation of PMV values based on real data is considered as an extension of this ongoing study. Therefore, for this paper, the thermal comfort levels of occupants are randomly generated based on a uniform distribution. Again, this comfort level will be different for winter and summer period. These preferred ranges are adopted from the ASHRE standard.

Every occupant is connected to a fixed number of other occupants in each zone, which is a factor that can be initialized during the start of the ABM simulation. These connected occupants can be assumed as people occupying the same room. Each occupant can influence the connected occupant thus reaching to a mutually agreed thermostat set point. This action can be considered analogous to the peer pressure concept originally proposed by Azar and Menassa in explaining the dynamic energy use of occupants, i.e., a high energy user can influence a low energy user and vice versa. Similarly, in this study, the peer pressure will result in occupants interacting and influencing other's thermal comfort level based on the overlap in the preferences between the connected occupants. In the OBM, occupants are represented using three colors, which are red, orange and green. During the wintertime, an occupant represented by red color means he/she have a higher temperature preference in the preferred range and orange and green color denotes progressively lesser temperature preferences. But, during the summer time a red color occupant means the occupant with a lower temperature preference and similarly, orange and green color denotes higher preferences. An overlap means how distant is one's thermal comfort level with the other one's level. If this overlap is large, then that can result in one occupant influencing the other occupant to change his/her preference and if it is small, the influence does not occur. In a real building scenario, this can be equivalent to a person who is comfortable at a lower thermostat setting during the winter season influencing other occupants to increase their clothing levels finally resulting in mutually setting a lower set point for the thermostat. Eq. 1 and Eq. 2 below shows the calculations involved in preferred thermal comfort level and the variability of the occupants. Readers are encouraged to read Azar and Menassa (2014) for drawing more details about the logic of this ABM.

$$t_j = t_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times (t_i - t_j) \right) \tag{1}$$

$$v_j = v_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times (v_i - v_j) \right) \tag{2}$$

Where,

t_j is the desirable thermal comfort level of an occupant *j.*

t_i is the desirable thermal comfort level of the connected occupant.

h_{ij} is the overlap of thermal comfort level between the two connected occupants.

σ is the peer increment factor, which denotes the effectiveness of the interaction.

v_j is the variability of the thermal comfort level of an occupant *j.*

v_i is the variation of the thermal comfort level of the connected occupant *i*.

As mentioned before, the comfort level of occupants differ for different zones in the building and this reflects as varied thermostat set points for each zones. In order to represent this difference, a mean value is calculated for each zone and is considered as the representative thermostat set point required for that particular zone. This mean value for each zone is communicated to the energy simulation program at each time step via LCM and this becomes a direct input to the energy model from the OBM. The variable, which is edited in the energy model, is the daytime thermostat set point for the weekday for each zone (i.e., from morning 8.00 am to evening 5.00 pm).

Receipt of this message will trigger energy simulation program to start a simulation for a one-month period. For this paper, a one-month period is considered as the time step. Once the energy simulation model performs the energy simulation and simulates the energy use information, this information is used to decide how many interventions needs to be performed in the building during the next month in order to influence the thermal comfort level of the occupants. Figure 3 below shows the time synchronization diagram for this particular study and the logic adopted for deciding the number of interventions.

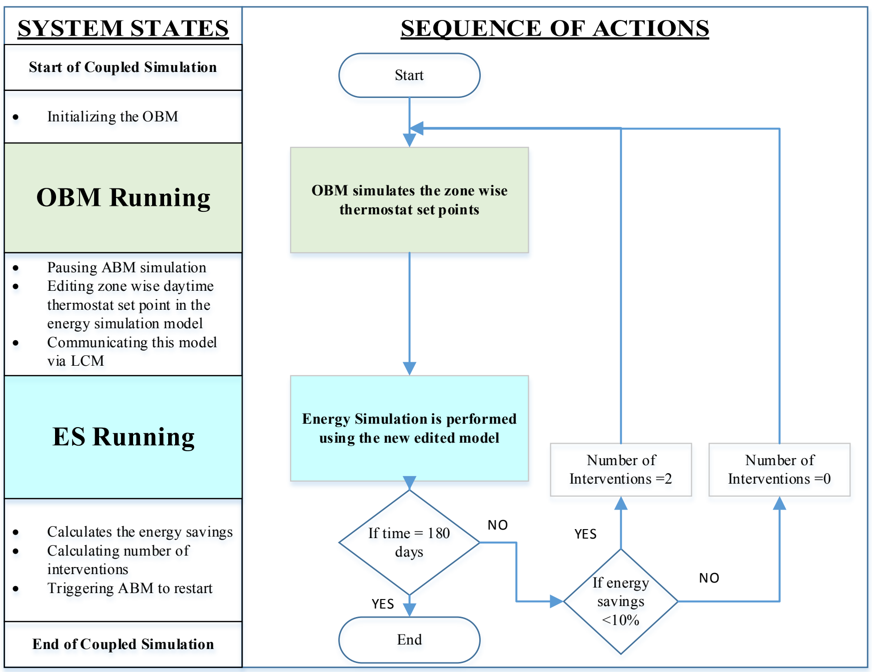

Figure 3: System States and sequence of action.

Prior to the start of the coupled simulation, an energy simulation is performed using the default energy simulation model to obtain the predicted energy consumption values for the specified time period (for e.g., six months, one year). Now in the OBM, for the first month, only the peer pressure is considered to be present, which means there are no interventions planned. At each time step, LCM will send the edited energy model to the workstation where energy simulation is programmed to run and will trigger starting the energy simulation automatically while pausing the OBM. Once the energy simulation is over, this triggers sending the energy use information back to the first workstation, which has the OBM running. This bi-directional information exchange occurs automatically for any specified period (i.e., six months, one year as specified by the user).

Upon receipt of this information, the OBM calculates the difference in the predicted (base case) versus the actual energy consumption and this determines the energy interventions to be planned for the next month. This is what mostly happens in any building. If the energy use is not happening as per the expectations of the facility managers, then interventions needs to be carried out in the building in the next period. These interventions directly influence the occupant to adapt to a different thermal comfort level. Once the number of energy interventions is calculated, this will trigger the OBM to restart and run the simulation for the next month based on the new information. The interventions are designed in such a way that the occupants with adverse temperature preferences (occupants who would like to have a higher thermostat set point in the winter time and a lower thermostat set point in the summer) would be targeted more. Adopting a strategy like this could result in influencing them to adapt better behavioral preferences such increase the clothing levels when it is cold, taking off some extra level of your clothes in hot weather, opening the windows to allowing natural ventilation in summer (Fabbri 2015).

Eq. 3 below gives the manner in which occupant's thermostat set point preference is modified by an intervention. Intervention efficiency in the equation refers to the type of intervention that can be planned in the building. Common interventions methods adopted by the facility managers are education programs (posters, mobile applications) and monetary rewards and the intervention efficiency varies across different intervention programs. The factor γ in the equation is designed to specifically focus on different types of occupants and this varies from 0 to 1. For adverse occupants, the value will be typically set at '1' which means targeting to influence their set point preference with the maximum intensity. This cycle will continue for any defined period by the user such as six months or one year and the energy savings for this entire period will be recorded for further drawing further inference.

$$t_i = t_i \times (1 - \gamma * uniform(0, intervention\ effciency) \tag{3}$$

Where,
t_i is the comfort temperature of occupant *i.*
γ is the factor that control the level of an intervention.

4 CASE STUDY

As mentioned earlier, the main objective of this paper is to propose the usability of LCM as a coupling aid. Hence the focus of validation of the framework is to model the energy effects of the zone wise thermal comfort level preferences of occupants in an office building using the OBM, demonstrating the exchange of variables between the OBM and the ESM and estimating the possible energy savings. For conducting detailed validation techniques such as historical validation or multistage validation, the major pre-requisite is the availability of adequate data points (in this case, the actual thermal comfort levels of the building occupants over a specified period) (Sargent 2000). The ongoing study is collecting those personnel comfort level data of occupants and hence the validation adopted in this paper is limited to technical validation, i.e., focusing on the technical and computing and data exchange mechanism of the framework.

Energy Plus is selected as the energy simulation software (EnergyPlus 2012). A medium sized office-building model provided by the Department of Energy is adopted as the ESM (DOE 2015). As was previously mentioned in the methodology section, the OBM is a direct case study application of the earlier published study (Azar and Menassa 2013, 2015). Brief details about the ESM and the general simulation details are summarized in Table 1 below. A total simulation for six months consisting of three winter months (January, February and March) and three summer months (April, May, June) are considered as the run period of the coupled framework. The zone wise thermostat set points are dynamically simulated as per the OBM logic outlined in the methodology section. The allowable temperature ranges for the thermostats are decided based on the ASHRAE recommended temperature ranges as given in Table 1.

Before starting the co-simulation, an EnergyPlus simulation is conducted for six months with the default energy model to obtain the energy consumption details for the base case, i.e., with fixed zone wise thermostat set points. After obtaining this default energy consumption for every month, the real co-simulation will be started by invoking the OBM. At each time step, i.e., one month in this case study, the OBM will create a new ESM with revised zone thermostat schedules. Creation of this new model will trigger EnergyPlus to start in a different workstation with the modified ESM. Once the EnergyPlus simulates the energy consumption for that time step, this energy consumption information will be conveyed back to the OBM. Upon receipt of this energy consumption information, the number of interventions for the next month will be estimated and the OBM will proceed with the simulation for the next time step. This process will be repeated for the specified time period (i.e., six months here) and that will complete one co-simulation. The actual energy consumption details can then be compared with the base case to calculate the overall savings possible. All inter communications are made possible with the help of LCM.

Table 1: Case study details.

Item	Description
Location of the building	Chicago
Type	Office
Shape	Rectangle
Building length	73.11m
Building width	48.74 m
No of stories	12 stories plus basement
Gross area	46, 320 sq. m
Number of zones	18
Occupancy in	16 zones
Number of total Occupants	2,397
Winter temperature range in degree Celsius	15.5-21
Summer Temperature range in degree Celsius	21-29

5 RESULTS AND DISCUSSIONS

The results from this coupled simulation is shown in Table 2. In six months, 10 interventions were implemented in the building (Two interventions applied for every month, from February through June). This has resulted in drifting occupants' comfort temperature levels downwards during the winter months and upwards during the summer months, which eventually resulted in an overall energy savings of around 10%.

Table 2: Energy consumption details.

Month	Energy Use measured in Giga Joules (Base Case)	Energy Use measured in Giga Joules (With energy interventions)
January	3938.125	3551.79
February	3153.28	2868.05
March	2575.519	2249.16
April	2,184.22	2173.02
May	2,093.09	1829.13
June	2,232.08	2091.7
Total	**16176.316**	**14762.85**

The main contribution from this study is the coupled framework. Once actuated, the framework runs and exchanges information between the contributing programs for the specified period, automatically. In addition, this does not involve any middleware to control this coupled simulation. Such a system could be of use to create efficient coupled frameworks in various domains of civil infrastructure systems. Another major inference from this study is about the energy savings possible by controlling and influencing the temperature preferences of the building occupants. In the next stage of this study, by feeding in real thermal comfort data, the energy savings can be accurately estimated.

6 CONCLUSIONS, LIMITATIONS AND FUTURE WORK

A simple framework that couples an OBM and an ESM is created. The energy effects of adaptive thermal comfort behavior of the occupants were tabulated. Since heating and cooling are the most significant modes of energy use in a building, these results can be considered to be very significant. This general framework can be extended to analyze the effects of many other behavioral traits of building occupants. The building managers can use this framework to show the building occupants about the possible energy saving opportunities in lieu of adopting good thermal comfort related behaviors.

The immediate extension of this study is in populating the thermal comfort based on the actual PMV level of all occupants. This requires extensive data collection about the occupants' actual thermal comfort and seamless integration of ESM model with the OBM to obtain the physical parameters such as zone wise ambient temperature, humidity, air velocity etc. The authors are adding this extended feature to the current model. This will provide a comprehensive framework that can be extended to analyze any given factor and its effects on the energy consumption level in the building. In addition, this general framework will have applications in many other domains that require co-simulation.

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