Related Commercial Resources

CHAPTER 65. OCCUPANT-CENTRIC SENSING AND CONTROLS

HUMANS generally spend 87% of their time in buildings, living and working (Klepeis et al. 2001). Understanding dynamic and diverse occupant comfort needs as well as occupant interactions with building systems is therefore crucial. Building design and operations must meet energy performance goals while providing healthy and productive living and working environments. At the same time, occupants also influence building performance (not just the other way around). For example, the International Energy Agency (IEA) Energy in Buildings and Communities (EBC) Programme Annex 53 (*Total Energy Use in Buildings: Analysis and Evaluation Methods)* identifies and evaluates occupant behavior as one of six key factors influencing energy use in buildings (IEA 2016).

Occupant actions such as adjusting a thermostat for comfort, switching lights on/off, using appliances, opening/closing windows, pulling window blinds up/down, and moving between spaces can significantly impact both energy use and occupant comfort. Depending on the building type, climate, and degree of automation in operation and controls, such behaviors can impact energy use by up to a factor of three for residential buildings (Andersen 2012), and result in an up to 80% increase or 50% decrease for single-occupancy offices (Hong and Lin 2013). One simulation study (Sun and Hong 2017) also estimated occupant behavior measures to have a 41% energy savings potential for office buildings.

Nevertheless, there is currently little integration of information about occupancy and occupant preferences in building control systems. Taking advantage of this information, energy use can be reduced with optimized sequencing of HVAC systems, lighting systems, or even operable windows and blinds (Sun et al. 2014); herein, such sequencing is referred to as *occupant-centric building control*. Occupant-centric sensing and controls include detection or monitoring of occupant presence, movement, comfort level, interactions with building systems, and other environmental adaptations, as well as the operational strategies required to meet occupants' needs with respect to thermal, visual, and acoustic comfort, and indoor air quality.

Figure 1 demonstrates an occupant-centric control scheme in which occupancy information (e.g., presence, count, and activity) and indoor environmental parameters (e.g., temperature, humidity, and CO_2 concentration) are detected and transferred as a feedback signal to the control system (Park et al. 2019). Control algorithms find optimal set points for zone parameters (e.g., temperature, illuminance, ventilation), accounting for occupant comfort models and feedback, and implement the chosen control action.

This chapter provides a technical overview of occupant-centric sensing and control, including data collection and modeling approaches for occupancy-based control and occupant preference-based control. Focus is primarily on HVAC-related controls (e.g., where zone temperature is set based on real-time occupancy and/or comfort measurements); in many cases, such control schemes also incorporate predictions about future occupancy and/or comfort states. Current mainstream HVAC control practice depends on the choice of predefined deadband values, which involves a significant amount of tedious tuning. In fact, this tuning has become increasingly challenging as modern HVAC systems grow in complexity, particularly with regard to the uncertain characteristics of occupancy and occupant behavior. However, with decreased costs and advances in data processing, storage, and computing, it becomes feasible to adopt an occupant-centric control approach to overcome such inherent issues in HVAC controls. In previous applications, such occupant-centric HVAC control schemes have demonstrated energy savings potential ranging from 10% to 40% in residential (Pang et al. 2021), office (Ghahramani et al. 2014; Gunay 2016; Park et al. 2020; Pang et al. 2020; Williams et al. 2012) and primary school buildings (Ye et al. 2021) across different climatic zones while maintaining or improving occupant comfort outcomes. For a detailed description of design and commissioning of HVAC control system, see Chapter 48.

1. COLLECTING REAL-TIME OCCUPANCY AND OCCUPANT COMFORT FEEDBACK

Occupant feedback to a building management system can be categorized as indirect, where the system passively monitors occupants and takes appropriate actions; direct, where occupants provide information to control the system; or a hybrid of indirect and direct (Munir et al. 2013). Feedback may be further categorized as solicited (requiring periodic prompting of occupants for information) or unsolicited (collected without prompting occupants for information).

1.1 INDIRECT OCCUPANT FEEDBACK

Indirect occupant-centric control schemes use measured variables as proxies for real-time occupancy and/or occupant comfort information. Such variables may include infrared light, pressure, equipment power consumption (e.g., computers and other plug loads), control states (e.g., VAV damper position, door or window status, heating, cooling, lighting set-point overrides), Wi-Fi network logs, and environmental measurements (e.g., volatile organic compound [VOC], CO, or CO_2 concentration; ultrasonic or audible sound; illumination; temperature; humidity). Statistical or physical models are used to uncover latent occupancy information in data and infer the presence and/or number of occupants in a zone. These data may also be used to infer occupants' comfort states.

Examples of indirect occupancy feedback schemes are found in Labeodan et al. (2015), where chair sensors are used in an office building to provide fine-grained occupancy information for demand-driven control applications; Ardakanian et al. (2016), where apparent zone-level occupancy is inferred from building automation system data and used to tune set points to real-time occupancy patterns; Goyal et al. (2015), which examines the relative benefits of rule-based and model-predictive control of commercial HVAC using real-time occupancy measurements from a passive infrared sensor; Agarwal et al. (2010), which uses a combined passive infrared and reed switch sensor to detect occupancy in an office and set back thermostat set points when no occupancy is detected; Jin et al. (2015) and Hobson et al. (2020), where occupant counts respectively inferred through (1) supply and return air CO_2 concentrations and (2) WiFi device counts drive a demand-controlled ventilation strategy; Alishahi et al. (2021), Ashouri et al. (2019), and Wang et al. (2019), which use WiFi device counts to identify occupancy patterns and indicators; and Hobson et al. (2019), which combines sensing of several indirect variables, including WiFi device counts, CO_2 concentration, passive infrared (PIR) sensor triggers, and plug loads to predict occupant counts.

For indirect comfort feedback, proxy measurements include outdoor temperature, which can be translated to group-level comfort predictions using the adaptive comfort standard, as well as indoor temperature, humidity, and air velocity, which can be paired with assumptions about typical occupant clothing and metabolic rate (Erickson and Cerpa 2012), or indirect measurements of such variables, (e.g., via respiratory sensors) to calculate predicted mean vote (PMV) (Fanger 1973).

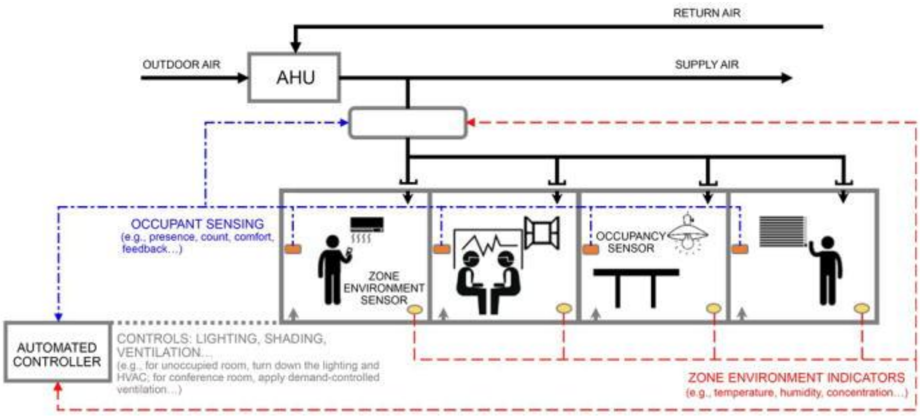

Figure 1. Occupant-Centric Sensing and Control Scheme

Additionally, recent research suggests that measurements from wearable devices for skin temperature, perspiration rate, and heart rate may be used as proxies for individual-level occupant comfort, though the accuracy and large-scale deployment potential of such techniques remain uncertain (Abdallah et al. 2016). Other studies suggest that occupants' control interactions (e.g., interactions with personal comfort systems [Kim et al. 2018a, 2018b] or with zone thermostats) may also be effective proxies for individual-level comfort. Finally, body shape inferred from depth-based camera systems has recently been suggested as another promising predictor of thermal comfort (Francis et al. 2019).

Examples of indirect comfort feedback schemes are found in Abdallah et al. (2016), where traditional environmental sensing data streams are fused with wearable sensing information to predict PMV; Klein et al. (2012), where occupant preferences and schedules are coordinated with building system device control using a multiagent framework; Gunay et al. (2018a), where a thermostat set-point learning algorithm is developed based on thermostat override behavior and implemented in multiple private offices, resulting in a wider heating and cooling set-point band; Jayathissa et al. (2019; 2020), where smartwatch data on occupants' heart rate and on-body temperature and light sensor are paired with environmental sensing data and trained against periodic thermal and visual comfort votes; and Nagy et al. (2015), where set points for switching artificial lighting on and off are derived dynamically from statistical analysis of occupancy sensor data and occupant lighting control actions.

Because indirect feedback schemes do not require occupant input, occupant data are generally collected in an unsolicited manner without prompting occupants for information (e.g., see Gunay et al. 2018b). Although indirect feedback is less intrusive to collect, the effectiveness of such schemes is subject to contextual factors. For example, occupants may be less likely to interact with thermostats in shared spaces versus in private offices due to concerns about affecting the comfort of other occupants in the space and/or because it is expected that thermostat adjustments will have minimal effect on reducing discomfort in larger shared spaces. Moreover, indirect schemes that rely on occupant interactions with controls may be limited by the infrequency with which these interactions tend to occur, leading to unreasonably long periods of data collection before one can reliably infer occupant preferences.

1.2 DIRECT OCCUPANT FEEDBACK

Direct occupant-centric control schemes require occupant input to determine real-time occupancy and/or occupant comfort. In the case of the former, direct feedback may include visual, infrared, or depth camera-based determination of occupant presence and/or count; radio frequency tagging of occupants; or detection of personal devices using Bluetooth beacons. Here, occupancy is determined through physical interaction with spaces and sensing instruments, rather than inferred through proxy variables (as in indirect feedback schemes). Similarly, direct comfort feedback schemes determine comfort states via occupant reporting of those states, rather than based on proxy variables for comfort.

Examples of direct occupancy feedback schemes are found in Newsham and Arsenault (2009), where a digital-camera-based system for lighting and shading control was developed using an image subtraction technique; Sangogboye et al. (2017) and Munir et al. (2017), which use depth sensors to detect occupant counts and occupancy; and Li et al. (2011), where a radio frequency identification (RFID)-based occupancy detection system estimates occupant counts across multiple spaces in real time, supporting demand driven HVAC operations.

Direct comfort-feedback schemes collect real-time occupant comfort input via survey interfaces on personal electronic devices such as smart phones, tablets, and computers. Such surveys typically ask an occupant to register their current environmental preference (e.g., cooler or warmer, darker or lighter, no change), feeding these preference votes back to the building management system to drive heating, cooling, and lighting adjustments. Various preference scales are suggested in existing literature, including the ASHRAE *Standard* 55 thermal sensation scale, the Bedford comfort scale, the McIntyre three-point preference scale, the binary thermal acceptability scale, and combinations or simplifications of these (Jazizadeh et al. 2014a; Zhang et al. 2015). In building zones with multiple occupants and preference votes, votes must be aggregated by the building management system before a control action can be determined. This aggregation may be achieved through simple averaging or with determination of a simple majority consensus (Shin et al. 2017). Alternatively, more sophisticated vote aggregation approaches may be used, such as when errors between each occupant's vote and a reference vote are summed across occupants and minimized by the attendant control strategy (Purdon et al. 2013) or votes are weighed differently according to occupant type (e.g., employee versus visitor) and vote history (Erickson and Cerpa 2012).

Direct comfort feedback schemes are characterized by the persistent requirement for occupant votes to change building operation; in the absence of these votes, control states remain unchanged from default schedules and unaffected by dynamic variables that might serve as proxies for occupant comfort, as previously discussed.

Examples of direct comfort feedback schemes are found in Chen et al. (2015), wherein a dynamic thermal sensation (DTS) model that incorporates real-time thermal sensation votes is used to optimize the control temperature of an experimental chamber; Purdon et al. (2013), where a model- and sensor-free control algorithm paired with real-time user comfort votes drives HVAC operation; Pritoni et al. (2017), where student comfort votes collected and averaged every five minutes override thermostat set points which, in one case, are allowed to slowly drift towards outdoor temperatures to yield energy savings; and Khan et al. (2021), which develops a simple thermal voting interface and assesses its use when distributed near points of entry of both open and private office spaces.

Collection of direct occupant feedback may be either solicited or unsolicited. Examples of solicited direct occupant feedback include a smartwatch or phone app that periodically reminds occupants to provide comfort votes, whereas instances of such apps that collect comfort votes and/or complaints without direct prompting are examples of unsolicited direct feedback schemes.

1.3 HYBRID OCCUPANT FEEDBACK

Hybrid occupant-centric control schemes merge direct occupant feedback with indirect occupant measurements in order to minimize the burden of reporting for occupants and increase the accuracy and coverage of real-time occupancy and/or occupant comfort measurements. Hybrid approaches to both occupancy and comfort involve learning schemes in which direct input informs and trains models that use occupant proxy variables as inputs. Once trained, such models predict real-time occupancy and/or comfort, given changes in the proxy inputs and without the need for direct occupant input. In some instances, occupant inputs beyond the initial training period are used to update model input coefficients (Lee et al. 2017), while in others, control actions accommodate requests for changes while keeping model coefficients consistent (Ghahramani et al. 2014).

Several examples of hybrid occupancy and/or comfort feedback schemes are found in the existing literature, including Peng et al. (2017), where temperature setbacks are inferred based on occupancy profiles learned from historical (two to four weeks into the past) occupancy data collected by motion sensors; Jazizadeh et al. (2014a, 2014b), which fuse comfort votes and ambient temperature data, compute comfort profiles using a fuzzy rule-based descriptive and predictive model, and use the learned comfort profiles to control an HVAC system; Lee et al. (2017) and Sadeghi et al. (2017), which use a Bayesian approach to efficiently learn and update personalized thermal and lighting preference profiles, clustering occupants based on preferences; Kim et al. (2018a, 2018a), where several different machine learning approaches effectively predict individual-level thermal comfort, leveraging data on occupant interaction with personal comfort systems and other local environmental data; Ghahramani et al. (2014), which trains zone-level personalized comfort profiles and selects zone temperature set points based on an optimization of energy, comfort profile, air quality, and system performance; Winkler et al. (2016), which explores several HVAC control strategies that incorporate occupant thermal preferences learned from comfort voting feedback; Daum et al. (2011), where user comfort votes are translated to probabilistic comfort profiles that serve as optimization functions for blind control; and Park et al. (2020), where thermal votes are coupled with monitored temperature and occupancy in an agent-based determination of adaptive thermostat set points that balance occupant comfort and energy efficiency goals.

Figure 2 provides a diagrammatic overview of an occupant-centric control system architecture that incorporates both direct and indirect occupant feedback. As shown in the figure, occupant data drawn from a variety of sources, including environmental and wearable sensors and mobile devices, are merged with data from the building management system and personal environmental control devices (Zhang et al. 2015) on control states and local environmental conditions. This figure pertains to HVAC control, but the same feedback loop applies to lighting, ventilation, and plug load control schemes. A more complete characterization of the types of sensing equipment available for occupant data collection is provided in the following sections.

1.4 STATE-OF-THE-ART OCCUPANT SENSING

A wide range of sensor types has been implemented in the field to collect information on occupants and their interactions (presence, actions, power consumption, etc.) with the built environment. This information establishes a foundation to study the physiological, psychological, and social aspects of occupant behavior. This section summarizes existing data acquisition technologies in terms of field applications and develops nine performance metrics for evaluation. The reviewed technologies focus on both occupant presence and interaction with the built environment, and are categorized into six major categories: threshold and mechanical, image-based, motion sensing, radio-based environmental, human-in-the-loop, and consumption sensing (Andreas et al. 2018). See Chapter 63 for a discussion on smart sensing methods that can be adopted for occupant-sensing technologies.

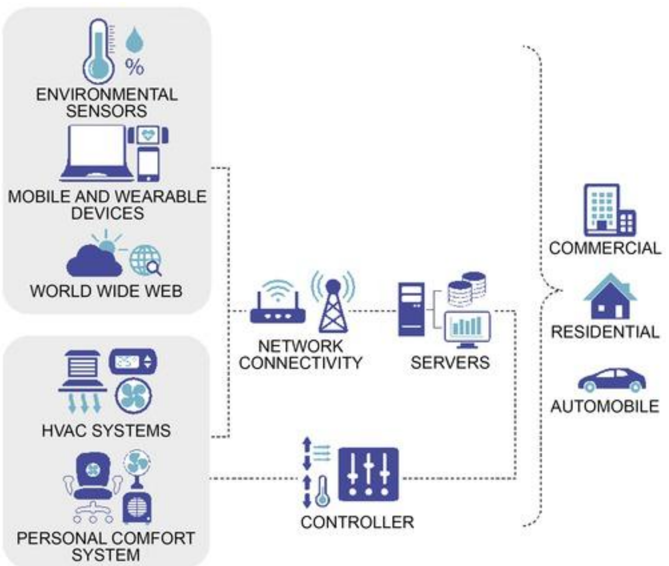

Figure 2. System Architecture for Occupant-Responsive Environmental Control (Adapted from Kim et al. [2018)])

Threshold and Mechanical Sensing. Threshold and mechanical sensors detect or change the acquired state of building components with which occupants frequently interact, such as windows or doors. Examples in this category include

- *Reed contacts*, which detect whether a door or window has been opened or closed
- *Door badges*, which an occupant must swipe to access a room
- *Piezoelectric mats*, which produce an electric signal when an occupant stands or walks on them
- *Infrared (IR) beams*, which produce a signal when the beam is blocked at the entrance.

Image-based Sensing. Image-based sensing collects objective and quantitative occupant data. The primary focus of image-based occupant detection technologies is to track people as they move through spaces (Erickson et al. 2014; Gade et al. 2012, 2013; Kamthe et al. 2009; Kumar et al. 2014). If errors can be excluded (such as accounting for noncovered areas in a space), image-based sensing can provide ground truth information for studies using other sensors (Dong and Lam 2011; Dong et al. 2015; Erickson et al. 2009; Hutchins et al. 2007; Lam et al. 2009; Li and Dong 2017; Meyn et al. 2009) and to study occupant interactions with building elements such as windows (Inkarojrit 2005; Konis 2012), blinds, and shades (Kapsis et al. 2013; Reinhart 2001), or occupant evacuation (Proulx and Reid 2006). The most advanced versions of image-based technology use detection algorithms running within the packaged visible light camera hardware to detect the direction and number of people traveling through a space (Wang and Fesenmaier 2013). Simpler approaches use visible light cameras to detect motion (Ding et al. 2011). Challenges associated with this data collection method include the analysis of visual information and ethical considerations.

Motion Sensing. Passive infrared (PIR), ultrasonic Doppler, microwave Doppler, and ultrasonic ranging sensors (Agarwal et al. 2010, 2011; Hnat et al. 2012; Yavari et al. 2013) are commonly used motion sensors. PIR is by far the most common. This sensor can be used for lighting control and to verify occupant presence models (Dong and Lam 2011; Dong et al. 2015; Yavari et al. 2013). PIR sensors are only accurate if mounted to achieve good coverage of the areas of occupancy. These sensors often under count because they require line of sight and become inactive when occupancy activity is low. The ultrasonic and microwave Doppler sensors measure frequency (the speed at which an object is moving toward or away from the sensor). Doppler sensors are technically advanced and have greater sensitivity than PIR sensors, yet are not commonly applied for building automation. They also tend to over count due to extreme sensitivity to smaller movements. Ultrasonic range sensors, meanwhile, measure the distance to objects and have been used to measure motion through doorway passing events (Hnat et al. 2012). Ultrasonic range sensors have moderate cost, and accuracy is only good if the mounting environment is free from ultrasonic noise and no nonhuman objects are moved through the doorway.

Radio Signal Sensing. Radio signals cover the range of electromagnetic wave frequencies from 10 kHz to 300 GHz (Misra and Enge 2011) and are sent from a transmitting node to a receiving node. The signal consists of a short series of pulses or a modulated radio signal. Radio signals can provide occupancy information such as user location, presence, count, identity, and movement (Martani et al. 2012). It is important to consider that radio signals transmitted through air are affected by humidity, the presence of other signals, and many other environmental factors that can have a significant impact on the accuracy of the sensing results. Different types of radio-based technologies have been standardized and commercialized and can be used for occupancy detection. Relevant radio technologies for occupancy detection include radio frequency identification (RFID) (Nan et al. 2012), Wi-Fi/Bluetooth® (Alishahi et al. 2021; Park et al. 2018), and ultra-wideband (UWB).

Human-in-the-Loop. The human-in-the-loop method requires humans to be involved in the measurement and collection of occupancy and/or comfort or behavior data. There are three approaches in this category. **Manual observations** cover the logging of data by a person directly sensing the information being relayed (e.g., counting the people walking through a hallway in person or watching a video recorded in a building and annotating the video with occupancy information). Manual observations are often used as the ground truth when evaluating the accuracy of other occupancy sensors. This method is costly because of the labor required, but can achieve high accuracy if it is possible to precisely define the task to ensure consistency in interpretation and recording. **Internet-based occupant data** cover various types of data provided by occupants and collected by applications such as social networks, calendars, or surveys. Although there are some privacy concerns associated with this approach (e.g., collecting sensitive information), many organizations already gather such data, which brings down the cost of occupancy sensing. Methods combining social networking and calendar data have been proposed for the estimation of cubicle occupancy (Ghai et al. 2012). **Device interactions** include occupant action data registered through interaction with control interfaces. Common interfaces include thermostats, light switches, and controls for motorized blinds. Wall thermostats and other modern control interfaces often contain programmable buttons to execute occupants' control decisions, such as increasing/decreasing temperature set points, turning on/off lighting, and adjusting the position of motorized blinds. Logging occupant manipulation of motorized blinds is a more common method of using sensors for monitoring blinds.

Consumption Sensing. Consumption sensing derives information about occupant presence or behavior from measured water and energy consumption in buildings. The accuracy of such methods depends on the level of metering granularity, which ranges from one meter per building to one meter per receptacle/fixture. Better metering granularity can be obtained via algorithmic methods (i.e., nonintrusive load monitoring methods) that split total consumption into its individual components. The cost of such methods is directly related to the cost of installing relevant metering. Existing studies have shown that the power consumption of electric appliances in offices and homes has a very high correlation with usage of appliances (Dong et al. 2015) and occupancy status of the space (Zhao et al. 2014). More recently, smart water meters have been used for detailed monitoring, but the deployment of smart water meters is still far behind that of electricity meters (Ranjan et al. 2014; Xue et al. 2017).

Table 1 Overview of Occupancy Sensing Technologies and Their Performance Metrics

			Power Type		Data Storage		Deployment Type		Sensing Range		Data Sensed					
	Specific Sensing Technology	Relative Cost	Battery	Wired	Internal	Network	Industry/Comm./Public	Residential	Distance from Sensor	Angle from Sensor	Presence	Count	People Tracking	Actions	State	Collectio Style
Image-based	Video	$$$	Y	Y	Y	Y	Y	N	Infinite	90 to 180°	Y	Y	Y	Y	Y	Periodic/Eve
	IR Camera	$$$$	Y	Y	Y	Y	Y	N	Infinite	90 to 180°	Y	Y	Y	Y	Y	Periodic/Eve
Threshold and mechanical	IR beam	$	N	Y	N	Y	Y	N	20 m	N/A	N	N	N	N	N	Events
	Piezoelectric mat	$$	N	Y	N	Y	Y	N	N/A	N/A	Y	N	N	N	N	Events
	Reed switch	$	N	Y	N	Y	Y	Y	N/A	N/A	N	N	N	Y	Y	Events
	Door badges	$$$	N	Y	N	Y	Y	N	N/A	N/A	Y	Y	Y	Y	Y	Events
Motion sensing	PIR	$$	Y	Y	Y	Y	Y	Y	10 m	110°	Y	Y	N	N	N	Events
	Ultrasonic Doppler	$$	Y	Y	Y	Y	Y	Y	20 m	360°	Y	N	N	N	N	Events
	Microwave Doppler	$$	Y	Y	Y	Y	Y	Y	20 m	360°	Y	N	N	N	N	Events
	Ultrasonic ranging	$$	Y	Y	Y	Y	Y	Y	4 m	90°	Y	Y	N	N	N	Events
Radio-based	RFID	$$$	Y	N	N	Y	Y	Y	3 to 200 m or greater	N/A	Y	Y	Y	N	N	Periodic
	UWB	$$$	Y	N	N	Y	Y	N	3 to 200 m or greater	N/A	Y	Y	Y	N	N	Periodic
	GPS	$$$	Y	N	N	Y	Y	N	Infinite	N/A	Y	Y	Y	N	N	Periodic
	Wi-Fi/Bluetooth®	$$$	Y	N	N	Y	Y	Y	32 m	N/A	Y	Y	Y	N	N	Periodic
Environmental	Air properties	$$	Y	Y	Y	Y	Y	Y	Per space	N/A	Y	Y	N	N	N	Periodic
	Acoustic	$$	Y	Y	Y	Y	Y	Y	Per space	360°	Y	Y	N	Y	Y	Periodic
Human-in-the-loop	Observation	$$$$	N/A	N/A	N/A	N/A	Y	Y	N/A	N/A	Y	Y	Y	Y	Y	Periodic/Eve
	Occupant data	$$	N/A	N/A	N/A	N/A	Y	Y	N/A	N/A	Y	Y	Y	N	N	Events

Consumption sensing	Building data	$$	Y	Y	Y	Y	Y	Y	N/A	N/A	Y	N	N	Y	Y	Events
	Energy	$$	Y	Y	Y	Y	Y	Y	N/A	N/A	Y	Y	N	Y	Y	Periodic
	Water	$$	Y	Y	Y	Y	Y	Y	N/A	N/A	Y	Y	N	Y	Y	Periodic

Mixed Sensing. Due to the daily interactions between occupants and indoor environment (generation of heat, pollutants [e.g., CO_2, odor] and sound, opening and closing of windows, and lights being turned on and off), a single sensing technology often cannot cover the full range of occupant comfort/behavior and presence. A mixed sensing approach can be adopted, whereby various types of sensors are used together (sensor fusion). A typical example is an information technology enabled sustainability testbed (ITEST), developed by Dong and Lam (2011). This includes occupant sensing, data acquisition, data storage and management, and data processing. ITEST uses PIR and an array of sensors, including cameras and devices measuring total volatile organic compound (TVOC) concentration, CO_2, temperature, illuminance, relative humidity, and acoustics. Together, these detect and predict occupant presence and numbers in an office building (Dong and Lam 2011).

Performance Metrics for Occupancy Sensing Technologies

The following performance metrics, shown in Table 1, are developed based on review of current sensing technologies and adapted from Andreas et al. (2018).

Cost. The total cost of deploying an occupant sensing technology. The cost encompasses several elements, such as hardware, installation and integration, and operation.

Power Type. The manner in which a sensing technology is powered (such as external or self-powered).

Data Storage. Data storage options provided by a given sensing technology. Internal storage uses an onboard device. If data from the sensor(s) is stored on a server or a distributed environment (networking), details of that architecture should be reported.

Deployment Type. Any description of an occupant detection technology should specify how it is deployed, including three key components: type of building, type of room(s), and specific deployment.

Sensing Range. Where applicable, an occupant sensing technology should be tested to find the maximum (and if relevant, minimum) range, as well as the area or view angle that it can cover.

Data Sensed. Data can be divided into five categories: presence, count, people tracking, state, and actions. Most technologies are only concerned with one type of data at a time. This distinction is the most critical for occupant sensing technology and should be precisely and clearly noted.

Collection Style. The collection method of an occupant detection technology should be reported, distinguishing between periodic (taking a sample at a fixed time period) and event-based (taking a sample when triggered).

Accuracy and Failure. Where possible, the absolute accuracy should be reported, compared to a manual observation or other relevant methods. In addition, any report on a new technology or deployment area should consider potential situations of sensor failure, such as failure due to environmental conditions, system failures, or inaccuracies.

Demonstrated Control Applications. Demonstration level of an occupant action and presence detection technology can be evaluated by two main factors: the number of papers reporting on it and whether or not it is commercially available.

2. INTEGRATING OCCUPANT FEEDBACK INTO HVAC CONTROL SCHEMES

Traditional Control Methods for HVAC Systems

Traditionally, a building automation system (BAS) provides a centralized management system to control heating, ventilation, air conditioning, lighting, safety, and security, to achieve occupant comfort and efficient building operation (Carlson and Giandomenico 1991). Most control methods used in traditional BAS can be divided into two main categories: supervisory and local controllers.

Supervisory (high-level) controllers define set points for local controllers to achieve cost-efficient thermal comfort without violating system constraints (Wang and Ma 2008). Local (low-level) controllers manage each low-level hardware component of the system to achieve their functions.

The low-level category can be divided further into the subcategories of sequencing and process control. Sequencing control turns each component on and off, while process control brings each component state to desired values. Over the past few decades, different supervisory control methods have been developed, including PID, optimal, model predictive control (MPC), robust, nonlinear, and adaptive controllers (Naidu and Rieger 2011a, 2011b). Optimal and model predictive control methods are known for their attractive energy savings potential; MPC and robust controllers are recognized for their capability in dealing with model uncertainties and disturbances (Gang et al. 2015). Among all these controllers, PID and on/off controllers are most popular, due to their simplicity and ease of implementation.

Occupant-Driven Rule-Based HVAC Controls

Occupancy measurements have commonly been integrated into building controls for lighting and HVAC systems (Bourgeois et al. 2006; Erickson et al. 2009; Hoes et al. 2009; Roetzel et al. 2010). Typically, a motion or PIR sensor is installed in a space to indicate whether the space is occupied or not. If the space is occupied, lighting is turned on and the temperature set point is aligned with the daytime preference temperature. Otherwise, lighting is turned off and the temperature set point goes to setback mode. Such occupancy-driven rule-based HVAC controls have demonstrated significant energy savings in both simulation case studies and field experiments. For example, PIR sensors were installed for two weeks in ten offices to measure occupancy presence and then a simulation study carried out to show that 10 to 15% energy savings in VAV boxes can be achieved. Erickson et al. (2011) found that 42% energy saving is achieved using an occupancy-driven rule-based controller, compared to use of a baseline controller that does not know occupancy information in advance. Ding et al. (2016) demonstrate 35.9% energy saving in simulation using a Markov-model-trained occupancy prediction for cooling control.

Most of the time, overtime work in companies is not accounted for. There are some studies that attempt to model the number of occupants in the building after regular working hours in commercial buildings (Sun et al. 2014). Gunay et al. (2015) models occupancy arrival and departure in commercial buildings with data from PIR sensors, with a resulting 10 to 15% energy saving in an EnergyPlus simulation.

In addition to the temperature set-point controls, occupancy measurement is also used for room ventilation control. Yuan and Perez (2006) introduce an algorithm to pre-ventilating each room based on occupied status of neighboring rooms and demonstrate 6.1 to 19.7% energy savings compared to a traditional control. Specifically, each unoccupied room is preconditioned if a neighboring room is occupied.

Table 2 Optimization Methods and Related Software for Solving Occupancy-Based MPC Problem

Study	Building Type	MPC Prediction Horizon	Optimization Method	Software
Freire et al. (2008)	Single-zone building	10 steps	Quadratic programming	MATLAB
Xu et al. (2009)	8 zone commercial building	5 min	GA	TRNSYS
Mady et al. (2011)	Single Room	1 hour	Quadratic programming	MATLAB
Cigler et al. (2012)	TRNSYS	8 to 32 steps	Quadratic programming	TRNSYS, MATLAB
Aswani et al. (2012)	Computer laboratory on university campus	5 hours	Sequential quadratic programming	MATLAB, SNOPT solver
Brooks and Barooah (2014)	Commercial building, room-level climate control	120 minutes	Broyden-Fletcher-Goldfarb-Shanno (BFGS)	IPOPT, MATLAB
Dong and Lam (2014)	Solar house office test bed	Heating: 24 hours Cooling: 3 hours	Dynamic programming	MATLAB Simulink
Bengea et al. (2014)	Commercial building	3 hours	Interior-point nonlinear programming solver	IPOPT
Dobbs and Hencey (2014)	Single-zone building	24 hours	Dynamic programming	MATLAB
Gruber et al. (2014)	Office site	90 min	Least-square	MATLAB
Parisio et al. (2014)	Laboratory room	9 hours	MPT, parametric programming	MATLAB
Goyal et al. (2015)	Single office space in university building	60 minutes	Interior-point nonlinear programming solver	IPOPT, MATLAB
Lim et al. (2015)	Four rooms	N/A	MILP, LNS	Gurobi 5.6
Li et al. (2015)	Medium-sized commercial building	2 hours	Programming solver	TRNSYS, MATLAB, IPOPT
Huang et al. (2015)	Airport check-in hall	6 hours	Linear programming	MATLAB
Sturzenegger et al. (2015)	Office building	58 hours	Sequential linear programming	CPLEX
Ascione et al. (2016)	Multizone	24 hours	GA	MATLAB, EnergyPlus
Fiorentini et al. (2016)	University lab house	24 hours	Hybrid Toolbox	MATLAB
Coninck et al. (2016)	Medium-sized office building	24 hours	Nonlinear programming	IPOPT
Khakimova, et al. (2017)	Small-size building	12 hours	Mixed-integer linear programming	MATLAB
Hilliard, et al. (2017)	Academic building	2 hours	GA	EnergyPlus

Joe et al. (2019)	Office	24 hours	Linear & Quadratic programming	MATLAB, TRNSYS
Finck et al. (2019)	Residential building	12 hours	Dynamic programming	MATLAB
Drgona et al. (2020)	Office building	24 hours	Quadratic programming	MATLAB, GUROBI, Python
Yang et al. (2020)	Office and lecture theater	1 hour	Sequential quadratic programming	MATLAB

2.1 OCCUPANT-DRIVEN MODEL PREDICTIVE CONTROL

MPC is a method to design control sequences based on a prediction of future inputs to best optimize an objective function considering system constraints. It references a physical model of the system, system inputs, and potential disturbances (e.g. outdoor weather, occupancy, solar gain) to predict future system states (e.g., indoor temperature) and implement the most efficient control action (García et al. 1989; Hazyuk et al. 2012). A detailed description of MPC can be found in Chapter 43. MPC has been applied to occupant-driven HVAC controls, and Table 2 lists the recent field studies, optimization methods, and related software platforms for such control.

2.2 OCCUPANT-DRIVEN MPC-BASED HVAC CONTROLS

In an occupant-driven, rule-based HVAC scenario, occupant measurements are fed back into an HVAC control system to save energy during unoccupied periods while maintaining thermal comfort. However, a preferred temperature is often not guaranteed upon occupancy arrival. Therefore, a predictive HVAC control is needed. In this case, occupancy information is first predicted (based on past measurements) for the future time steps that are aligned with the MPC prediction horizon. Meanwhile, future model disturbances (e.g., weather) are also predicted for the same time steps. Then, the MPC optimizes the objective function and provides a control sequence.

In recent years, over 200 papers have been published describing different approaches, methods, and energy saving results from occupant-based HVAC control (Esrafilian-Najafabadi and Haghighat 2021; Mirakhorli and Dong 2016; Yao et al. 2021). Almost all these studies focus on better temperature set-point controls for air-handling units (AHU) and variable-air-volume (VAV) boxes. In particular, there is a report from Pacific Northwest National Laboratory (PNNL) on occupant-based VAV box control for 0.4 billion m^2 commercial buildings (6% of total commercial floor space) in different climate zones, showing an energy saving opportunity for energy savings of up to 23% through control of VAV airflow based on room occupancy sensors (Zhang et al. 2013). Only approximately 22 studies have implemented the developed control algorithm and verified actual energy savings (Mirakhorli and Dong 2016). Xu et al. (2009) demonstrate up to 12% energy saving considering number of occupants, while minimizing energy use and maintaining air quality and occupant comfort in a multizone building. They found that use of model predictive control just to minimize temperature deviation from the comfort zone can result in a higher air quality compared to that achieved with a conventional controller. Goyal et al. (2013) consider four HVAC control methods that have been contrasted for complexity and performance: a baseline controller (1) with and (2) without occupancy measurements, (3) optimal control with occupancy measurement, and (4) MPC with occupancy prediction. Among all approaches, MPC with occupancy prediction results in greater energy saving and fewer occupant comfort violations.

There are a few experimental studies on occupant-based MPC. For example, a seven-day experiment was conducted with a three-story building, testing the rule-based controller using occupancy measurements (Brooks et al. 2014). A network of wireless sensors (PIR, CO_2, temperature, and humidity) was used for occupancy measurements, and a baseline schedule with setback rules was used to control zones' temperature. This exercise resulted in an average of 37% energy savings on the testing AHU for one floor. Another experiment was conducted in a solar decathlon house during both the heating (two months) and cooling (one week) seasons. In this experiment, local weather forecasting and occupancy presence predictions were used to minimize total building energy use. This study shows nonlinear model predictive control allowing 30 and 17.8% energy savings during the heating and cooling experiments respectively, in contrast with the use of scheduled temperature set points (Dong and Lam 2014).

Occupancy Prediction

Prediction of the future occupancy status or even number of occupants in a room is a necessary to implement occupant-based MPC. The first arrival and last departure time of an occupant for a single occupied office is of especial interest (Li and Dong 2017, 2018; Lu et al. 2010). Markov chain models can be used to predict occupancy based on previous occupancy measurements (Dong and Lam 2014; Dong et al. 2010; Page et al. 2008). In most cases, the number of occupants in the room cannot be observed directly. Hence, the occupancy presence or number is the hidden state, and the sensor data or system output is the observable state for a hidden Markov model (Dong and Lam 2011). There are also studies that compare the ability of neural network, support vector machine, and hidden Markov models to detect the number of occupants in a building (Dong et al. 2009; Lam et al. 2009; Li and Dong 2018).

Comfort-Driven MPC-Based HVAC Controls

Although there are a few studies that focus on personalized thermal-comfort-driven HVAC control through learning individual preference (Ghahramani et al. 2015; Kim et al. 2018a) and RGB video images (Jazizadeh and Jung 2018), comfort-driven MPC studies are scarce (Pandey et al. 2021).

3. MODELING AND EVALUATING OCCUPANT-CENTRIC HVAC CONTROL SYSTEMS

Modeling occupant-centric HVAC controls in whole-building performance simulation (BPS) programs enables estimation of energy savings potential and evaluation of indoor environment considering the diversity and impact of occupant behavior on HVAC system operation and performance. Such modeling efforts require the integrated simulation of three components: (1) thermal dynamics of building envelope, lighting, and plug loads; (2) dynamics of HVAC systems; and (3) stochasticity in occupant behaviors of presence, movement, interactions with building systems and their preferences. BPS programs (e.g., EnergyPlus) can realize the overall simulation of the building envelope and energy systems, and occupant behaviors and interactions, as well as the occupant-centric HVAC controls.

A direct approach for modeling HVAC controls is to extract the key OCC variables through offline learning and incorporate them into BPS by using user-defined modifications such as the Python-based Energy Management System (EMS) feature in EnergyPlus (Hobson et al. 2021). OCCs that are intended for online learning allowing individual occupants' preferences to change over time, may be implemented as learning algorithms in real-time. These complex control algorithms are simulated by using separate modules coupled with whole-building BPS programs, using tools like Building Controls Virtual Test Bed (BCVTB) (Wetter et al. 2011) or through cosimulation using functional mockup units (ASHRAE 2019; Nouidui et al. 2013, 2014). There also exist dedicated occupant modeling tools such as obFMU, a functional mockup unit of occupant behavior models (Hong et al. 2016); Occupancy Simulator (Chen et al. 2018); and the Buildings.Occupants Modelica package (Wang et al. 2018).

3.1 WHOLE-BUILDING PERFORMANCE SIMULATION PROGRAMS

Whole-building performance simulation programs, such as EnergyPlus (DOE BTO 2017), ESP-r (Hand 2015), IDA-ICE (EQUA 2017), DeST (Yan et al. 2008), and TRNSYS (2012), are widely applied to evaluate the performance of building technologies and energy systems, with the aim of reducing energy use and associated greenhouse gas emissions. However, the functionalities of modeling the occupant behavior and HVAC controls among BPS tools are generally inconsistent and lack flexibility for user customization (Cowie et al. 2017; Crawley et al. 2008). For instance, schedules of casual gains from occupants are generally used, or control of window opening may be applied based on temperature set points. There are minor variations between programs (e.g., some are limited to hourly resolutions whilst others can handle subhourly resolution; some have provision for control in aspects others do not). Yet, input requirements and functionality are broadly similar across programs. In particular, occupant behavior is typically represented in current BPS programs via oversimplified static schedules or fixed rules. This leads to deterministic and homogeneous simulation results that do not fully capture the stochastic nature and diversity of occupants' energy behavior in buildings.

Cowie et al. (2017) provide an overview of the stochastic occupant modeling capabilities in current BPS programs. BPS programs such as EnergyPlus provide generalized model input functionality, allowing users to program or customize models or control logics through the interface (without requiring recompilation of the BPS programs) in a proprietary language. Some BPS programs (e.g., EnergyPlus, ESP-r) allow cosimulation with stand-alone external programs to model occupant behaviors (see subsequent section). Although some BPS programs include built-in stochastic modeling capabilities, these functionalities are inconsistent across programs. Addressing this gap, cosimulation platforms centralize functionality, allowing models to be implemented in a consistent way among different BPS programs (Cowie et al. 2017). However, the success of this approach depends on the ability of BPS programs to exchange data with this platform, which in turn requires a cosimulation standard that is adopted by as many BPS programs as possible. Such progress could potentially be stimulated by the existence of such a cosimulation platform, because this would provide a demonstrable contribution to the functionality of BPS programs.

3.2 HVAC CONTROL MODELING

Most whole-building BPS programs can model the dynamic performance of HVAC systems, but system types, configurations, and control strategies are usually predefined or lack flexibility for users to customize. To address the limitations of whole-building BPS programs in modeling HVAC control, EnergyPlus allows Python code into its EMS feature to enable user-defined script writing. The EMS module allows practitioners to design and implement the customized advanced control sequence in the native environment of EnergyPlus (Pand et al. 2021).

An alternative way to address HVAC control modeling needs in BPS programs is the cosimulation approach. The approach integrates separate HVAC modeling modules or tools with the whole-building BPS programs through coupled technique, using tools such as the BCVTB (Wetter 2011), a software environment that serves as middleware, connecting different simulation programs to exchange data during the time integration. The HVAC modules can be implemented in various software languages including MATLAB and Modelica (Wetter et al. 2014), an equation-based object-oriented programming language. For BPS programs implementing the functional mockup interface (Nouidui et al. 2013) such as EnergyPlus and ESP-r, direct cosimulation is possible with HVAC modules or tools implemented as functional mockup units (Nouidui et al. 2014). A recent advancement in this direction is the development of Spawn-of-EnergyPlus (www.energy.gov/eere/buildings/articles/spawn-energyplus-spawn) that reuses EnergyPlus modules and couples them with HVAC system and control models from the Modelica Buildings Library using the Functional Mockup Interface (FMI) standard (Wetter et al. 2020).

3.3 OCCUPANT BEHAVIOR MODELING

As aforementioned, BPS programs use varying and nonstandardized input syntaxes to represent OB models (Hong et al. 2017). Cowie et al. (2017) conducted a comprehensive review to identify and compare approaches to representing and implementing OB models in eight of the most widespread BPS programs in the engineering and simulation community. For OB model implementation in BPS programs, four approaches were used: (1) direct user input or control using BPS input syntax (all eight BPS programs), (2) user functions or custom code (EnergyPlus, DOE-2, and IDA-ICE), (3) built-in OB models (DeST and ESP-r), and (4) cosimulation with dedicated OB software tools such as obFMU (EnergyPlus and ESP-r). Generally, current BPS programs use diverse approaches to represent and implement OB models, which hinder the exchange, reuse, and comparative analysis of OB models. There is a significant need for a common ontology (data dictionary) and data model to standardize the representation of OB models and enable their flexibility and exchange; and a modular software implementation of OB models adopting the common data model and enabling a robust and an interoperable integration with multiple BPS programs.

Occupant models are grouped into three types:

- *Adaptive behavior models* (e.g., opening or closing windows to maintain thermal comfort or indoor air quality)
- *Nonadaptive behavior models* (e.g., turning on/off computer monitors)
- *Occupancy models*

The adaptive behavior models have typically been developed as weekly schedules, Bernoulli models, discrete-time or discrete-event Markov models, and survival models. Bernoulli models predict the likelihood of a building component (with which occupants frequently interact) for a given circumstance (e.g., the percentage of lights switched on at a given outdoor illuminance). Markov models predict the likelihood of an adaptive action as a function of explanatory variables (e.g., the probability of a light switching on in the next time step in a discrete-time Markov model, or at the next arrival in a discrete-event Markov model). Survival models, suited for infrequently executed adaptive behaviors, predict the lifetime of an occupant action or the state of a building component with which occupants interact (e.g., lifetime of blind status as a function of indoor temperature).

Nonadaptive behavior models include weekly schedules, survival models, or occupancy schedules from a similar building. Similar to adaptive behavior models, the survival models for nonadaptive behaviors predict the duration of a state right before an event happens (e.g., plug-in appliance load intensities as a function of the duration of vacancy period).

Occupancy modeling aims to determine the occupants' presence either as the occupancy status at the space level or as the number of occupants in a space or the entire building. Occupancy models can take the form of weekly schedules, inverse transform sampling, discrete-time Markov models predicting the timing and frequency of arrivals and departures, and survival models predicting the duration of an uninterrupted occupancy/vacancy period.

Numerous window opening models have been introduced as input for BPS programs. Markov chains, generalized linear models, generalized linear mixed effects models, and Bayesian networks have been used to model window openings in residential and office buildings. Window shading models are less common and use logistic or linear regression and Markov chains. Models of occupants' light switching behavior have mostly focused on small offices and residential buildings. The typical approach is to use Markov chains and Poisson processes. The relatively few statistical models for thermostat use behavior in homes and offices rely on Markov chains and discrete Weibull distributions. In most models of appliance use, the switch-on times of the appliances are determined via Monte Carlo simulation. The models often rely on Markov chains, and many occupant behavior models use data that have been aggregated over dwellings, offices, or occupants (Haldi and Robinson 2011). As a result, the models may fail to capture details of individual occupants and the diversity amongst them (O'Brien et al. 2017). It is suggested that behaviors of switching on lights, closing blinds, and opening/closing windows are most accurately represented with discrete-time or discrete-event Markov models. On the other hand, survival models adequately characterize occupant plug-in equipment use, blind opening, and light switch-off behaviors (D'Oca et al. 2019; Yan et al. 2017).

3.4 MODELING TOOLS AND SUPPORTING DATABASE

To address the limitations of whole-building BPS programs in modeling occupant behaviors, a cosimulation approach can be adopted that enables BPS programs to cosimulate with dedicated occupant behavior modeling modules or tools, as mentioned. A suite of occupant behavior modeling tools are now available to support cosimulation, including (1) obXML, (2) obFMU, (3) Occupancy Simulator, and (4) Buildings.Occupants (part of the Modelica Buildings Library). These tools help standardize the input structures for occupant behavior models, enable the collaborative development of a shared library of occupant behavior models, and allow for a rapid and widespread integration of occupant behavior models in various BPS programs. This ultimately improves the simulation of occupant behavior and the quantification of its impact on building performance.

obXML (Hong et al. 2015a, 2015b) is an XML schema that standardizes the representation and exchange of occupant behavior models for building performance simulations. It builds on the drivers-needs-actions-systems (DNAS) ontology to represent energy-related occupant behavior in buildings. *Drivers* comprise environmental and other contextual factors that stimulate occupants to fulfill a physical, physiological, or psychological need. *Needs* include the physical and nonphysical requirements of occupants that must be met to ensure satisfaction with the environment. *Actions* are the interactions with systems or activities that occupants can perform to achieve environmental comfort. *Systems* refer to the equipment or mechanisms in the building that occupants may interact with to restore or maintain environmental comfort. A library of obXML files, representing typical occupant behavior in buildings, was developed from the literature (Belafi et al. 2016). These obXML files can be exchanged between different BPS programs, different applications, and different users. Figure 3 includes the four key elements of the obXML schema and their subelements, showing the DNAS ontology.

obFMU (Hong et al. 2016) is a modular software component represented in the form of FMUs, enabling its application via cosimulation with BPS programs using the standard functional mockup interface. It reads the occupant behavior models represented in obXML and functions as a solver. A variety of occupant behavior models are supported by obFMU, including (1) lighting control based on visual comfort needs and availability of daylight, (2) thermostat set-point adjustment, (3) HVAC system on/off control based on occupants' thermal comfort needs, (4) plug load control based on occupancy, and (5) window opening and closing based on indoor and outdoor environmental parameters. obFMU has been used with EnergyPlus and ESP-r via cosimulation to improve the modeling of occupant behavior. Figure 4 shows the workflow of cosimulation using obFMU and EnergyPlus.

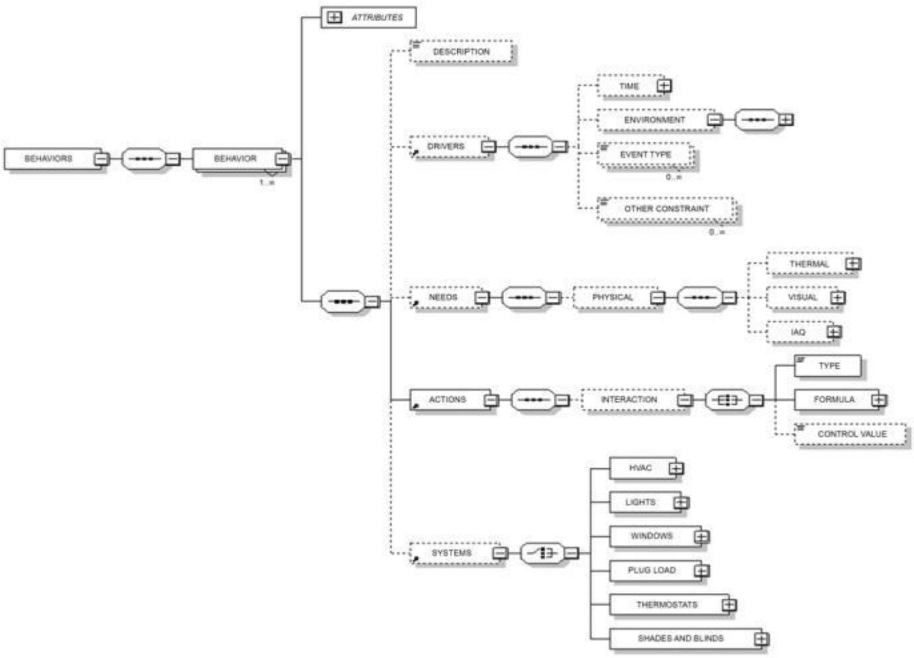

Figure 3. obXML Schema

Occupancy Simulator. Occupancy Simulator (Chen et al. 2018; Luo et al. 2017) is a web-based application running on multiple platforms to simulate occupant presence and movement in commercial buildings. The application can generate subhourly occupant schedules for each space and for individual occupants in the form of CSV files and EnergyPlus IDF files for building performance simulations. Occupancy Simulator uses a homogeneous Markov chain model (Feng et al. 2015; Wang et al. 2011) and performs agent-based simulations for each occupant's presence and movement. A hierarchical input structure is adopted, building on the input blocks of building, space, and occupant type, to simplify the input process while allowing flexibility for detailed information capturing the diversity of space use and individual occupant behavior. Users can choose to see simulated occupancy results for an individual space or the whole building.

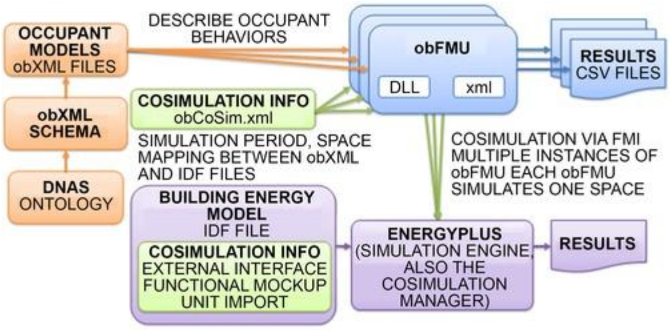

Figure 4. Cosimulation Workflow of obFMU with EnergyPlus

Buildings.Occupants. To simulate the continuous interaction between occupants and building systems, Buildings. Occupants, an open source occupant behavior package in Modelica (Wang et al. 2018), can be used. The Buildings.Occupants package, as part of the Modelica Buildings Library, supports fast prototyping by seamlessly integrating occupant behavior models with Modelica models from existing libraries for building dynamics. Additionally, the structure of the package has been designed to allow for flexible implementation of user-defined models by tuning the parameters and calling functions defined in the BaseClasses package. The Buildings.Occupants package includes reported occupant behavior models in the literature that are more commonly used and well documented in terms of the data source, mathematical equation, independent variables, parameter values, etc. The models are categorized into subpackages based on the building types and systems. There are 34 occupant behavior models for office and residential buildings that are included in the first release of the Buildings.Occupants package. Included in the office building models are eight on windows operation, six on window blind operation, four on lighting operation, and one on occupancy.

ASHRAE Global Occupant Behavior Database. To overcome the gaps in occupant behavior modeling related to data availability, a worldwide database on occupant behavior in the built environment, the *ASHRAE Global Occupant Behavior Database* has been recently developed (ASHRAE 2021; ashraeobdatabase.com). This open-access repository enables users to develop and benchmark various types of occupant behavior models for local context that can be used in BPS to inform design and operations of energy efficient buildings. The database is assembled from 32 occupant behavior field studies from fifteen countries in various climatic zones and across different seasons. The web-based interface features a query builder that allows users to customize data filtering based on their own (multiple) selection criteria, including behavior attributes, building typology, geographical location, or published studies. The database is categorized into 12 different occupant behavior attributes such as occupant count, window adjustment, shading adjustment lighting adjustment, or HVAC measurements. Three major building typologies (residential, educational, and commercial) are covered within the dataset, with subcategories within each typology. The web interface also offers interactive data visualization to allow the users to explore and navigate the database.

3.5 BEST PRACTICES ON OCC MODELING AND SIMULATION

The choice of an appropriate OCC modeling approach and the level of complexity (i.e., the amount of detail and the spatial and temporal granularity) is specific to the goal of the simulation. The model selection is case specific and depends on several aspects related to the simulation object, the aim of the simulation, performance indicators (e.g., annual energy use, annual electric peak demand, cooling and heating equipment capacity, a typical working day load shape, demand flexibility, aggregate or individual occupant comfort metrics), interaction between object and user, and climate (Gilani and O'Brien, 2018). Simply increasing the model complexity by including all the available information, which would require additional time, computing resources, and cost efforts (as well as being prone to the estimation errors), may not always be necessary. For instance, Gilani et al. (2018) observed that for modeling buildings at a larger scale of 100 offices, deterministic light switch models reasonably represent occupants' impact on annual lighting energy use and a parsimonious model is suitable for this particular use case. To balance the needs, resources, validity, and expertise for determining an appropriate model complexity, a **fit-for-purpose strategy** to occupant modeling is recommended. This approach presents a step-wise method across building typology, scales, geographical location, design stages, and modeling objectives for selecting the most appropriate modeling approach (Gaetani et al. 2020). It also offers alternative methods to manage model complexity such as the static-stochastic or the hybrid modeling method, where the stochasticity in the modeling process is introduced by weighing the static simulation inputs such as schedules with randomly selected coefficients. An optimal solution for model selection should aim at minimizing the overall potential approximation and uncertainty error while taking into account the resources required for modeling such as the time and cost efforts or data availability.

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