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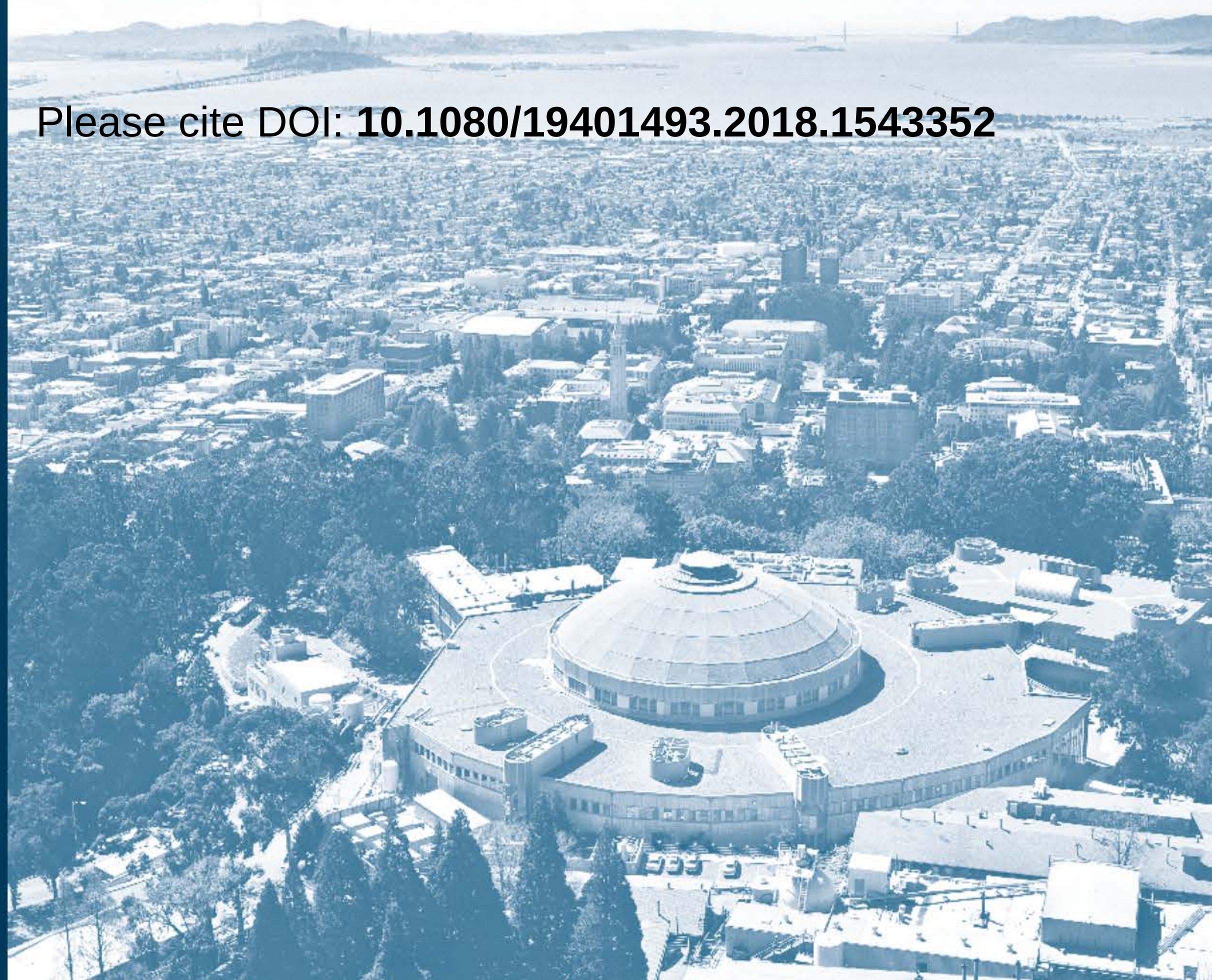

***Buildings.Occupants*: A Modelica package for modeling occupant behavior in buildings**

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Abstract
Energy-related occupant behavior is crucial to design and operation of energy and control systems in buildings. Occupant behaviors are often oversimplified as static schedules or settings in building performance simulation ignoring their stochastic nature. The continuous and dynamic interaction between occupants and building systems motivates their simultaneous simulation in an efficient manner. In the past, simultaneous simulation has relied on co-simulation approaches or customized source code changes to building simulation programs. This paper presents Buildings.Occupants, an open-source package implemented in Modelica, for the simulation of occupant behaviors of lighting, windows, blinds, heating and air conditioning systems in office and residential buildings. Examples were presented to illustrate how the models in the Occupants package are capable to simulate stochastic occupant behaviors. The major contribution of this work is to introduce the equation-based modelling approach to simulate occupant behaviors in buildings, and to develop an open-source Occupants package in the Modelica language.

Keywords: Occupant behavior; Modelica; Modelica Buildings Library; Modelica Occupants Package; Occupant behavior modeling

Contents

1. Introduction

1.1 Modeling occupant behaviors in building simulation

Occupants are not passive participants in buildings. Rather, they actively respond to and interact with building systems [1]. Occupant's energy-related behavior in buildings include their comfort (thermal, visual, aural and olfactory) preference, presence and movement, and interactions with building components and systems (lighting, HVAC, windows, blinds). Previous researches ([2], [3], [4], [5], [6]) have confirmed that occupant behaviors have significant impacts on building energy performance and occupant comfort. Different occupant behaviors, as simple as window opening, might lead to a significant variation in the building Energy Use Intensity (EUI), e.g., by a factor of four in commercial buildings in United States [7], and by a factor of three in identical apartments in Denmark [8]. Additionally, occupant behaviors are one of the key reasons of the performance gap between the design and operation stage of buildings [9], [10]. It is argued that the difference between the actual and designed energy use depends, to a large degree, on the different use patterns of energy systems between the designed and actual operation of buildings [11].

Despite the significant influence of occupant behaviors on building energy consumption, occupant behaviors are often over-simplified in the building simulation for the design, commissioning and operation of buildings [12]. It is a common practice to treat occupant behaviors as static, deterministic schedules or settings in building performance simulation [13], ignoring the stochastic, diversity and dynamics of occupant behaviors in reality. A more realistic and robust representation and modelling of occupant behaviors could help to improve building simulation accuracy and to understand the building design-operation performance gap.

Accurate modelling and prediction of occupant behavior could not only improve the accuracy of building simulation but also enhance the performance of building control systems. Mirakhorli and Dong (2016) concluded that incorporating the prediction and modelling of occupant behavior into HVAC system control could achieve three benefits: to decrease discomfort when the room is first being occupied, to improve energy efficiency of HVAC system through control optimization, and to save energy when a room is unoccupied [14]. Goyal et al. (2012) found that the errors in occupancy modelling have a stronger effect on the performance of model predictive control [15] compared with errors in predicting outdoor temperature or solar load. The stochastic nature of occupant behavior requires and facilitates the stochastic model predictive control [16], which could demonstrate an energy saving potential of 5% - 38.3% [17], [18].

1.2 Modelica & Buildings Library

Currently, the field of building simulation is dominated by the imperative programming. Imperative programming languages assign values to functions and declare the sequence of execution of these functions, which tightly couples the numerical solution methods with model equations and input/output routines [19]. The imperative programing facilitates efficient computation in building energy simulation and performance assessment, in which cases all the inputs (for instance the physical parameter of), boundary conditions and initial conditions have been given. However, the tight coupling of numerical solutions with equations and input/output of imperative programming limits the applicability and extensibility of models in other uses, which becomes increasing important recently [20], such as models for control optimization, commissioning and operation [21], coupled models of thermal and electrical systems (systems combining large and small time constants, algebraic and differential equations [22], continuous time and discrete event dynamics [23]).

To complement the current simulation tools and to efficiently simulate the important problems which could not be efficiently computed by imperative programming, the equation-based modelling emerges and becomes increasingly popular. An equation-based model specifies the mathematical equations, in contrast to specifying the sequence of computing assignments as in the imperative programming [19]. A major benefit of the equation-based modeling is in solving optimization problems, because equation-based modeling could 1) support automatic conversion of simulation models into optimization problems, 2) provide analytic expressions for gradients to facilitate gradient-based optimization methods, 3) allow automatic generation of the finite dimensional approximations defined by the collocation methods [19]. In paper [19], an example was presented to show that the equation-based language could speed up the solution of an optimization problem by a factor of 2200 compared with traditional imperative language modeling.

As a representative of the current trend towards equation-based modelling, Modelica, an equation-based, object-oriented language [24], has been introduced and applied in building simulation [25], [26]. Currently, applications of Modelica are majorly from researchers rather than practitioners. One obstacle limiting the wide application of Modelica in building performance simulation is the lack of standardized library. To fill in the gap, Wetter et al. (2014) developed a free open-source building simulation library with Modelica [27]. The latest version, Modelica Buildings library 6.0.0, has been released on June, 14, 2018, which contains over 500 models for:

- HVAC systems,
- controls,
- heat transfer among rooms and the outside,
- multi-zone airflow, including natural ventilation and contaminant transport,
- single-zone computational fluid dynamics coupled to heat transfer and HVAC systems,
- data-driven load prediction for demand response applications, and
- electrical DC and AC systems with two- or three-phases that can be balanced and unbalanced.

The primary use of the library is for flexible and fast modeling of building energy and control systems to accelerate innovation leading to cost-effective low energy systems for new and existing buildings. The library is particularly suited for

- rapid prototyping of new building systems,
- analysis of the operation of existing building systems,
- development, specification, verification and deployment of building controls within a model-based design process, and
- reuse of models during operation for functional testing, verification of control sequences, energy-minimizing controls, fault detection and diagnostics.

1.3 Objectives

The major goal of the *Buildings.Occupants* package is to facilitate the occupant behavior simulation in Modelica language. One way to realize this goal is to utilize the standardized co-simulation interface. For example, Plessis et al. (2014) [28] implemented a co-simulation between the SMACH platform for occupant behavior and the BuildSysPro library for the building and its energy system using the standardized Functional Mockup Interface (FMI) [29]. Hong et al. (2015) proposed and implemented a new occupant behavior ontology with the eXtensible Markup Language (XML) schema obXML [30], [31], and then developed obFMU for co-simulation [32] using FMI. Belafi et al. used the obXML to compile a library of occupant behavior models in 2016 [33].

Although obFMU can be used with Modelica tools through co-simulation, there are challenges of computing performance due to the Modelica's differentiability requirements. Occupant behaviors are often in the form of discrete event, and introduce abrupt changes into building environments. Differentiability requirements in Modelica are vital since they are necessary and sufficient conditions to establish existence and uniqueness of a solution to the differential equations. In addition, they are also needed to avoid computational problems. Contrarily, if the occupant behavior events are modeled directly within Modelica, the Modelica complier can study the structure of the problem a prior, and will instruct the integrator to simply integrate exactly up to the point where an abrupt change occurs and then restart when the event occurs. This completely addresses the computational difficulties resulting from the discontinuous change in system variables. Therefore, there is a need to develop a library of occupant behavior models in Modelica. Besides, a Modelica package of occupant behavior models could be more conveniently integrated into Modelica models compared with the co-simulation approach. This paper introduces an effort to develop such a package, the *Buildings.Occupants*, which is open source, and would be a package of the Modelica Buildings Library.

In Section 2, the subpackages and models of the Occupants package are introduced with more details. The model validation is presented in Section 3. Three models were selected as examples to illustrate how the Occupants package could be utilized to simulate complex occupant behaviors. The three selected models represent three model types implemented in the Occupants package, i.e. the *state* model, the *transition* model, and a combination of *state* and *transition* model. Section 4 addresses the key issue of occupant model selection. Conclusions are drawn in Section 5.

The major contribution of this study is to introduce the equation-based modelling approach to simulate occupant behaviors in buildings, and to develop an open-source *Buildings.Occupants* package in Modelica to share with the building simulation community as well as to encourage co-development. The *Buildings.Occupants* could be downloaded from Github[1] in the next official release of Modelica Buildings Library and is currently available at a custom branch on Github[2].

2. The Occupants Package

2.1 Overview

The Occupants package was developed as part of the *Buildings.Library* [27]. Therefore, the convention of annotations and variable names are consistent with the *Buildings.Library*.

Many occupant behavior models have been developed and reported in the literature. We categorized and selected some models to be implemented in Modelica as a starting point of the initial release of the Occupants package. These models are selected because they are more commonly used and are better documented in terms of the data source, mathematical equation, independent variables, parameter values etc. We did not propose any new occupant behavior models in this work. Instead, we selected and implemented models proposed by other researchers. Table 1 lists occupant models included in the package. Summary of these selected models are available in [34] as well as full details in the original reference papers.

To summarize and present the occupant behavior models in a consistent form, the Drivers-Needs-Actions-Systems (DNAs) framework proposed by Hong et al. [28] were utilized, as illustrated in Figure 1.

- **Drivers** refer to the environmental factors that stimulate occupants to take an action. In the Occupants Library, drivers are the model inputs, varying from indoor/outdoor air temperature, to solar intensity/altitude.
- **Needs** represent occupants' requirement, which has not been explicitly represented but would be implicitly reflected by the dynamic characteristics of the models. For instance, occupants need to remain thermal comfort in buildings. Therefore, the model dynamics would demonstrate a trend that it is more likely for occupants to turn on the air-conditioning when the indoor temperature rises above the comfort limit.
- **Actions** describe how the occupants interact with the building systems. In the Occupants library, actions are the model outputs. In the current version of Buildings Library, only the

[1] https://github.com/lbl-srg/modelica-buildings

[2] https://github.com/lbl-srg/modelica-buildings/tree/issue1162_obModelica

binary-variable actions were included, i.e. turn on or turn off a specific equipment. In the future, models with actions to adjust the temperature set-point might be added to the library.

- **Systems** refer to which building (residential, office, schools, etc.) and equipment (lighting, blinds, windows, heating, AC, etc.) the occupants are interacting with.

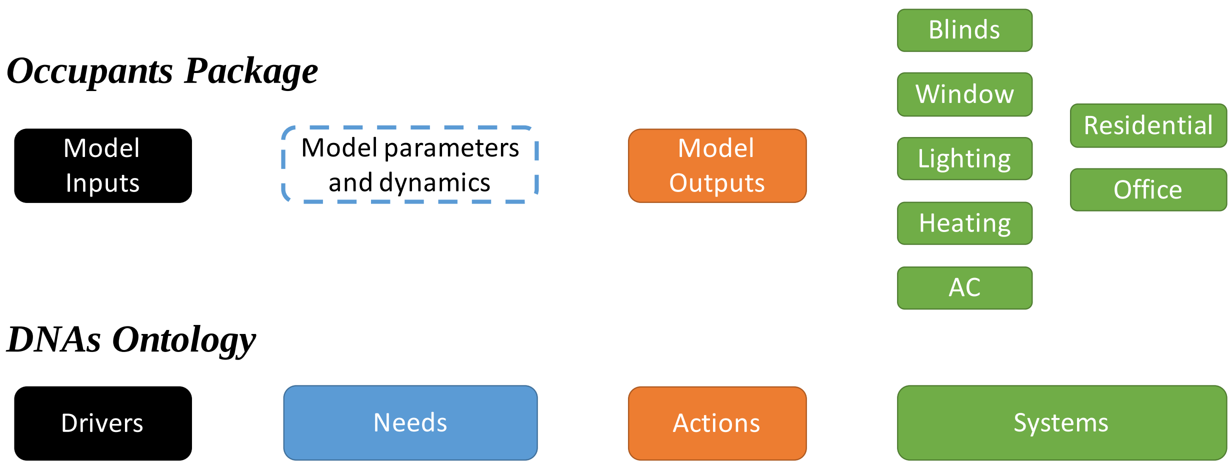


Figure 1: Application of DNAs ontology to the Occupants Package

The Version 1.0 of Occupants Package contains 34 models to simulate occupants' interaction with windows, blinds, air conditioning, lighting, and space heating systems in two building types, residential and office buildings. The structure of the Occupants package is illustrated in Figure 2.

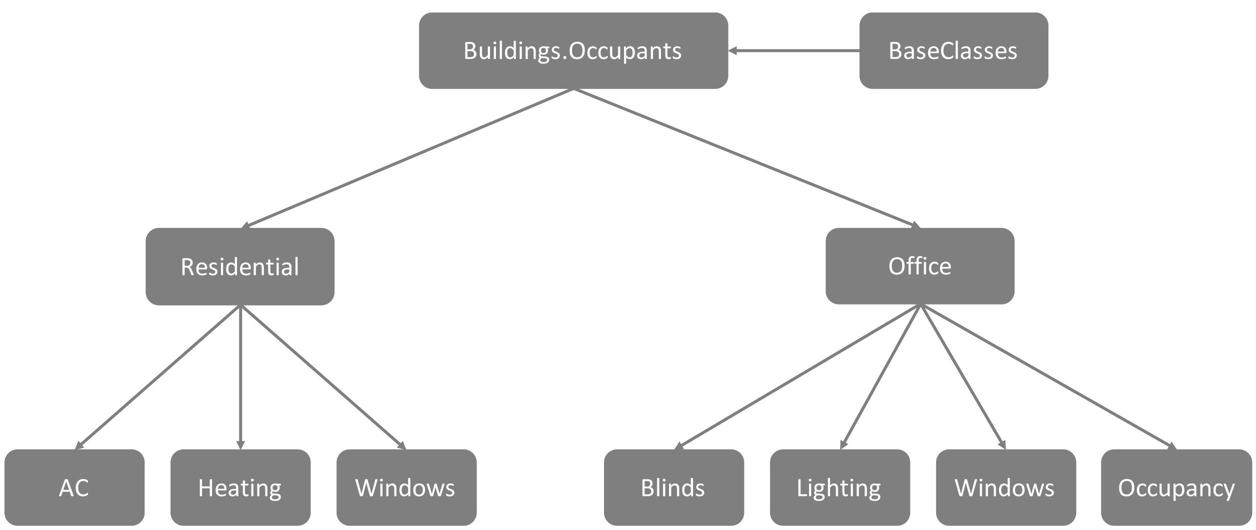


Figure 2: Overview of the Occupants package

Table 1: List of occupant behavior models included in the Occupants package

	Building System	Reference	Survey Region	Drivers (inputs)	Actions	Remarks

Office	Occupancy	Wang et al. 2005 [35]	California, US	N/A	Occupied /not	For single person office only
	Blinds	Newsham 1994 [36]	Japan	Solar Intensity	On/off	
		Inkarojrit 2008 [37]	California, US	Solar Intensity, Self-reported sensitivity to brightness	On/off	
		Haldi and Robinson 2008 [38]	Swiss	Indoor Temp.	On/off	
		Haldi and Robinson 2008 [38]	Swiss	Outdoor Temp.	On/off	
		Zhang and Barrett 2012 [39]	Sheffield, UK	Solar Intensity	On/off	
		Zhang and Barrett 2012 [39]	Sheffield, UK	Solar Altitude	On/off	
	Window	Rijal et al. 2007 [40]	UK	Indoor Temp., Outdoor Temp., Comfort Temp.	On/off	
		Haldi and Robinson 2008 [38]	Swiss	Indoor Temp.	On/off	
		Haldi and Robinson 2008 [38]	Swiss	Outdoor Temp.	On/off	
		Herkel et al., 2008 [41]	Freiburg, Germany	Outdoor Temp.	On/off	3 models, for different window types
		Yun and Steemers [42]	Cambridge, UK	Indoor Temp.	On/off	

		Yun and Steemers [42]	Cambridge, UK	Outdoor Temp.	On/off	
		Haldi and Robinson 2009 [43]	Lausanne, Switzerland	Indoor Temp., Outdoor Temp.	On/off	
		Zhang and Barrett 2012 [39]	Sheffield, UK	Outdoor Temp.	On/off	5 models, for different window orientations
	Lighting	Hunt 1980 [44]	Germany	Illuminance	On/off	
		Love 1998 [45]	Calgary, Canada	Illuminance	On/off	2 models generated from different occupants
		Reinhart and Voss 2003 [46]	Germany	Illuminance	On/off	
		Gunay et al. 2016 [47]	NA	Illuminance	On/off	
Residential	AC	Ren et al. 2014 [48]	China	Indoor Temp.	On/off	2 models, for bedroom and living room
	Heating	Nichol 2001 [49]	UK	Outdoor Temp.	On/off	
		Nichol 2001 [49]	Europe	Outdoor Temp.	On/off	
		Nichol 2001 [49]	Pakistan	Outdoor Temp.	On/off	
	Windows	Nichol 2001 [49]	UK	Outdoor Temp.	On/off	
		Nichol 2001 [49]	Europe	Outdoor Temp.	On/off	
		Nichol 2001 [49]	Pakistan	Outdoor Temp.	On/off	

2.2 BaseClasses

This package contains models in the generic form, used for instantiating specific occupant behavior models for windows, blinds, air-conditioning, lighting and heating. In general, the behavior models implemented in the Occupants package are categorized into two types: the *state model* and the *transition model*. The *state* model, also called the *Bernoulli* model, characterizes the probability of occupant behavior at different states. For instance, ON and OFF are two states for lighting behavior; opening and closing are two states for blind behavior. In the *state* model, occupant behavior state at different time steps is treated as independent and identically distributed (i.i.d.) random variables. The distribution of random variables is modeled as a function of indoor and outdoor environmental parameters/variables, as illustrated in the Inputs column of Table 1. The models in the package falling into this category include:

- Linear regression, which models the probability as a linear function of predictors;
- Logistic regression with one or two predictors, where the probability that occupant behavior state is modeled as a logistic/sigmoid function of linear combinations of predictors;
- Weibull model, where the behavior state is represented as i.i.d. Weibull random variables.

The state model needs to generate random variables at each simulation step. To avoid the frequent change of states, the default simulation time step is set to 120 seconds, which is adjustable for users by tuning the parameter of *samplePeriod* to make sure the time step is suitable for their simulation purpose.

The second type of occupant behavior model is the *transition* model, which calculates how frequently the occupant behavior changes and characterizes the duration of certain occupant behavior as a random variable. An example of a *transition* model is the so-called *survival* model. The *survival* model only needs to draw a random number when there is a change in the occupant behavior, and is therefore more computationally efficient. The *Wang2005Occupancy* model belongs to the *survival* model. We incorporate two types of *survival* models in the *BaseClasses* package for extensibility: one is to model the duration as an exponentially distributed random variable while the other model as a Weibull distribution.

2.3 Occupant behavior models

These packages include models for occupants' interaction with windows, blinds, air conditioning, lighting, and space heating systems. All models in these packages call functions defined in the BaseClasses. The occupant behavior models are grouped into two packages based on the building types they are applied to: one package for residential buildings, and the other for office buildings.

***Residential* buildings**

Currently, there are eight occupant behavior models in the *residential* package to simulate occupants' interaction with air-conditioning, heating and windows. The Weibull distribution was utilized to characterize how the probability of occupants to turn on/off the air-conditioning varies with indoor air temperature, different parameter values were chosen for the AC behaviors in the bedroom and living-room [48]. The logistic regression was used to describe how the outdoor temperature influence the probability of occupants to turn on/off the window and heating [49].

***Office* buildings**

There are four sub-packages to simulate occupant behavior in *office buildings*.

- There are six models in the *Blinds* sub-package. Simple threshold method [36] and logistic regression model [37], [38], [39] were chosen to fit occupants' blinds behavior. The drivers (model inputs) include solar intensity ([36], [37], [39]), solar altitude [39], indoor air temperature [38], and outdoor air temperature [38].
- There are 14 models in the *Windows* sub-package. The threshold method [40], one-dimensional logistic regression ([38], [39], [41], [42]), and two-dimensional logistic regression ([40], [43]) were chosen as the model equation forms. The indoor air temperature ([40], [38], [43], [42]), outdoor air temperature ([40], [38], [43], [41], [42], [39]), and occupants' comfort temperature ([40]) serve as the model inputs. Different parameter values were chosen for different window types ([41]) and different window orientations ([39]).
- There are five models in the *Lighting* sub-package. Probit curve ([44], [46]) and logistic regression ([45], [47]) were chosen to build up the lighting behavior models. The model input is illuminance level on the working plane/desk ([45], [46], [47]). Since occupants are more likely to turn on and off the lighting when they enter or leave the space compared with when they stay in the space, different parameter values were chosen to specify this difference ([46], [47]) and are subscripted as *Arriv* and *Inter,* separately.
- There is one model in the *Occupancy* sub-package. The survival model was utilized to simulate whether the office is occupied or not in office settings based on a field study in California with 35 single-person offices at a large office building [35]. No model input is needed for this model.

Previous researches pointed out the distinction between individual occupant behavior models and aggregate models for occupant behavior simulation [50], [51]. Individual models are derived based on data obtained from each occupant while aggregate models are derived from an aggregated group of people. To estimate the peak load, the individual models might outperform aggregate models, while to estimate the aggregated energy consumption, aggregate or individual models have similar performance [50]. We do not distinguish individual models from aggregate models, and have included both of them in the *Buildings.Occupants* package. For instance, the *Love1998Light1* and *Love1998Light2* are individual models while *Reinhart2003Light* is the aggregate model. The users could tell the model type according to the models' *information* page. For advanced users, they could define either individual or aggregate models by inheriting from *BaseClasses* and tuning the model parameters.

2.4 Implementation of stochastic behavior

A key feature of occupants' interaction with buildings lies on its stochastic behavior. Given the same physical environment, even the same person might respond differently. It is a common practice to use a probability function to characterize occupant behaviors. However, in building simulation, an explicit state is needed to describe the state of a specific building equipment. For instance, given an indoor temperature, occupant might have a probability to turn on the AC. But in a specific simulation, we need to know exactly whether the AC is on or off.

To generate a random binary variable from the value of probability, a seed is usually needed. By fixing the seed value, simulators could replicate and verify the result in a later simulation. In the Occupants package, we need to repetitively call the *binary variable generation* function every *samplePeriod*. If the seed is fixed as the implementation shown in Equation 1, the same number would be generated each time when calling the function, which could not reflect the stochastic behavior as we wish. To solve this problem, we multiplied the parameter *seed* with the *time* to generate a series of time-dependent seeds, and input this series of seeds into the random variable generator as shown in Equation 2. Through this way, we could generate the same results in two simulations once the seed is fixed, and meanwhile we could randomly generate different values in two time steps within the same simulation due to the time- dependent input *globalSeed*.

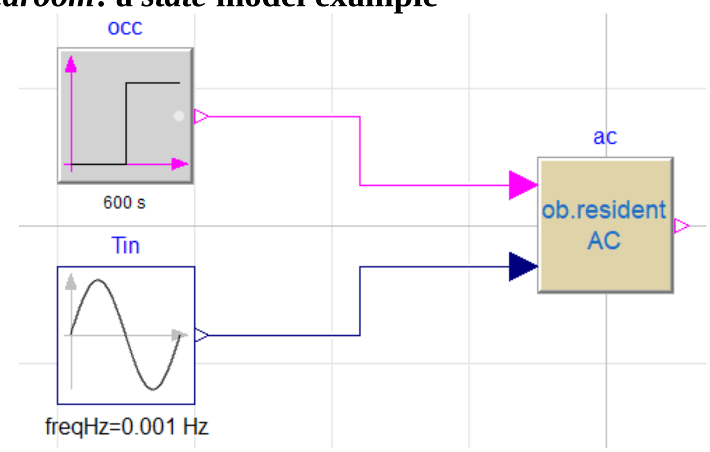
```
on = Buildings.Occupants.BaseClasses.binaryVariableGeneration(p=
p, globalSeed=seed)
```
Equation 1

```
on = Buildings.Occupants.BaseClasses.binaryVariableGeneration(p=
p, globalSeed=integer(seed*time))
```
Equation 2

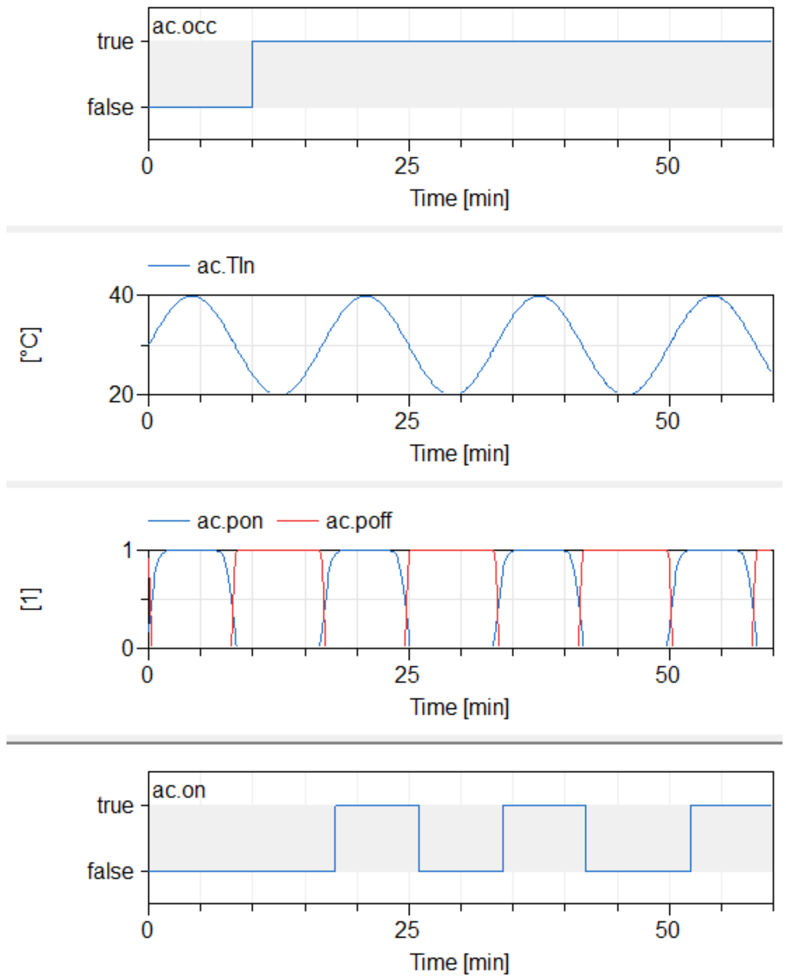
3. Validation and Examples

A validation model has been created for each model included in the Occupants package for two purposes, first for debugging, and second to serve as an illustration to users on how the models could be used. In this section, three models were selected as the representatives of three model types implemented in the Occupants package, i.e. the *state* model, the *transition* model, and a combination of *state* and *transition* model.

3.1 *Ren2014ACBedroom*: a *state* model example



(a) Photographic modeling interface



(b) Modeling results

Figure 3: Validation of the *Ren2014ACBedroom* model

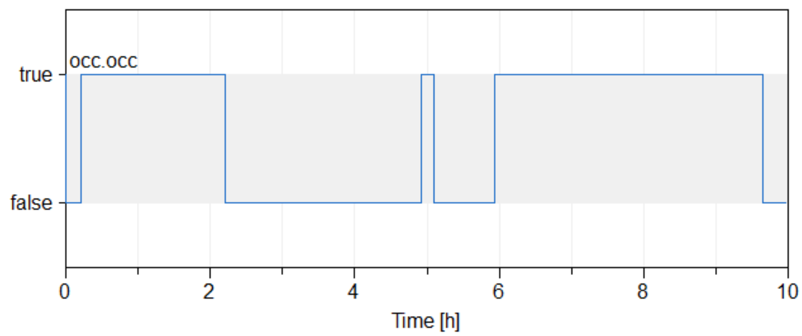
The *Ren2014ACBedroom* model simulates occupants' AC behavior in the bedroom of residential buildings, which was originally fitted from the field study in China in 2014 and documented in [48]. Weibull distribution was utilized to characterize how the probability to turn on or turn off the air-conditioning is influenced by the indoor air temperature. Two inputs are needed in this model: occupancy and indoor air temperature. In real practice, users could plug in the scheduled or simulated occupancy as the first input, and plug in the simulated indoor air temperature as the second input. The output state of AC, rather than a pre-defined fixed schedule, could serve as an input for the building energy/thermal environment simulation, which could be a more realistic representation of occupant behavior and accordingly help to improve simulation accuracy.

In this demonstration, the Modelica built-in *Step* function was utilized to simulate occupancy, and the Modelica built-in *Sine* function was utilized to simulate the variation of indoor air temperature, as illustrated in Figure 3(a). Two indoor-temperature-dependent probability functions (turn on probability and turn off probability, respectively) need to be calculated to determine the state of AC.

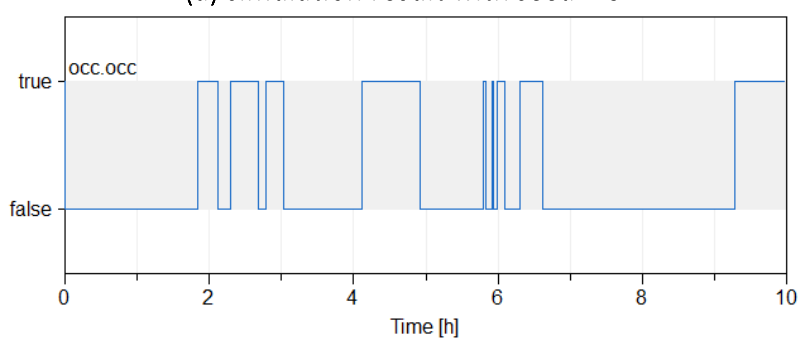
Figure 3(b) shows the input, intermediate and output variables for a 3600-second-period simulation. When the space is unoccupied, the AC is always off. When the space is occupied, the state of AC is determined by the indoor air temperature. Higher indoor air temperature, higher chance to turn on the AC and lower chance to turn off the AC. Then a binary random variable will be generated every 120 seconds based on the calculated *pon* and *poff* to determine the state of AC. The frequency of random variable generation could be tuned by the user by adjusting the parameter *samplePeriod.* To save computation power, *pon* and *poff* could be calculated at the interval of *samplePeriod*. In this case, a more frequent calculation of *pon* and *poff* is requested for a better demonstration of how the probability is influenced by the indoor air temperature.

3.2 *Wang2005Occupancy*: a *transition* model example

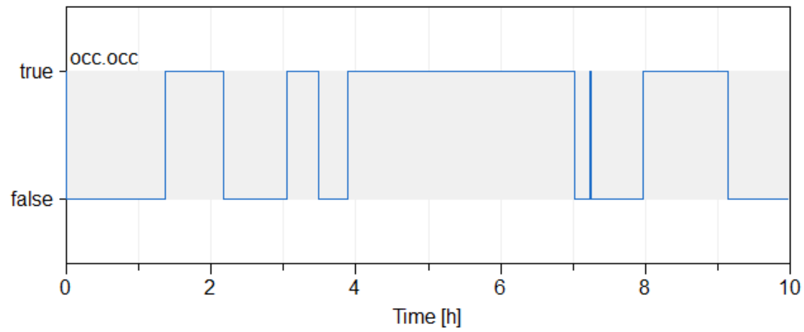
The *Wang2005Occupancy* model simulates the occupancy state of a single-person office, which was originally documented in [35]. As a *transition* model, the duration of each occupancy state is characterized and calculated as a Weibull random variable. For instance, at the point the space starts to be occupied, the duration of this occupancy, or in another words, when the occupant will leave the room, will be calculated from the Weibull distribution. No model inputs are needed. The model parameters were fitted from a field study in California with 35 single-person offices at a large office building lasting for almost one year starting from 1998.



(a) simulation result with *seed* = 5



(b) simulation result with *seed* = 10



(c) simulation result with *seed* = 30

Figure 4: Validation of the *Wang2005Occupancy* model

Figure 4 presents the simulation results with three different seeds. Though sharing exactly the same mathematical models and parameter values, each run with different seeds produce markedly different behaviors. However, the occupied/unoccupied time ratios almost keep the same, and are close to the ratio of two key parameters of the model, i.e. *one_mu (mean of occupancy duration)* to *zero_mu (mean of vacancy duration)* in all the three cases simulated.

3.3 *Rijal2007WindowsTInTOutTComf*: a combination of *state* and *transition* model

As the last example in this section, a more complicated model was chosen to show how the models of the Occupants package are capable to simulate relatively complex occupant behaviors.

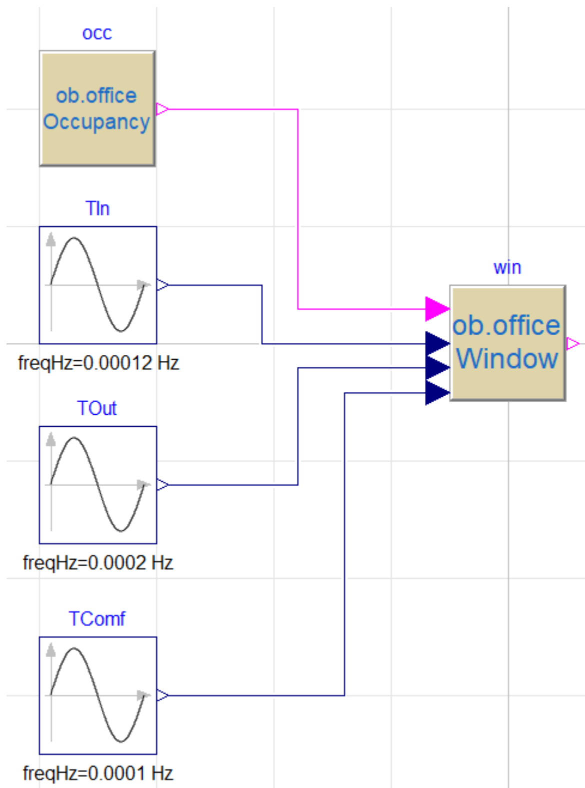
The *Rijal2007WindowsTInTOutTComf* model simulates occupants' window behavior in the office buildings. The model was fitted from the field studies in 15 office buildings in Oxford and Aberdeen, UK, and was originally documented in [40]. The window state is determined by four inputs: occupancy, indoor air temperature, outdoor air temperature and occupants' comfort temperature. In this demo, the *Wang2005Occupancy* model was utilized to simulate occupancy state, and three Modelica built-in *Sine* functions were utilized to simulate the variation of indoor, outdoor and comfort temperatures, as illustrated in Figure 5(a).

The dynamics of the *Rijal2007WindowsTInTOutTComf* model is shown in Figure 5(b):

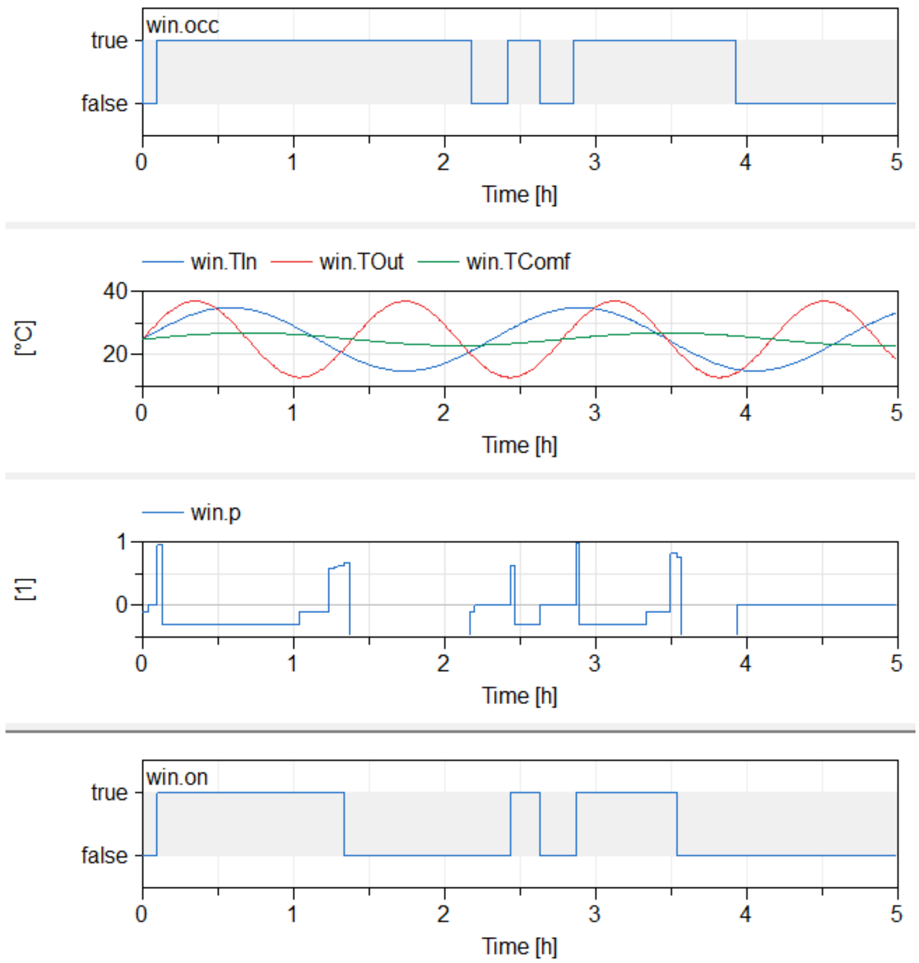
- Case 1: When the space is unoccupied, the window is always closed, for instance during the period 3.85 h and 5.00 h
- Case 2: When the indoor temperature is within the comfort temperature plus and minus 2 ^{o}C, the window state will not be changed, for instance during the period between 1.05 h and 1.25 h
- Case 3: When the indoor temperature is above the comfort temperature plus 2 ^{o}C:
    - Case 3.1: If the window is open, it would be kept open, for instance during the period between 2.45 h and 2.60 h
    - Case 3.2: If the window is closed, the probability to open the window is determined by the indoor and outdoor temperature through a two-dimensional logistic regression
- Case 4: When the indoor temperature is below the comfort temperature minus 2 ^{o}C

- Case 4.1: If the window is closed, it would be kept closed, for instance during the period between 1.30 h and 2.10 h
- Case 4.2: If the window is open, the probability to close the window is determined by the indoor and outdoor temperature through a two-dimensional logistic regression.

In the released Version 1.0, to speed up the computation, the probability of window opening would only be calculated in Case 3.2 and Case 4.2, and set to the default value of 0 in other cases. In this example, in order to demonstrate and highlight different cases, the probability of window opening has been manually set to non-zero values: -0.1 for case 2, -0.3 for case 3.1 and -0.5 for case 4.1.



(a) Photographic modeling interface

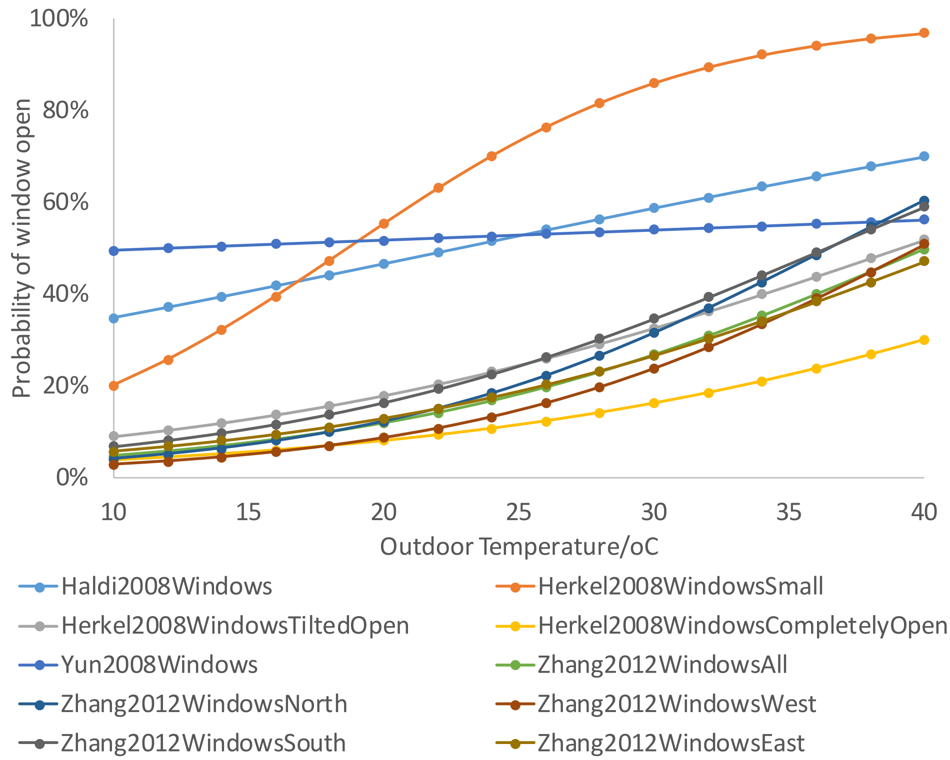


(b) *Rijal2007WindowsTInTOutTComf*

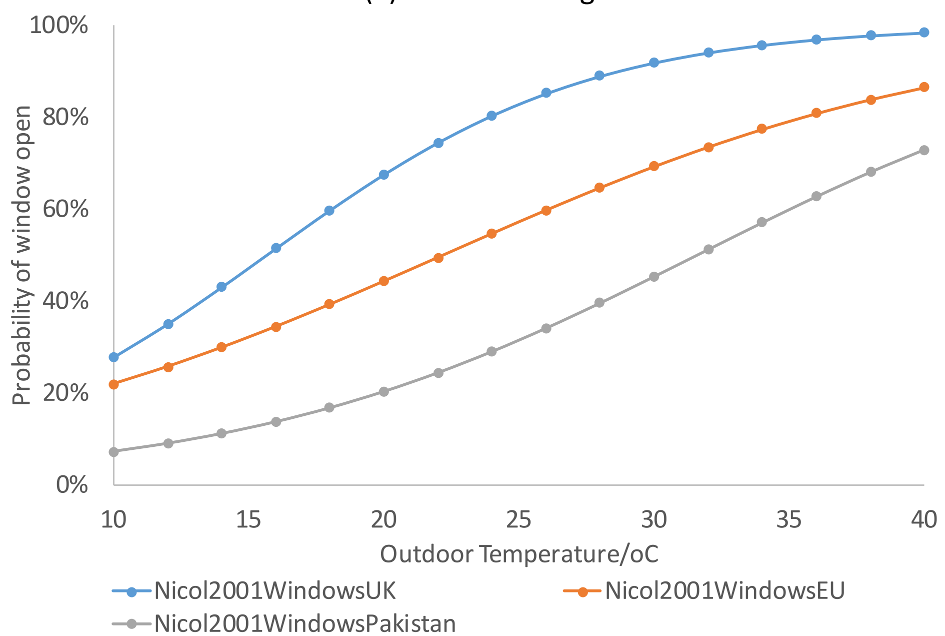
Figure 5: Validation of the *Rijal2007WindowsTInTOutTComf* model

4. Model selection

It should be acknowledged that the mathematical forms, the choice of input variables (indoor air temp. vs. outdoor air temp.), and the parameter values of each model were derived from field studies conducted in a limited number of buildings in a specific climate zone on a certain group of occupants with specific cultural background and behavior preference, which should not be considered as universal. As the result, given the same environment conditions, the occupancy behaviors simulated from different models might vary significantly. Figure 6 selected and plotted the window behaviors of 13 models included in the Occupants package, which all use the outdoor air temperature as the model inputs. Though sharing similar trends, these 13 models produced markedly different results.



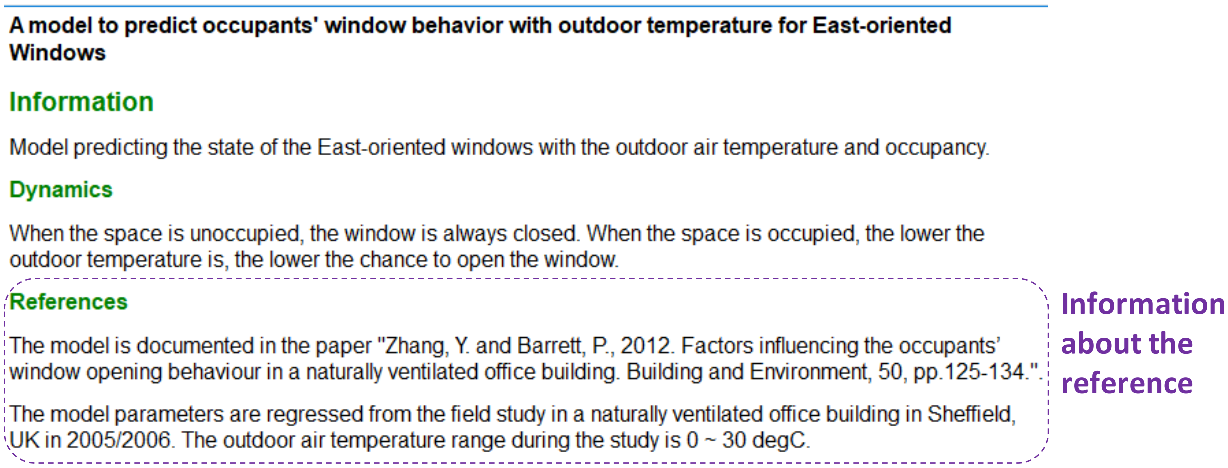
(a) Office buildings



(b) Residential buildings

Figure 6: Comparison on window behavior models

The significant behavioral differences predicted by different occupant behavior models are understandable due to the marked inter-occupant diversity. Different subject might respond differently to the same ambient environment [50],[52]. However, because of the significant behavioral differences, careful selection of proper models for a specific simulation purpose is of high importance. It is also possible that neither of the models included in the package suits your simulation case. The model selection and parameter tuning relies on users' expertise and prior knowledge. What we could offer in the package are: first, necessary information about the reference which we think might be of value for your decision, as shown in Figure 7(a). Second, an interface to easily adjust the parameters, as shown in Figure 7(b).


A model to predict occupants' window behavior with outdoor temperature for East-oriented Windows

Information

Model predicting the state of the East-oriented windows with the outdoor air temperature and occupancy.

Dynamics

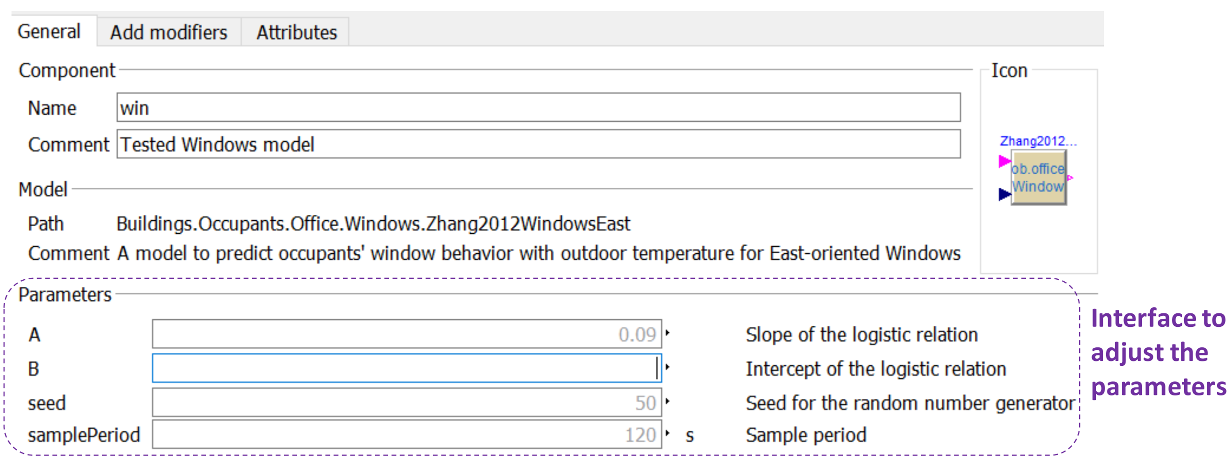
When the space is unoccupied, the window is always closed. When the space is occupied, the lower the outdoor temperature is, the lower the chance to open the window.

References

The model is documented in the paper "Zhang, Y. and Barrett, P., 2012. Factors influencing the occupants' window opening behaviour in a naturally ventilated office building. Building and Environment, 50, pp.125-134.".

The model parameters are regressed from the field study in a naturally ventilated office building in Sheffield, UK in 2005/2006. The outdoor air temperature range during the study is 0 ~ 30 degC.

(a) Information session



(b) Parameter tuning interface

Figure 7: Information session and parameter tuning of each occupant behavior model

To select the proper model for your simulation cases, we would recommend you to review the original paper to see if the assumptions and the data sources documented in the paper fit well with your simulation purpose. For instance, the window behavior models derived from European residents might not be suitable to simulate residential buildings in China or in the U.S. Based on our experience in implementing the models, we would suggest you to carefully consider the following three factors when choosing occupant behavior models:

- Model inputs: for instance, whether you are going to use the indoor temperature, outdoor temperature, solar intensity or solar altitude to predict the occupants' blinds behavior.

- Data source: where the field study was conducted. For instance, the model *Zhang2012WindowsAll* regressed the probability to open the window with outdoor temperature: the higher the outdoor temperature, the higher the chance to open the window. This could be the case in the UK, where the climate is mild and the outdoor temperature would seldom be too high. But this dynamic would not be the case in tropical areas, where occupants would choose to close the window and turn on the AC when the outdoor temperature is too high.
- Range of input variables: almost all the models included in the Occupants package are data-driven models and derived from field studies. Therefore, the models might only be valid in a limited range and could not be extrapolated outside the range. For example, the *Haldi2008WindowsTOut* model was derived from data with the outdoor temperature range of 5 to 35°C. Accordingly, the *Haldi2008WindowsTOut* model might not be applicable when the outdoor temperature is either below 5 or above 35 °C.

More diversified while well documented occupant behavior models will be added to the Occupants package in future releases. Contributions from the simulation community is warmly welcome.

5. Conclusion

This study presents the *Buildings.Occupants*, a new package of occupant behavior models implemented in Modelica, an emerging equation-based object-oriented modelling language, as part of the Modelica Buildings Library. The Occupants package contains commonly used occupant behavior models covered in the literature, including six Blinds, fourteen Windows, five Lighting, and one Occupancy models for office buildings; and two AC, three space Heating, and three Windows models for residential buildings. Validation examples showed that the models in the Occupants package are capable to simulate stochastic occupant behaviors in buildings.

Considering that different occupant behavior models might produce markedly different results, library users should be careful in model selection. Additionally, a *BaseClasses* package has been developed and included in the library, so that users could easily define their own occupant behavior models by tuning the model parameters or inheriting from *BaseClasses*. The *BaseClasses* package defines Logistic, Weibull and random-variable-generation functions which are commonly used in occupant behavior modeling.

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