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‘Review of existing occupant behavior models’

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Rekenmodellen, simulaties en gebruikersgedrag

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Review of existing OB models

Please note that this TRECO progress report reflects the results per January 2016. Later the two sections in this TRECO report are published in the journal article: "Gaetani, I., Hoes, P., & Hensen, J. L.M. (2016). ***Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy****. Energy and Buildings, 121, 188-204".*

1. Overview of existing occupant behavior models

Occupant behavior models are commonly divided into occupant movement and presence models, and action models. Action models comprise various types of (adaptive) behavior, such as adjusting shades and windows, switching on/off lights, using appliances, setting the thermostat, etc. A comprehensive occupant behavior model thus includes a series of sub-models.

In general, existing behavioral models can be classified according to their complexity [1], [2]. In this report *complexity* is defined, following [3], as the amount of detail in a model, which in turn depends on its *size* and *resolution*. *Size* refers to the number of components in a coupled model, while *resolution* refers to the number of variables in the model and their precision or granularity. Fixed, *a priori* schedules (also called diversity factors or profiles) represent the lowest level of complexity and are commonly implemented in BES software. Schedules are hourly fractions from 0 to 1 that act as multipliers of maximum quantities to define actual internal gains due to people, lighting loads, equipment loads, etc. Schedules are defined independently of the predicted conditions during the simulation. Hence, they represent a simplified scenario where the building operation is very predictable according to day-types. Schedules can either derive from standards or from observation-based statistically aggregated data. They can include deterministic rules, where actions are perceived as direct consequences of one or more drivers e.g., variation of indoor temperature or direct solar radiation. Given their deterministic nature, such models typically average out diversity of individuals, spaces/locations or time; therefore, they represent environments where the modeled behavior is always fully foreseeable and repeatable. While the size of the model is not directly affected, deterministic models add granularity by specifying various behavioral triggers, hence increasing the model resolution and the complexity. Data-based models are determined by the training profile and supposedly contain information about environmental triggers, but they cannot be referred to as deterministic models. We will refer to them as non-probabilistic models [16]. The main drawback of non-probabilistic models is their dependency on the dataset. Researchers have developed stochastic (or probabilistic) models to capture the variability of human behavior. In stochastic models, actions occur based on a probability function as a consequence of stimuli. Such models require a high number of runs to achieve reliable results [17], and cannot capture (e.g. time-) consistency. Also in this case, the size is not directly affected as the models still only consider the interactions between the occupants and the building. The resolution increases due to the multiple runs. Schedules, deterministic models, non-probabilistic models and probabilistic models represent the conventional simulation framework. A more complex simulation framework is defined by agent-based models, which switch from *group-level* to *individual-level* behavior predictions. Agent-based models predict the influence of occupants by modeling individuals, their mutual interactions and the interaction with the building. However, the huge amount of information typically required (e.g., role of agents, relationship between agents, etc.) may not always be available. Despite this drawback, agent-based modeling currently commands the biggest share of publications in this niche [18]. Agent-based models markedly increase the size of the model as each individual is separately modeled; the resolution is still based on stochastic modeling and the resulting complexity is very high. Nonetheless, agent-based behavioral models can be characterized by different levels of complexity, depending on the complexity of the sub-models which they include. Table 1 is a graphical representation of how modeling size, resolution and complexity are affected by changing the modeling strategy. The overall modeling complexity always derives from the complexity level of each sub-model. A detailed description of the available models follows next.

Simulation framework	Type of model	Size	Resolution	Complexity
Conventional	Schedules	•	•	•
	Deterministic	•	↑	↑
	Non-probabilistic	•	↑	↑
	Probabilistic/stochastic	•	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

Table 1: Overview of the most common occupant behavior modeling approaches according to size, resolution and complexity.

Various reviews of existing occupant behavior models are available [19,20]. A first question to answer when performing a review is how to categorize the models. The most common categorizations are: according to complexity [1], according to object of investigation (occupancy or type of behavior) [21], and according to research approach [19]. Some authors have focused on one level of complexity or one object of investigation only, e.g. [18] on agent-based modeling and [21] on occupancy models. In this report existing models have been classified according to complexity as the study deals with selecting the most appropriate level of modeling complexity. The focus of this literature review is on models that go beyond *a priori* schedules and simple deterministic rules, which are thus not considered. As briefly stated above, three main categories are identified: non-probabilistic models (defined as level “0”), which mainly include diversity factors resulting from data-mining; probabilistic or stochastic models (defined as level “1”), which represent the majority of the considered publications and rely on Logit analysis, Probit analysis, Markov chain processes, Poisson processes, and survival analysis [22]; agent-based and object-oriented models (defined as level “2”), also known as object-based models.

Table 2 provides an overview of the current status of occupant behavior modeling for building energy simulation. As well as the level of complexity (0, 1 or 2) and the references for each model, seven other categories are specified, namely: model (M) or simulation framework (S); type of behavior; keywords; building typology; location; pros; cons. The distinction between model and simulation framework is made for practical purposes to underline whether particular attention has been placed on the integration of the model in BES or not. The type of behavior, building typology and location were identified as the main variables to take into account the case-specificity of each presented model. Keywords provide information about the modeling approach, the existing implementation in BES software, the validation status and the name of the model (where applicable). Lastly, pros and cons aim to highlight possible improvements to previous models, limitations to overcome, and general features and capabilities.

It has to be noted that this list does not claim to be exhaustive since new models are constantly being developed. Nevertheless, it gives an impression of the complexity of the occupant behavior modeling research field, of some recurrent issues and of the vast number of aspects that ought to be considered.

Complexity (0=non-probabilistic, 1=probabilistic, 2=agent-based models)	**Author(s) year [Ref.]**	**Model (M) or Simulation framework (S)**	**Type of behavior**	**Keywords**	**Building Typology**	**Location**	**Pros**	**Cons**
1	Hunt 1979 [23]	M	Lighting control	Probit analysis; integrated ESP-r	Office and school	UK	Pioneer field-based stochastic modeling; function of work plane illuminance	No combination with other control laws (e.g. dimming, occupancy sensors)
1	Fritsch et al. 1990 [24]	M	Windows opening	Markov chain; validated	Office	CH	Window opening angle; function of T_{out}	High dependence on time series; winter only
1	Capasso et al. 1994 [25]	M	Load	Monte Carlo; partially validated	Household	I	DSM application; accuracy; aggregation and ownership	High dependence on outdated ('88-'89) data; complexity of input data
1	Newsham et al. 1995 [26]	M	Lighting control + occupancy	Markov chain; not validated	Office	CA	Function of work plane illuminance; variety of lighting controls	Switch-on events during occupation period not considered
1	Degelman 1999 [27]	M	Lighting control	Monte Carlo; integrated ENER-WIN	Office and university	US, JP	Energy saving potential with sensors/dimmers	Not calibrated; no real utility records
1	Nicol 2001 [28]	M	User behavior (windows, lights, blinds, heaters and fans use)	Logit analysis	Office and household	F, GR, P, PAK, S, UK	Function of T_{out} and T_{in}; first coherent prob. distribution for windows' state	Survey in form of charts; no consideration design, systems etc.
1	Yamaguchi et al. 2003 [29]	M	User behavior	Markov chain	Office	-	Realistic presence/absence; 4 working states; cogeneration; costs and energy saving strategies	2 buildings' combinations only; not based on TUS; not clear if whole year or 1 day; long absences neglected
1	Reinhart 2004 [30]	M	Lighting and blinds control	Inverse transform sampling; integrated Lightswitch Wizard, DAYSIM and ESP-r; Ligtswitch2002	Office	CA	Function of occupancy/work plane illuminance; active/passive user; switching actions depend on random probability; blinds control function of glare risk; improves Newsham et al.'s model	Fixed profiles 7h45-18h15; presence overestimation (no absences apart from break); no intermediate switch-off; blinds fully open or closed; no thermal considerations for blinds activation
2	Stokes et al. 2004 [31]	M	Lighting control	Object-based; validated	Household	UK	Fine time-scale (1 min); flexible model design (single/multiple dwellings); aggregated demands	Old ('96-'97) TUS; dependence on large amount of input data/assumptions; complexity
1	Pfafferott and Herkel 2005 [32]	M	User behavior	Monte Carlo; integrated ESP-r	Office	DE	Considers passive cooling specifically	Adiabatic boundary conditions between rooms; data for 42 days

1	Wang et al. 2005 [33]	M	Occupancy	Non-homogeneous Poisson process; partially validated	Office	US	Vacant intervals' distribution (improves Reinhart's model); time varying; matches with observation	Fixed profiles weekends/weekdays; total presence overestimated; intervals do not fit well
2	Bourgeois et al. 2006 [34]	S	User behavior (lights, blinds, windows and equipment use)	Object-based; integrated ESP-r; SHOCC	Office	CA, I	Self-contained simulation module; fully expandable; improves Nicol's and Reinhart's models	No advanced solar shading; lacks flexibility; deterministic definition of passive users
2	Zimmermann 2007 [23]	M	User behavior	Agent-based; validated; integrated BES	Office	US	First agent-based application; satisfactory fit; whole office building	Building/service/control models need refinement; activity patterns need validation; lacks generalization
2	Tanimoto et al. 2008 [24]	M	User behavior	Agent-based; validated;	Household	JP	Pioneers of TUS data use; considers electricity and DHW	
1	Yun and Steemers 2007 [25]	M	Windows opening	Logit analysis; validated; integrated in ESP-r	Office	UK	Function of T_{in}, time of day, previous window state; separate sub-models for WO at arrival, departure, during occupancy	Summer only; 6 offices only; considers natural ventilation behavior but not exhaustively
1	Rijal et al. 2008 [26]	S	Windows opening	Logit analysis; validated; integrated in ESP-r	Office	UK	Function of T_{out} and T_{in} (to include building design); active/passive user; develop robust design solutions	Old ('96-'97) TUS; not clear how Tout is considered; window opening deadband needs revision
1	Page et al. 2008 [27]	M	Occupancy	Markov chain non-homogeneous 2 states; validated; MATLAB script	Office and Household	CH	Vast range of applications (given the right inputs); includes long absences; comprehensive; realistic	Long-term monitoring; complex input; underestimates total absence; calibration on 5 university offices
1	Haldi and Robinson 2008 [28]	M	User behavior (windows, blinds, fans, doors, cold drinks, activity and clothing)	Logit analysis	Office	CH	Function of work plane, outdoor illuminance and occupancy; covers many activities; personal/environmental adaptation	No reversal of adaptive behavior; function of T_{out} and T_{in} only
1	Herkel et al. 2008 [29]	M	Windows opening	2 stochastic processes for occupancy and window opening; sub-models arrival, occupancy, departure	Office	DE	Correlation with season; used to assess robustness of natural ventilation; most openings at arrival	Only predicts windows status; lacks generalization
1	Richardson et al. 2008 [30]	M	Lighting control + occupancy	Markov chain non-homogeneous 2 states MC; partially validated; implemented Excel	Household	UK	Active/inactive users; sharing behavior; combined with activity model; free download	Only classification weekdays/weekends and people/household
2	Tanimoto 2008 [31]	M	Load	Agent-based; validated	Household	JP	Public statistical data (improves Page et al.'s model); coupled with load calculation	Complexity (32 activities); only summer, only cooling loads; needs further validation
1	Widén et al. 2009 [32]	M	Activities	Conversion of activity data to energy load profiled; validated; MATLAB script	Household	S	Realistic load distributions; simplicity; considers various household typologies	Old ('96) TUS; heavy dependence on TUS
1	Widén et al. 2009 [33]	M	Lighting control + occupancy	Markov chain non-homogeneous 3 states MC; validated	Household	JP	Absent/present inactive/present active user	Old ('96) TUS; problems in night-time demand data collection; lighting sharing not included
2	Erickson et al. 2009 [34]	M	Occupancy	Agent-based; integrated eQuest	Office	US	Optimize HVAC loads with occupancy-based energy control	Poor fit of occupancy estimation (20% error, but shown to have low impact); relatively low possible savings
0	Gaceo et al. 2009 [35]	M	Load	Artificial Neural Network; integrated TRNSYS; ESOM	Household	E	Comparison with Spanish Technical Code for Buildings (CTE); extensive data	No comparison with real data; overall unclear
0	Armstrong et al. 2009 [36]	M	Load	Profiles derived by measured data; validated	Household	CA	Considers system performance in cogeneration; typical households function of demand	Limited available information; underestimation of base-loads; does not consider HVAC
1	Haldi and Robinson 2009 [22]	M	Windows opening	Bernoulli process based on logit distribution, Markov chain, extension of Markov chain to a continuous-time random process; integration possible in any BES; validated	Office	CH	Extensive (7 yrs.) measurements; function of T_{out}, T_{in}, humidity, wind speed; refinement active/passive; extensive cross-validation	No extensive elaboration on BES integration; building-specific calibration; windows angle opening needs refinement
0	Davis and Nutter 2010 [37]	M	Occupancy	Profiles derived by extensive measured data	University	US	Clustering for weekday type; estimate of uncertainty (measurements)	Building-specific; many info needed; high dependence on data
1	Haldi and Robinson 2010 [38]	M	Shades control	Markov chain MC; validated	Office	CH	Initial blind status, indoor/outdoor illuminance input to Markov process; separate sub-models for chosen shaded	Single configuration of blinds

							fraction	
2	Tabak et al. 2010 [39]	M	Activities	Agent-based MC	Office	NL	Many activities; realistic events; whole office building	Very building specific input; lacks generalization
1	Widén and Wackelgard 2010 [40]	M	Activities	Markov chain non-homogeneous MC; validated	Household	S	Balanced complexity/output quality; considers various household typologies	Only covers electricity demand; limited TU data
2	Azar and Menassa 2010 [41]	M	User behavior	Agent-based; integrated eQuest	University	US	Includes change over time by considering word-of-mouth	No extensive description of used agent-based model; similarity among scenarios
1	Parys et al. 2011 [20]	S	User behavior	Markov chain MC; integrated TRNSYS 6	Office	B	Holistic approach; improves Bourgeois et al.'s model	Built-in error from choice of drivers (not exhaustive); not validated; modest change in energy consumption due to OB (in contrast with other studies)
2	Robinson et al. 2011 [42]	S	User behavior	Agent-based		CH	Basis for future simulation at various scales (from building to urban)	Huge amount of info needed; not clear if integrated; not clear if fully developed
1	Yamaguchi et al. 2012 [43]	M	User behavior	Markov chain; modified Tanimoto's approach (Roulette Selection)	Household	JP	Considers weekday, Saturday, holiday; electricity consumption; 27 behaviors; compare different modeling approaches	Model underestimates changes in behavior; unclear integration BES
1	Wang et al. 2011 [44]	M	Occupancy	Markov chain homogeneous; partially validated; MATLAB script	Office	-	Produces non-synchronous change of O in time/uneven distribution of O in space; simplicity, accuracy	Probability functions not time-dependent; arithmetic speed problem [Feng.]; simple validation/calibration missing
1	Schweiker et al. 2012 [45]	M	Windows opening	Markov chain	Household	CH, JP	Comparisons with Haldi and Robinson 2009 and Rijal et al. 2007	Issues with external calibration; poor window use prediction of models calibrated from Swiss data for Japan
2	Liao et al. 2012 [46]	M	Occupancy	Agent-based; validated	Office	US	Relates with former state [Feng]; parallel low-complexity model based on covariance graphical model framework; improves Page's model	Much information in an instance [Feng]; high complexity; not suited for real-time occupancy estimations; no clear integration
1	Zhang and Barret 2012 [47]	M	Windows opening	Probit analysis	Office	UK	Considers orientation; consider non-office spaces in office buildings	No presence/absence data; only one driver T_{out}<20°C; only one building; no validation nor integration in BES
0	Duarte et al. 2013 [2]	M	Occupancy	Descriptive statistics; validated	Office	US	Clustering per weekday and month type; comparison with ASHRAE guidelines and Page et al.'s model	Open plan offices not accurately described; comparison with Page et al.'s model unclear
2	Wilke 2013 [48]	M	Activities + occupancy	Logit analysis multinomial; Markov chain higher-order pre-process; Weibull distribution; validated	Household	F	Assigns duration at the start of new occupancy state; activities function of week day, 17 socio-demographic variables	No simultaneous activities; no electrical/water appliances
1	Andersen et al. 2013 [49]	M	Windows opening	Logit analysis	Household	DK	Considers 4 groups of dwellings: owner-occupied/rental, naturally and mechanically ventilated	Occupancy function of CO_2 levels; only data Jan to Aug
1	Chang and Hong 2013 [50]	M	Occupancy	Cumulative and probability distribution function	Office	-	5 occupancy patterns; extensive database (200 cubicle offices)	Occupancy only
1	Aerts et al. 2014 [51]	M	Occupancy	Probabilistic; hierarchical clustering	Household	B	3 states, 7 occupancy patterns; key variables transition probability and duration probability; improves Wilke et al.'s; calibration for download; low complexity	Strong dependence on TUS; occupancy only
2	Lee 2014 [52]	M	User behavior	Agent-based	Office	US	Considers optimized behaviors and sensitivity to different climate conditions	1 agent; no validation; no calibration
1	Fabi et al. 2014 [53]	M	Windows opening	Logit analysis; not validated	Office	CZ	Extensive range of measured variables	No validation; some variables only monitored in some rooms
0	Buso et al. 2014 [54]	M	Load	Calibrated realistic schedules; validated; integrated IDA Ice	Household	I	Comparison with UNI/TS 11300; issue of system sizing	1 key user; data from 1 dwelling; no data for DHW and heating; case-specific; based on past history of consumption

2	Chapman et al. 2014 [55]	S	User behavior	Agent-based; integrated EnergyPlus	Office and Household	UK	Comparison with deterministic simulation (window model most impact on difference); coherent, general, extensible	No validation; not yet DHW, appliances, HVAC set points, interactions among agents
2	Rysanek and Choudhary 2014 [56]	S	User behavior	Object-based; not validated; *integrated* TRNSYS, EnergyPlus; tool DELORES	-	-	Ease of use comparable/better than deterministic approach; straight-forward	Stand-alone software (not clear influence of environment); time step 1h; no relation lights/occupants; no clustering holiday periods; lighting method not established nor validated
1	Gunay et al. 2014 [57]	S	User behavior	Logit analysis; integrated EnergyPlus	Office	CA	Overcome conceptual problem that occupant actions are discrete events	Probability of adaptive behavior always non-zero
0	Mahdavi and Tahmasebi 2014 [16]	M	Occupancy	Statistically aggregated profiles; building systems control	Office	A	Separate sets of data used for training and evaluating the models; comparison with Reinhart's and Page et al.'s models	It returns the same daily occupancy profile for any given aggregate profile of presence probability used for model training (deterministic nature)
1	D'Oca et al. 2014 [58]	M	Windows opening + thermostat	Logit analysis; integrated IDA Ice	Household	DK	Active/medium/passive user; compares 5 scenarios from deterministic to probabilistic	No comparison with measured values; case specific
2	Langevin et al. 2014 [59]	S	User behavior	Agent-based; integrated EnergyPlus with BCVTB; HABIT	Office	US	Considers energy and thermal comfort; multiple zones, offices	Interaction between EP simulation and MATLAB behavior model takes place at every time-step; multiple runs needed (probabilistic nature)
2	Alfakara 2014 [60]	S	Windows opening + cooling	Agent-based; integrated TAS	Household	UK	Response to summer overheating	Agents' actions (lighting, windows, cooling,…) fed to BS model every time step; only 2 occupants
2	Feng et al. 2015 [21]	S	Occupancy	Object-based; co-simulation for integration	Office	-	Various occupancy levels integrated; flexible and extensible, ease of updates or maintenance	Occupancy only; complexity
1	Zhou et al. 2014 [61]	M	Lighting control	Poisson process; validated for weekdays	Office	CN	Considers time-varying nature peak usage; uncertainties in occupant behavior (main driver)	Case specific (large offices with no daylight control)

Table 2: Review of available models according to: level of complexity; reference; simulation or modeling framework; type of behavior; modeling approach, validation, implementation in BES and model's name; building typology; location; pros; cons.

Some conclusions can be drawn from Table 2: i) many models are available; ii) models are rarely developed as a simulation framework: the implementation in BES mostly takes place on a project-based level, without guidelines for future use or measures for public availability; iii) models are generally developed for a specific type of adaptive behavior, but recently there has been an increase of models which address the whole spectrum of user behavior; iv) households and offices are the most investigated building typologies, and a large share of the investigated offices are single occupancy; v) models are developed for specific locations, which might undermine their generalizability to other locations; vi) different models are characterized by different specific advantages although a number of recurrent limitations are reported, e.g. complexity, case-specificity, lack of validation, calibration, generalizability, heavy dependency on (outdated) time use surveys. The findings of this overview are in line with the barriers that IEA-EBC Annex 66 (Definition and Simulation of Occupant Behavior in Buildings) aims to overcome [62]. These conclusions reveal the difficulty for a potential simulation user to choose the most suitable model for a specific case. Moreover, inter-comparison among different models represents a knowledge gap, and the differences among models' outcomes are not clear. The few existing examples of inter-comparisons among models of different complexities are the focus of section 5.1.1.

2. Inter-comparisons of models with different complexities

Section 5.1 illustrates how the existing models are difficult to compare, both because of their case-specific nature and because of the lack of standardized methods to report and compare results [63]. Nevertheless, some comparisons among different models are available. For example, existing stochastic models have been researched [22,57] to test for specific behaviors in offices and dwellings in order to define the best probabilistic approach. In this research only comparisons among models of different complexities are taken into account, which to the best knowledge of the authors represent a very small share of publications.

Mahdavi and Tahmasebi [16] evaluated the probabilistic occupancy models developed by Reinhart for Lightswitch-2002 [30] and by Page et al. [27] by comparison with a newly developed non-probabilistic model. The object of the investigation is eight workspaces (single-occupancy, semi-closed individual, open-plan area) in an office area of the Vienna University of Technology. Notably, the authors use separate sets of data to train and evaluate the models. Data are collected over nine months (November 2011-July 2012) with a 1.6 minute time-step to generate 15-minute interval data. The predicted and actual occupancy profiles are compared by means of a 100-run Monte Carlo simulation using 4 statistics (first arrival, last departure, duration and transitions errors) for 90 working days between April 2012 and July 2012. The overall goal of the study is to support building systems controls. The results show that Reinhart's and Page et al.'s models perform quite similarly, with Reinhart's model offering slightly better prediction of first arrival and intermediate transitions. Overall, the prediction capability of all models was found to be low and none of them performed below the threshold error value considered acceptable by the authors. The non-probabilistic model is found to perform best. The authors suggest that the random diversity in occupancy patterns reproduced by probabilistic models may be crucial for other aims of simulation (e.g. design and sizing of building systems), but they are not suitable to provide short-term occupancy predictions based on past data such as is needed in building systems control. In this case, non-probabilistic models that better fit historical data have a better predictive performance.

Tahmasebi et al. [64] apply occupancy, lighting and plug loads schedules from ASHRAE 90.1-2013 and Page et al.'s stochastic model [27] to a small-sized reference office model from the U.S. Department of Energy [65]. The aim of the study is to quantify the impact of stochasticity on annual and peak energy predictions for heating and cooling. The ASHRAE schedules were used as input for the stochastic model. The authors concluded that for the considered case the predictive ability of a simplified occupancy modeling approach is analogous to a more complex stochastic approach.

Duarte et al. [2] evaluated new non-probabilistic occupancy diversity factors for private and open plan commercial office buildings against ASHRAE 90.1 2004 profiles and Page et al.'s model [27]. The schedules are based on data collected in 223 private offices over about two years (November 2009-October 2011) in a multi-tenant 11-story office building in Boise, Idaho. Although the overall trend throughout the day is similar, ASHRAE 90.1 2004 overestimated the occupancy level (peaks of 95% as opposed to about 50% predicted by the newly developed schedules for private offices). In addition, when comparing a typical high occupancy week and a typical low occupancy week with Page et al.'s model [27], the two models show similar characteristics, but the new data-based schedules do not register the great variation during the day found by the stochastic model. The authors hypothesize that this could be due to the restricted data set used to calibrate Page et al.'s model. Overall, the authors prove that the model resulting from measured data shows up to a 46% reduction in average day profile peaks for private office and about a 12% reduction for open plan office spaces when compared to the ASHRAE values. Interestingly, they point out that energy modelers could conduct two sets of simulations – one with typical low and another with typical high occupancy profiles – in order to produce a range of expected energy consumption during the lifetime of the building, as opposed to a single value. This method would allow energy modelers not to unnecessarily complicate the model inputs.

D'Oca et al. [58] developed probabilistic user profiles for window opening and thermostat set-point adjustment. The yearly heating consumption obtained by implementing their profiles in IDA ICE is compared with the one from deterministic schedules of European standard EN 15251:2007. The new probabilistic model consists of logistic regression formulas and it is based on field measurements collected from January to August 2008 of 15 naturally ventilated dwellings near Copenhagen. The used time-step is 10 minutes. The authors study 4 scenarios, namely: a deterministic scenario both for window opening and T_{sp} that should function as a reference; a scenario where window opening is treated in a probabilistic way while T_{sp} follows deterministic schedules; a probabilistic model for both behaviors; a probabilistic model which includes active, medium and passive users; a final model with 3 different thermostat adjustments. The three considered climates are: Athens, Stockholm and Frankfurt. When compared to the reference case, the last model showed the greatest discrepancy. Overall, it was pointed out how the deterministic approach generally underestimates the heating consumption, by the greatest magnitude in Athens (+61%). The authors are confident that their findings can be applied during the whole-building lifecycle, namely: design phase, operation phase, building retrofit, building management and building codes and policy.

Langevin et al. [59] present the Human and Building Interaction Toolkit (HABIT), a co-simulation tool for comfort and behavior predictions based on a field-validated, agent-based scheme. The tool is developed in MATLAB and implemented in EnergyPlus by means of the Building Control Virtual Test Bed (BCVTB) middleware. The object of the investigation is a 3-story air-conditioned office building in Philadelphia, which was monitored for 1 year. The considered variables are: $T_{sp,}$

$_{heating}$, $T_{sp,\ cooling}$, heater and fan equipment energy per person, clothing adjustment, fans/heaters, and window and thermostat adjustment. The various behaviors were grouped into three scenarios, namely: “Base”, “Typical” and “Set Point Float” scenarios. The overall finding is that by considering a realistic behavior, expected energy use during winter in cold climates increases by up to 15%. On the other hand, the authors point out that increasing the thermostat set points could counteract this rise and instead would significantly decrease the energy consumption in summer (up to 32%).

Chapman et al. [55] propose a multi-agent simulation (MAS) approach to combine stochastic models into a single tool. This model-of-models integrates Page et al.’s presence model [27], Fanger’s PMV model for metabolic gains calculation [77], Jaboob and Robinson’s unpublished activities model, Haldi and Robinson’s windows and shading devices model [22,50] and Lightswitch2002 lighting algorithm [30]. The model is applied to a hypothetical house and a shoe box office; the results are compared with those obtained by means of a default Design Builder schedules for each typology. The results for the residential building show a decrease from 68.7 kWh/m^2 heating demand to 59.0 kWh/m^2 (-16%) using the MAS model. The discrepancy increases to -45% when considering the non-residential building (91.0 kWh/m^2 and 62.4 kWh/m^2 for schedules and MAS model, respectively). The window model represents the greatest contribution to the difference between results.

Azar and Menassa [41] take a slightly different approach when comparing the traditional eQuest building energy estimating model with an agent-based model. The authors consider three categories of occupants (high, medium and low energy consumers) according to blind position, lighting/equipment schedules and hot water consumption. The reference building is a 1000 sq. ft. graduate student room accommodating 10 students for over 60 months and is located in Madison, Wisconsin, US. The base case consists of all 10 students belonging to the category “medium energy consumers". The authors use an agent-based model to simulate the effect of "word of mouth", presumably leading towards lower energy consumption. As a first step, the authors determined the share of electric and gas consumption directly influenced by occupants (79% and 13%, respectively). As far as it concerns electric use, the proposed method's consumption is – in the best-case-scenario – 21.6% lower than the eQuest average.

Yamaguchi et al. [43] developed two occupant behavior models based on the Monte Carlo approach (just as Richardson et al. [78] and Widén et al. [40] models) and on Tanimoto's [31] approach, and applied them to an household in Osaka, Japan. The modified version of Tanimoto's model is named Roulette Selection. The time-use data are collected during 9 days only. The results were evaluated in terms of: duration time for behaviors per day, time at which the routine behaviors start and end, number of behavior transitions per day, probability distribution showing percentage of behaviors at each time step, and number of different patterns of occupant behavior transition in 500 simulations. The authors conclude that the Markov Chain model well replicates behavior duration and transitions. However, the Roulette Selection better approximates the variety of behavior patterns, even with limited time use data, but it performs worse in terms of predictive capability of behavior transitions and duration.

Table 3 gives an overview of the considered comparisons. In most cases, such studies investigate differences between data-based, newly developed models and standard profiles.

			Models considered for comparison ✓ = best performing model(s) × = other considered model(s)			
Author(s) year [Ref.]	**Type of behavior**	**Aim of simulation; performance indicator; building typology**	**Schedules**	**Non-probabilistic**	**Probabilistic**	**Agent-based**
Mahdavi and Tahmasebi [16]	Occupancy	Systems control; daily occupancy profile; (single, semi-closed, open-plan) office		✓	×	
Tahmasebi et al. [64]	Occupancy, lighting and plug-loads	Annual and peak energy demand for heating and cooling; office	✓		✓	
Duarte et al. [2]	Occupancy	Daily occupancy profile; (single, open-plan) office	×	✓	×	

D'Oca et al. [58]	Window opening and thermostat adjustment	Design; energy demand for heating; household	×	✓	
Langevin et al. [59]	User behavior	Energy demand and thermal acceptability; office	×		✓
Chapman et al. [55]	User behavior	Design; energy demand; office and household	×		✓
Azar and Menassa [41]	Blinds regulation, lighting/ equipment, DHW	Electric/gas demand; university	×		✓
Yamaguchi et al. [43]	User behavior	Behavior duration, start/end time, number of transitions, probability distribution, number of different patterns		✓ (behavior duration, transitions)	✓ (variety of behavior patterns)

Table 3: Considered comparison studies.

Other studies consider the issue of model complexity. However, their goal is not to compare the predictive performance of two or more models, hence they have not been included in Table 3. Among them, Hong and Lin [68] investigate the effect of occupant behavior on a private office with three levels of complexity: direct use of EnergyPlus, use of the advanced Energy Management System in EnergyPlus, use of modified code of EnergyPlus. The different complexities are used to model different aspects of occupant behavior. Neither the first nor the second approaches are suitable to represent a stochastic occupant schedule. The most complex approach requires great expertise and offers good flexibility; it is used to model the cooling start up control. Three different work styles are identified in respect to energy consumption: austerity, standard, wasteful. Although the impact of the three approaches to modeling occupant behavior is not clear as different complexities are used to model different behaviors, the authors conclude that an austerity work style can save up to 50% of source energy, while the wasteful work style results in an 89% increase of energy use compared to the standard. Liao et al. [46] acknowledge the need for different resolutions for different aims. For this reason, they propose the Multiple Modules (MuMo) model, a stochastic agent-based model for occupancy simulations over time, and a low-complexity occupancy model for real-time estimations. The MuMo model is shown to have a similar predictive capability to Page's model.

The comparisons presented in Table 3 imply that the models showing the best predictive ability are, namely: non-probabilistic schedules [15,16]; probabilistic user profiles [58]; agent-based models [41], [55], [59]. One study [43] points out that probabilistic and agent-based models show a better predictive performance for different aspects of occupant behavior, while [64] indicate that schedules and stochastic model have an analogous predictive ability. Moreover, some studies state that the models deemed to have a worse predictive performance overestimate the energy consumption and that other studies come to the opposite conclusion. It is important to note that the comparison studies are performed for different aims of simulation, performance indicators and building typologies (see Table 3). Therefore, it is not possible to conclude that the most complex model always performs best, as e.g. in [16] a simple non-probabilistic model showed better convergence than a probabilistic one when compared to measured data. Nonetheless, two conclusion can be drawn, i.e. that standard profiles are mostly considered not to be suitable for describing complex occupant behaviors, and that models derived by measured data always perform best when describing the investigated case study. However, such conclusions are of little help when facing a practical choice of which modeling complexity to use.

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