The role of user behavior modeling on the energy performance simulations

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Abstract

Energy consumption strongly depends on the occupants' behavior for all types of buildings. However, the impact is greatly increased in high performance building, in which users can freely interact with the envelope system (opening widows and shading management) and with the HVAC control systems. The robustness of a design solution to suboptimal user´s behaviors can thus become a distinguishing factor among different design alternatives.

One of the main issues regards the predictability of user choices and actions and its codification into a plausible simulating algorithm. Several strategies are presented in the literature, however energy modelers adopted to a large extent the schedule approach, to take into account users in energy simulations.

This paper describes two stochastic methods implemented in EnergyPlus to simulate the users' behaviors in managing opening surfaces and thermostat setpoint temperatures.

Using these methods, the impact of different user behavior on the energy performance of a multistory building is investigated. The aim of this work is to quantify the impact of users´ behavior modeling on the results of dynamic energy simulations.

1. Introduction

After the coming into force of the European Directive EPBD on energy performance of building (European Commission, 2010), low energy consumption of buildings has become an important target to achieve and nearly zero energy buildings (nZEB) as well as comfort conditions are becoming essential requirements for the new generation buildings.

Nevertheless, sustainable and passive buildings, usually with a high level of thermal insulation, are subjected to a more active role of users' behavior (Hoes et al., 2009). Several studies in the literature compared energy consumption of identical buildings but subjected to different users. In these works, the ratio of the maximum over the minimum value is roughly in the range 1.2 ÷ 3 (Fabi et al., 2012).

The role of users' behavior assumes significance especially in naturally vented buildings, where air change rates per hour (ACH) due to window opening by users can be up to 87% greater than the ACH measured during the non-occupied period (Iwashita and Akasaka, 1997).

Users' behavior has a particular significance for those constructions in which users can interact with the electric devices, shadings, lighting and HVAC system controls. In this way, occupants must be considered an integral and active part of the energy balance of a building, not limited to internal contributions due to their metabolic activity (Mahdavi, 2011). Scheduling occupancy is itself a source of uncertainty and its description could be dealt with non-probabilistic models rather than stochastic approaches (Mahdavi and Tahmasebi, 2015).

The base assumption in modeling occupancy interaction with the building is the adaptive comfort principle (Humphreys and Nicol, 1998). According to this approach, the occupant interacts with the HVAC and building envelope in order to restore the comfort conditions. Nonetheless, the parameters inducing users' interaction with the environment as well as the extent to which they

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effectively manage their actions are not fully defined.

This study presents a comparison between two different models to take into account the users in building energy simulations.

The goal is to evaluate the stochastic distribution of results obtained from the user simulating approach and to compare it against the result provided by a scheduled approach, following the tailored rating simulation inputs according to the EN ISO 13790 standard (CEN, 2008). For this purpose, two user behavior models were implemented in EnergyPlus to simulate the users' behavior in managing opening surfaces and thermostat control setpoint. Additionally, the schedule approach proposed by the technical specification UNI/TS 11300 (UNI, 2008) was also adopted. The study focused on a new multistory residential building with a cross-laminated timber envelope (Xlam) built in Trento in 2013.

2. Models and simulations

2.1 Case of study

The construction (built in Trento - Italy in 2013) is a five-floor residential building composed of 14 residential units of various sizes.

The original structure is part of a residential complex composed of two twin dwellings.

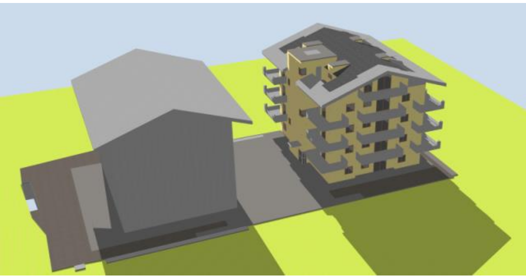

Fig. 1 – Model of the analyzed residential estate

Fig. 2 – Front view of the building (picture by ITEA s.p.a, 2014) and the geometric model used for numerical simulations

The southern building has a cross-laminated timber structure with a reinforced concrete stairwell and low emissivity windows. The northern building is identical except for a platform frame structure. The dwellings have a naturally ventilated wooden roof.

This study focused on the southern building, thus the north dwelling was modeled as an external obstruction. In the following table, the main parameters of the modeled envelope (transmittance and internal heat capacity) are reported.

Table 1 – Thermal transmittance (U value) and internal heat capacity (Cm) of the main envelope surfaces (* for Envelope walls the data refer to inner side; for Floors the data refers to the decking)

Surface type		U $Wm^{-2}K^{-1}$	Cm* kJ $m^{-2}K^{-1}$
Envelope walls	Floor 0, 1	0.16	46.70
	Floor 2, 3, 4	0.16	27.50
	Floor 4, terrace side	0.13	51.28
Internal walls	Room-room	0.49	31.10
	Room-bathroom	0.45	34.70
	Room-common space	0.21	46.70
	Room-common space	0.20	46.70
	Flat-flat	0.23	36.50
	Semi-exposed	0.32	232.00
Floors	Wood finishes semi-exposed	0.29	171.21
	Ceramic finishes semi-exposed	0.29	188.48
	Wood finishes internal	0.31	215.70
	Ceramic finishes internal	0.31	232.98
	Ceiling exposed terrace	0.41	13.75
Roof	Wooden naturally vented	0.18	81.07

The heating system is based on a centralized condensing boiler, with an outdoor reset control of the water supply temperature. The boiler produces the hot water that feeds the radiant floor systems. During the heating period, a mechanical ventilation system provides fresh air to the dwellings (with a lower threshold of 18°C for the supply air temperature). However, the occupants can freely interact with the envelope by opening and closing the windows. The ambient temperature controllers are set to the constant value of 20°C during occupied time, with a setback temperature of 16°C. The infiltration and ventilation leakages have been modeled by means of the airflow network.

The building has been modeled with the dynamic simulation engine EnergyPlus 8.1 in which two calculation methods were implemented: a Standard Input Model (SIM) and a Stochastic Advanced Model (SAM). In the SIM approach the internal gains, the ventilation rates and the occupancy schedules are defined according to the standard EN ISO 13790 (CEN, 2008) and to the technical specification UNI/TS 11300 (UNI, 2008). The following tables summarize the scheduled internal lumped gains and heating radiant plant timesheet related to zone occupancy.

Table 2 – Internal gains profile in SIM model (CEN, 2008)

Days	Hours	Living Room plus kitchen $(\varphi_{int,Oc}+\varphi_{int,A})/A_f$ W/m²	Other conditioned areas $(\varphi_{int,Oc}+\varphi_{int,A})/A_f$ W/m²
Monday-Friday	07:00-17.00	8.0	1.0
	17:00-23:00	20.0	1.0
	23:00-07:00	2.0	6.0
	Average	9.0	2.67
Saturday-Sunday	07:00-17:00	8.0	2.0
	17:00-23:00	20.0	4.0
	23:00-07:00	2.0	6.0
	Average	9.0	3.83
Average		9.0	3.0

Table 3 – Hourly thermostat setting in SIM model

Days	Hours	Living Area	Sleeping Area
Monday-Sunday	07:00-17:00	Setpoint	Setback
	17:00-23:00	Setpoint	Setback
	23:00-07:00	Setback	Setpoint

In the SAM method, the user's behavior was implemented through a stochastic algorithm while internal gains and schedules are defined with an occupant-tailored approach. The daily mean internal gain rate due to lighting system, electric devices and occupancy presence are equivalent in the two models.

2.2 Stochastic Advanced Model (SAM)

The SAM model simulates the user stochastic control of both the window opening and the adjustment of the thermostat setpoint temperature. The simulating process is obtained combining a series of sensors, programs and actuators organized to control independently each single zone and opening. These programs were implemented in EnergyPlus via the Energy Management System (EMS) module.

2.2.1 Windows Opening control algorithm

Humphreys' stochastic control algorithm (Humphreys and Nicol, 1998) was modeled to simulate user managing of the windows. The control system manages the window open factor, which, in our model, can be set to 0 or 1 with the hypothesis of a fully closed/open window. The algorithm can be summarized in the following steps:

1) The daily mean values of outdoor running temperature (T_{rm}) were calculated according to the relation provided by the standard EN 15251 (CEN, 2007) and based on the previous 20 days as follow:

$$T_{rm} = (1-\alpha)\cdot\{\Theta_{ed-1} + \alpha\cdot\Theta_{ed-2} + \alpha^2\cdot\Theta_{ed-3} + ...\} \quad (1)$$

where Θ_{ed-1} is the daily mean outdoor air temperature of the "i-th" day before the current day of calculus and the constant parameter α assumes the suggested value of 0.8.

2) A comfort temperature has been derived from the previous step, according to the relations proposed by Rijal et al., 2007.

$$\text{if } T_{rm} > 10°C : T_{comf} = 0.33\cdot T_{rm} + 18.8°C \quad (2)$$

$$\text{if } T_{rm} \leq 10°C : T_{comf} = 0.09\cdot T_{rm} + 22.6°C \quad (3)$$

3) The comfort temperature has been used to define a 4 K wide comfort band, whose limits are defined increasing and decreasing the comfort

temperature by 2 K. In this way, it is possible to define for each timestep whether the zone operative temperature, T_{op}, belongs to the comfort range and, consequently, the users are in a comfort condition. Otherwise, if the zone operative temperature is outside the comfort zone, a discomfort condition of cold/heat arises.

4) When the zone operative temperature is outside the comfort band, a certain probability (p_w) to open (if $T_{op} > T_{comf} + 2$ K) or close (if $T_{op} < T_{comf} - 2$ K) the windows is calculated by the following empirical equation proposed by Rijal et al., 2007.

$$\mathrm{logit}(p_w) = 0.171 \cdot T_{op} + 0.166 \cdot T_{out} - 6.4\ \mathrm{K} \quad (4)$$

$$\mathrm{logit}(p_w) = \ln [\ p_w / (1-p_w)\ ] \quad (5)$$

5) The probability, p_w, is compared with a pseudo random generated number between 0 and 1, $p_{w,lim}$, to define if a zone window is effectively opened or closed. If p_w is greater than $p_{w,lim}$, the T_{op} is greater than $T_{comf} + 2$ K and the window is closed, then its open factor is changed from the value of 0 to 1. If p_w is less than $p_{w,lim}$, the T_{op} is less than $T_{comf} - 2$ K and the window is open, then its open factor changes from the value of 1 to 0. In the other cases, the value of the open factor is not changed.

6) A minimum ventilation rate for sanitary purposes was set in addition to the Humphreys behavioral algorithm. In agreement with the hypothesis according to which the windows are open for 1% of the time, a rule that provides for the opening of the windows if they had been closed for the previous 8 hours was implemented. Once the window was open, its control falls within the provision of the Humphreys algorithm. Window control is performed only during the occupied hours and the value of the open factor during the unoccupied time is set to 0. Window control is performed with a frequency of 10 time steps per hour.

2.2.2 Temperature controller algorithm

The setpoint control algorithm, developed in this paper, is inspired by the Fanger comfort formulation. The user's control on the heating system is simulated with the possibility to increase or decrease the setpoint temperature by a pseudo random numbers of degrees and in relation with defined conditions. The simulating system works under certain main hypothesis:

1) The setpoint modification is permitted between 6:00AM and 11:00PM (avoiding non-realistic temperature controller adjustments during night sleep-time) and only during the occupied period;

2) The increment (or decrement) of the temperature setpoint is kept for 1 hour from the moment of the setting (emulating the "party or saving mode" available for many temperature controllers);

3) The increment (or decrement) of the temperature setpoint is available no more than once every 2 hours.

The following points explain the main steps of the algorithm:

1) The metabolic rate and clothing level are evaluated at each timestep using some coefficients to emulate the different thermal perception:

1.1) a random variation of ±10% from the original value is adopted for the metabolic rate.

$$Met_{STO} = Met_{DET} \pm 10\% \quad (6)$$

1.2) the clothing level, Clo_{DET}, is randomly changed by a coefficient (m_{clo}) in the range 0.9÷1.5, when a value of Clo_{DET}=1 is adopted (wintertime), or 0.6÷1.9, when a value of Clo_{DET}=0.5 is adopted (summertime). These values are derived from the standard EN ISO 9920 (CEN, 2009) indications.

$$Clo_{STO} = m_{clo} \cdot Clo_{DET} \quad (7)$$

2) Since the setpoint adjustment is not a certain event, a probability of the event should be defined. The proposed algorithm assumes the value of percentage of dissatisfied users, PPD, as the probability of setpoint temperature change, P_t, for a defined thermal zone. The temperature controller adjustment is defined by comparing the value of this probability, P_t, with a random number, $P_{t,lim}$, generated by a pseudo random uniform distribution. If the action probability, P_t, is greater than the random generated value, $P_{t,lim}$, the change of the setpoint temperature is actually performed.

Otherwise, the setpoint temperature is not changed. The potential setpoint temperature change (the comparison between P_t and $P_{t,lim}$), is applied with an hourly timestep.

3) The sign of the PMV in each thermal zone is used to define the type of potential action on the temperature controller for a zone (temperature increase or decrease). A positive PMV indicates a perception of "warm", thus the temperature adjustment will be negative (a decrement). A negative PMV implies the increment of the setpoint temperature while the PMV equal to zero implies no variation. If the potential action on the temperature controller is actually performed (P_t>$P_{t,lim}$), the absolute value of the increment/decrement is chosen generating a random integer number between (1-3) K using a uniform distribution.

2.3 Standard Input Model (SIM)

The implemented Standard input model is based on standard input provided by the EN ISO 13790 (CEN, 2008) and by the technical specification UNI/TS 11300 (UNI, 2008). It includes scheduled profiles regarding occupancy, internal gains and ventilation rates (both infiltration and ventilation).

The following table summarizes the main differences between the two calculation methods.

Table 4 – Natural ventilation and setpoint temperature in SAM and SIM

		SAM	*SIM*
Natural ventilation	From opening windows	Humphreys Algorithm	Scheduled 0.3 ACH
	Infiltration	Airflow Network	
Setpoint thermostat temperature		Stochastic Algorithm	Constant

2.4 Evaluation of Robustness

The effect of user behavior can be quantified by observing the standard deviation, σ, and the ratio of the maximum over the minimum value of annual energy consumption. In order to make a comparison between the robustness of different models, the use of a robustness index is proposed.

The robustness index signals the sensitivity of the building energy performance with respect to occupants' behavior. The robustness index is the reciprocal of the non-dimensional coefficient of variation for the stochastic data set:

$$i = \sigma^{*-1} = \mu / \sigma \qquad (8)$$

The numerical quantification of robustness is deeply related to the stochastic simulation model and the choice of a realistic simulation algorithm is of primary importance.

3. Results and Discussions

The hourly simulation was recursively run with different seed in the pseudo random generation in order to model different users' behaviors. The annual and monthly energy performance (EP) was computed for each of the 90 runs, starting from the hourly energy consumption of the heating and ventilation systems.

3.1 Annual energy consumption

The first result deals with the dispersion of the building annual EP caused by user behavior (Fig. 3). The interactions of the occupants with the thermostats and the windows opening induce a variability of the annual energy performance roughly equal to ±1 kWh m^{-2} y^{-1} with respect to the mean value that means ±950 kWh y^{-1}.

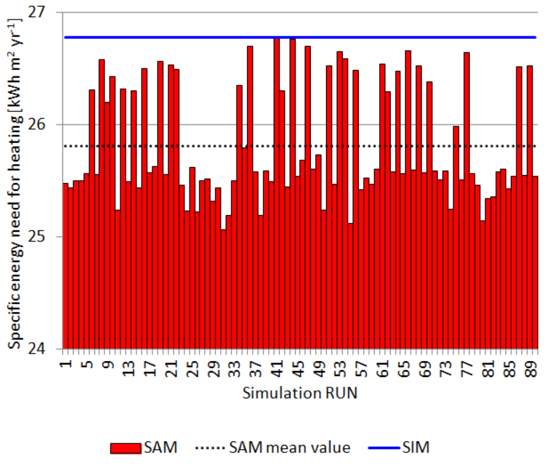

Fig. 3 – Distribution of annual EP of the building.

It should be stressed that this result has been obtained by considering independent user behaviors for each room of the building. This means that the variability of the EP takes into account the offsetting between virtuous and negative behaviors. Hence, the results do not represent a quantification of the maximum variation of the EP and, consequently, it is not a quantification of the maximum risk of an incorrect assessment of the energy label of the building. The graph in Fig. 3 highlights the sensitivity of the building to user behavior. Table 5 summarizes the output data values for SIM and SAM.

Table 5 – Simulation results

SAM data values		
MAX Yearly EP	26.77	[kWh $m^{-2}y^{-1}$]
MIN Yearly EP	25.06	[kWh $m^{-2}y^{-1}$]
MAX/MIN Ration	1.07	[-]
μ Yearly mean value	25.81	[kWh $m^{-2}y^{-1}$]
σ Standard deviation	0.508	[kWh $m^{-2}y^{-1}$]
SIM data values		
Yearly EP	26.78	[kWh $m^{-2}y^{-1}$]
Evaluation of robustness		
$\sigma^* = \sigma/\mu$	0.020	[-]
Robustness Index	50.826	[-]

The SIM and SAM models show similar results in terms of yearly energy consumption (the difference is roughly equal to 3.6%). The SAM model shows a lower energy consumption from 0.02% up to 6.41% if compared with the SIM model result. This result seems to indicate that the scheduled approach, according to the aforementioned technical standard, gives precautionary resultant energy consumption. Some conclusions on the sensitivity of the building can be drawn by analyzing the distribution of the results of the SAM model. The standard deviation, σ, assumes the value of 0.5 kWh m^{-2} y^{-1}, and the ratio of the maximum over the minimum value is 1.07.

The robustness index for the analyzed building, according to (8), are reported in Table 5.

3.2 Monthly energy consumption

The analysis on the distribution of monthly energy needs gives information about the different sensitivity of the building to the user´s behavior. In order to compare the distributions of monthly EP, the deviation of each simulation run of the SAM is normalized in relation to the mean value.

The graph in figure 4 shows the distribution of the normalized EP deviation obtained in February. Notice that the EP deviation is distributed according to a Gaussian distribution. The graph also highlights as the deviations are in the range of ±2.5 % around the mean EP. The limited percentage variation is closely related to the external air temperature. The cold external air in winter months greatly decreases the number and duration of windows opening by users.

Besides, this result stresses the role of the insulated envelope and of the correct energy system design in increasing the indoor thermal comfort. Thus, the number of setpoint adjustments by users is limited in the hourly energy simulations due to the low number of dissatisfied ones.

The shape of the distribution of monthly EP deviations is different for intermediate and warmer months. For instance, Figure 5 shows the distributions obtained in March. Note that the variance increases from 0.57 in February to 1.92 in March.

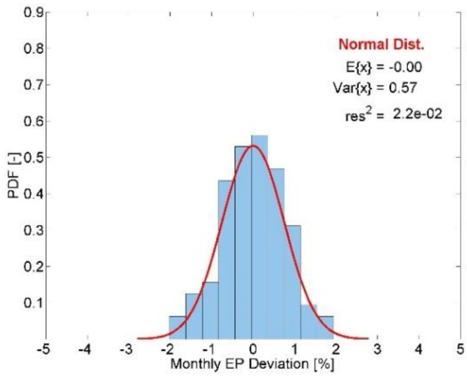

Fig. 4 – Distribution of February EP deviation caused by occupants

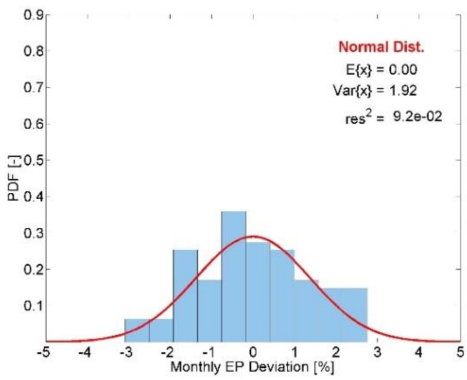

Fig. 5 – Distribution of March EP deviation caused by occupants

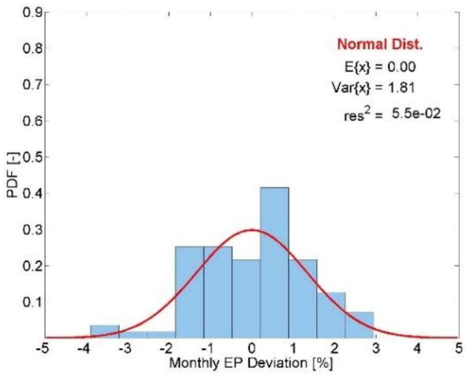

Fig. 6 – Distribution of April EP deviation caused by occupants

Therefore, the Gaussian distribution, which approximates the distribution of experimental data, demonstrates a greater dispersion of results around the mean value. In this case, the EP of the SAM runs are distributed around ± 3.7 % of the mean values. The distances increases up to ± 5 % at the beginning and ending of the heating season, i.e. in October and April.

These results highlight the greater impact on the EP variation of the window opening effect with respect to the setpoint adjustment. In fact, the data dispersion increases with a lower difference between internal and external temperatures. The behavior would be the opposite if the contribution due to the setpoint adjustment were larger than dispersions for ventilation.

The higher data dispersion in temperate months is linked to the intermittent operation of the energy systems that decrease the system efficiency. In fact, the manual window opening by occupants often induces the activation of the heating system. Probably, the use of a more sophisticated control of the setpoint temperature would ensure a greater sturdiness of the building in these months.

4. Conclusion

This study investigates the extent to which user behavior affects the predicted energy performance of a multistory building. For this purpose, a stochastic algorithm simulating the user´s interaction with the temperature controller setpoint and the windows opening was implemented in EnergyPlus through the Energy Management System sensors and rules.

For the test case, the average EP predicted by means of the stochastic method is about 3.6 % lower than the EP obtained using scheduled ventilation rate and thermostats setpoints. The two methods therefore show a good agreement when the same daily average is used.

The randomness of user behaviors causes a variability of annual EP roughly equal to ± 1 % around the mean values. This limited variation is linked to the stochastic nature of the model. Virtuous user behaviors in some rooms or in some periods balance out the increase in energy demand caused by some negative effects from occupant behavior. In fact, the results show how the behavior of the occupants tends to affect much more the forecasts of consumption over limited periods of time, such as a monthly time base.

5. Acknowledgement

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6. Nomenclature

Subscripts/Superscripts

clo	of clothing
DET	defined in a deterministic approach
i	current day of calculus
lim	Limit
STO	Stochastic
t	of thermostat management
w	of window management

Symbols

A	coefficient (-)
Clo_{DET}	clothing level (clo)
Clo_{STO}	clothing level (clo)
i	robustness index (-)
μ	mean value
m_{clo}	clothing coefficient (-)
Met_{DET}	metabolic rate (W)
Met_{STO}	metabolic rate (W)

PMV	predicted mean vote (-)
PPD	predicted percentage of dissatisfied (%)
p_t	probability of setpoint temperature change (%)
$p_{t,lim}$	limit probability of setpoint temperature change (%)
p_w	probability of open windows (%)
$p_{w,lim}$	limit probability of open windows (%)
σ	standard deviation
σ*	coefficient of variation
T_{comf}	comfort temperature (°C)
T_{op}	operative temperature (°C)
T_{out}	site outdoor drybulb temperature (°C
T_{rm}	daily running mean temperature (°C)
Θ_{ed}	site outdoor daily mean drybulb temperature (°C)

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