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Research Article

Measuring Occupants' Behaviour for Buildings' Dynamic Cosimulation

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Measuring and identifying human behaviours are key aspects to support the simulation processes that have a significant role in buildings' (and cities') design and management. In fact, layout assessments and control strategies are deeply influenced by the prediction of building performance. However, the missing inclusion of the human component within the building-related processes leads to large discrepancies between actual and simulated outcomes. This paper presents a methodology for measuring specific human behaviours in buildings and developing human-in-the-loop design applied to retrofit and renovation interventions. The framework concerns the detailed building monitoring and the development of stochastic and data-driven behavioural models and their coupling within energy simulation software using a cosimulation approach. The methodology has been applied to a real case study to illustrate its applicability. A one-year monitoring has been carried out through a dedicated sensor network for the data recording and to identify the triggers of users' actions. Then, two stochastic behavioural models (i.e., one for predicting light switching and one for window opening) have been developed (using the measured data) and coupled within the IESVE simulation software. A simplified energy model of the case study has been created to test the behavioural approach. The outcomes highlight that the behavioural approach provides more accurate results than a standard one when compared to real profiles. The adoption of behavioural profiles leads to a reduction of the discrepancy with respect to real profiles up to 58% and 26% when simulating light switching and ventilation, respectively, in comparison to standard profiles. Using data-driven techniques to include the human component in the simulation processes would lead to better predictions both in terms of energy use and occupants' comfort sensations. These aspects can be also included in building control processes (e.g., building management systems) to enhance the environmental and system management.

1. Introduction

Occupants are the key factor for the building energy assessment [1] since they influence the indoor environment both in a passive and active way [2]. The former is related to the presence of the users just in terms of sources of heat and CO_2 production. The latter concerns the direct interaction between the people and the building systems and devices (e.g., open and close the windows, switch on and off the heating system). The minimization of the importance of the human component in the simulation environment led to significant discrepancies (also known as "energy gap") between real and simulated building performances [3]. One of the main weaknesses of building performance simulation (BPS) programs is the lack of advanced, but also user-friendly, methods to measure and replicate real behaviours.

The majority of simulation software adopt deterministic rules and fixed settings (e.g., Department of Energy, ASHRAE 90.1) to model behavioural features. The standard profiles, although coming from real monitoring campaigns, barely reproduce the actual patterns of occupancy and the interactions with the building devices [4, 5]. Despite the fact that this approach is still the most diffused, some signs of progress have been achieved in the last years. For example, the EMS (energy management system) feature in EnergyPlus provides the opportunity to adjust the same controls available through EMSs in real buildings through an integrated interface inside the simulation engine [6]. Deeper customizations can be achieved by modifying the source code. However, the software houses do not usually provide the access to the source code, and even if it was possible, a very high level of expertise is required [7]. Recently, the cosimulation is becoming very popular since it provides the higher level of flexibility to the external user. Allowing data exchange between different modules in real time, this approach accurately reproduces the mutual interactions and influences between the occupants and the environment. Because of its potentialities, several cosimulation approaches have been proposed. The cosimulation can be performed by coupling PC-based energy engines (e.g., EnergyPlus and ESP-r) to a Functional Mock-up Unit [8] or using web-based applications (e.g., the Occupancy Simulator) [9] and external platforms (e.g., BCVTB to couple Matlab with EnergyPlus) [10–12]. The literature analysis provides a clear evidence of the advantages derived from cosimulation approach applied to building performance assessment. Therefore, there is the need to increase the knowledge on how behaviours can be accurately measured and fitted for wider application in the context of building design and management.

Endorsing this emerging approach, the NewTREND European project developed a cosimulation framework to empower the IESVE energy simulation engine with a stochastic behavioural tool. The software has been enhanced to allow user-defined functions and a two-way data exchange between different modules during the simulation runtime. Given the availability and the advantages of the cosimulation framework, a complete workflow to apply the tool to buildings' retrofit design has been performed. The proposed research is aimed at demonstrating how human behaviours can be measured and fitted to create calibrated functions suitable for the cosimulation in the building performance assessment.

Monitoring and data collection are the first steps to investigate occupants' behaviours in the built environment [13]. The measurement of human behaviour means building up a dedicated sensor network able to capture both physical and behavioural quantities and to define robust methods for the data fitting and model development [14]. Each building has its own contextual factors affecting human behaviours and comfort perceptions [15, 16]. Thus, a dedicated monitoring plan needs to be designed when starting the investigation, to rely on realistic basis rather than unfounded assumptions [17]. Moreover, IoT solutions can be exploited to gather the necessary information, given their growing popularity and employment [18]. According to these premises, the methodology proposed in this paper is based on environmental and occupants' data ingestion to apply statistical analyses and to determine correlations between a certain action (e.g., window opening) and the state of the surrounding environment. Collecting data is not enough, but also, the measurement accuracy plays an important role to allow the required understanding. For example, thermal comfort, one of the major factors motivating the interaction with the building, requires an accurate measurement [19], and in some cases, the mere environmental monitoring is not enough, but the inclusion of physiological measurements could provide the required level of accuracy in the determination of personal factors [20].

Experimental data need to be statistically analysed through data fitting procedures to identify correlations between users' actions and environmental drivers and, as a consequence, to obtain data-driven behavioural models. In recent years, the wide proliferation of behavioural approaches leads to the identification of the most important features that a model should incorporate [21]. Basically, a model should be stochastic to provide probabilistic and not fixed outputs. It could be presented both in an implicit (i.e., giving the status of the device) or explicit form (i.e., giving the probability of an action occurrence). Explicit models are preferred since they usually provide functions for reversal action too. In fact, even if the inclusion of the reversal form (e.g., opening and closing) is crucial for simulations, many models lack in this sense [22, 23]. Also, the contextual factors and the boundary conditions of the data monitoring (e.g., duration, sample frequency) and of the case study (e.g., building end-use, climate) must be explicitly described. In fact, this information can be useful for understanding models' applicability to other contexts. In this perspective, researchers should present a method including all the steps to obtain the models and not just a mathematical formula [21].

The stochastic attribute of behavioural models is essential to replicate the variability of the human nature; however, this feature leads to some issues in the simulation environment. In fact, probabilistic inputs can generate different output even under the same boundary conditions. This means that to reduce the uncertainty produced by the method, a number of simulations are required. However, performing multiple runs increases both the computing time and the examining efforts and, in parallel, it is not a synonym of greater accuracy in the results [24]. Uncertainty analyses offer a statistical procedure for estimating the coverage interval achievable running a predetermined number of simulations. In this paper, uncertainty estimation has been performed to evaluate the feasibility of running just one simulation.

Addressing the building performance gap, modelling the human-building interaction and integrating models within simulations have been recognised as three main current challenges of BPSs [25]. In the perspective of overcoming these issues, several EBC Annexes (53 and 66) focused on developing tools to understand occupants' behaviours and to calculate real building energy use [26]. Also, many behavioural models have been developed in the last decades [27]. Referring to either one or multiple actions, to several climate zones and to different building uses, such models are covering more and more cases and applications. However, the implementation of such models in BPS programs is still extremely rare since few simulation software provide options to implement or define custom settings, and those which allow such implementation usually do not have a user-friendly interface and require deep programming knowledge [21].

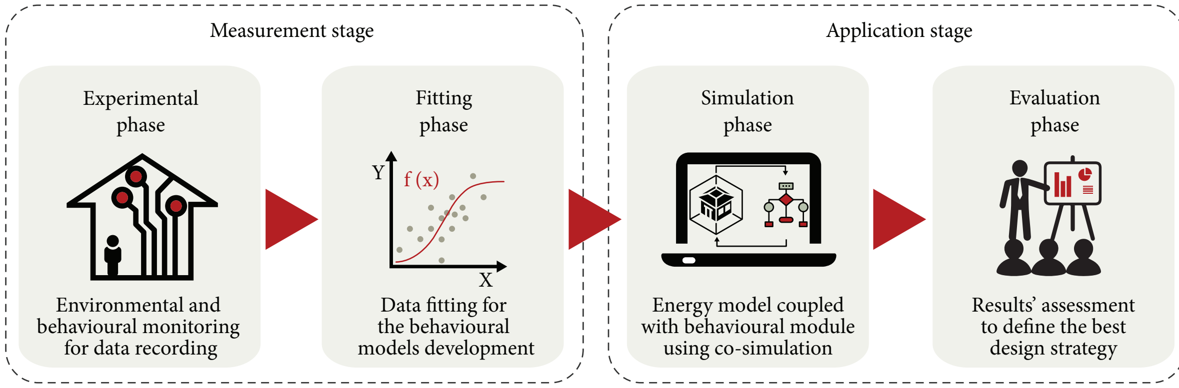


Figure 1: Sketch of the adopted methodology.

This study aims at bridging the gap between the measurement and development of behavioural models and their implementation within simulation software to enhance the predictions of energy consumptions. In particular, the paper presents (1) the development of explicit and data-driven behavioural models for window opening and closing and light switching in offices; (2) the implementation of the models in the IESVE environment; (3) the explanation of the cosimulation approach; and (4) the comparison between simulated and actual behaviours. The final aim is to provide a methodology flexible enough to be easily tuned to different contexts and research targets. Moreover, offering simulated building performances, which consider the occupants' perspective and the human-building interaction, the design team will be aided in the decision-making process and in the enhancement of the building design, retrofit, or renovation stages.

2. Materials and Methods

The general methodology followed during the present study is outlined in Figure 1. The methodology can be resumed in two main actions. The first stage is devoted to real measurements and to the data fitting targeting the development of behavioural models, while the second is directed to applications in the simulation environment for the building design. In detail, the first step concerns the acquisition of environmental and behavioural data in real buildings through monitoring campaigns. Then, the data fitting allows the development of data-driven behavioural models to predict users' interactions with building devices. The behavioural framework is coupled with the simulation engine through a cosimulation approach which allows the data exchange during the simulation runtime. Finally, simulation outcomes are evaluated to assess the design strategy which best fits users' preference and energy requirements.

To develop the abovementioned workflow, the following research steps have been carried out:

(1) Framework. Definition of the mandatory steps for developing the behavioural models in relation to data acquisition, algorithms, and model workflow.

(2) Experimental Phase. Identification of a case study building for monitoring and behavioural investigations.

(3) Data Analysis. Processing of one year of monitored data in three multioccupied offices and assessment of the drivers for users' behaviours.

(4) Fitting Phase. Development of behavioural models using regression methods to predict light switching and window adjustment.

(5) Implementation. Coupling of behavioural models and IESVE simulation software using a cosimulation approach.

(6) Simulation. Modelling of a portion of the case study building in the virtual environment and testing of both the standard and the behavioural approaches.

(7) Findings. Comparison of the energy performances related to the two approaches and the juxtaposition between standard, behavioural, and real profiles to assess which approach would provide the best predictions.

(8) Uncertainty Analysis. Estimating the uncertainty due to the number of stochastic simulations.

2.1. Measurement and Fitting of Human Behaviours. The behavioural approach requires realistic data for a knowledge-based modelling of occupants' behaviour. A monitoring campaign is thus needed to capture occupants' actions and the parameters related to the surrounding environment (indoor and outdoor) that potentially trigger those actions. A fine granularity of data acquisition allows the best data interpretation. For this reason, the monitoring approach used in this research included

(1) continuous measurements with a dedicated sensor network, acquiring data with a time interval of 10 minutes

(2) monthly occupants surveying about personal information and the thermal environment

The monitoring campaign had a duration of one year to cover all seasons and consequent changes in users' behaviours. In particular, window opening and light switching were the actions to be monitored. To this end, window status and illuminance on the work plane were measured. The illuminance on the work plane was used to derive turn on and off actions since it was not feasible to install sensors directly on the light switches. Concerning contextual factors, indoor environmental quantities were measured together with the occupancy, while outdoor environmental quantities were gathered from a local weather station. A detailed description of the monitoring is presented in the next sections and in previous studies [28].

The raw data recorded during the monitoring need to be analysed to assess whether any correlation exists between environmental parameters and people's actions. Regression methods allow fitting the data and to obtain behavioural functions.

The regression model adopted in this paper derives from the one proposed by Wang et al. [29]. It consists of a general formula to evaluate the probability of occupants' behaviour in relation to environmental conditions and (eventually) time-related events. Based on a "memoryless hypothesis," the probability is influenced only by the current environmental conditions and not by previous states. Equations (1a) and (1b) present the increasing and decreasing forms, respectively.

$$P(x_t) = \begin{cases} 1 - e^{-((x_t-u)/l)^k \Delta t/t}, & \text{if } x_t > u, \\ 0, & \text{if } x_t \le u, \end{cases} \tag{1a}$$

$$P(x_t) = \begin{cases} 1 - e^{-((u-x_t)/l)^k \Delta t/t}, & \text{if } x_t < u, \\ 0, & \text{if } x_t \ge u. \end{cases} \tag{1b}$$

A discrete three-parameter Weibull cumulative function is adopted to calculate the probability. The parameters u, l, and k are three constant coefficients which quantify the way the occupants react to a certain environmental discomfort. The parameter u, called the "threshold," represents the limit above or below which starts users' reactions to discomfort. It is the discriminating factor for the probability calculation. The coefficient l is the "scale," namely, the linear effect of the trigger, and k is the "shape," representing the power exponent for the effect of the environmental stimulus. The temporal frequency is provided by the parameters Δt and t. The first is a discrete time step in the measurement and/or simulation (set at 10 minutes), and the second is a known time constant (here fixed at 60 minutes).

This model is suitable to be used with every environmental variable, and in the case of behaviours driven by multiple effects, the system can be easily expanded to include further parameters.

The approach has been already adopted to predict air-conditioning usage in residential buildings [30] and light switching in offices [31]. The flexibility of the formula allows also the coupling with an agent-based model [32] and its application at the district level [33].

In the present study, the approach has been used to predict the light-switching behaviour towards the work-plane illuminance and the window opening and closing actions in relation to indoor and outdoor temperatures.

The strength of the correlations is evaluated by calculating two goodness-of-fit (GOF) estimators. The coefficient of determination (R^2) and root mean square error (RMSE) have been estimated for each correlation. The former is an adimensional index ranging between [0, 1] which explains the variation of the independent variable in the dependent variable. Higher values indicate better fits (especially when overcoming 0.75). The latter represents the standard deviation of the residuals and measures the spread of the data around the fit. Good fits are related to small RMSEs.

2.2. The Cosimulation Approach. In general, energy simulation software model occupants' behaviours adopting fixed schedules and deterministic rules. However, this method hardly captures the dynamic human-building interaction. To overcome such standard schedule-based approach, the IESVE software has been improved to support the cosimulation. A new type of profile has been created to describe user-defined functions (written in the Python language) which include also stochastic aspects. This new feature allows a two-way data exchange between different modules during the run.

Figure 2 sketches the general workflow of the simulation. At start, the software evaluates whether the preconditions are satisfied (in terms of building use and climatic conditions). If the answer is negative, the behavioural model cannot be applied and a standard simulation, with deterministic schedules, is performed. Otherwise, the behavioural models are initialised and kept active until the simulation end.

In detail, the engine calls the functions and provides the mandatory input to compile the algorithms. The output is sent back to the energy model, which sets the profiles and modifies the environmental conditions. This process is repeated at each time step, until the simulation end.

In this paper, the framework has been developed to modify lighting and ventilation profiles. Since occupants perform differently according to the action, two different workflows have been developed and reported in Figure 3.

The workflow is organised into three main sections, according to the occupancy profile. In fact, the behavioural models are active only when the room is occupied since people's presence is the main requirement for an action's occurrence. For this reason, at the first time step, the lights are off and the windows are closed. At arrival (i.e., at the first occupied time step), the models evaluate the probability to switch the lights on and to open the windows ($P_{0,1}$) in relation to the environmental conditions. During the intermediate period, the lighting model calculates the turn-on probability ($P_{0,1}$), and once the action is taken, the lights are maintained on until the users' departure. In fact, according to observations in offices, the workers switch off the lights only when leaving definitely the room [34]. The ventilation model is provided with both the direct and the reversal form. At each time step, the window status can turn from close ($P_{0,1}$) to open or vice versa ($P_{1,0}$), according to thermal

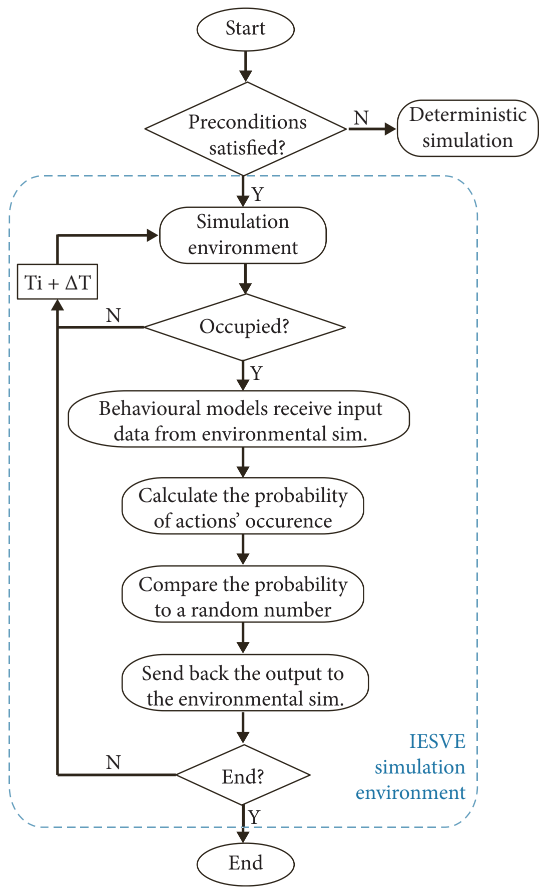


Figure 2: General simulation workflow.

conditions and previous status of the window. At departure (i.e., at the end of the working day), the status of the devices returns to its initial setting, independently from the environmental situation.

It should be noted that the behavioural functions provide as output a probability, which can range between [0; 1] (or, similarly, between 0% and 100%). However, the energy simulation needs a dichotomous output to modify the schedules (e.g., 0 = window closed; 1 = window open). To overcome this issue, the probability P (to take the action) is compared to a random number R_n stochastically generated from a uniform distribution. If P is greater than R_n, the action is taken; otherwise, the device status remains unchanged. This technique has been widely adopted in the literature as a criterion for decision [35, 36].

The workflow presented to model ventilation and lighting profiles can be easily tailored to many other behavioural aspects (e.g., heating and cooling) by adjusting few settings and input/output parameters.

3. Experimental Application

This section describes the experimental application of the methodology reported in the previous section. At first, the features of the case study building and the monitoring campaign are presented. Then, the thermal environment is characterised both in objective and subjective terms. Finally, the energy model built up with the IESVE energy software and the simulation settings are detailed.

3.1. Case Study Description. The study took place in a university building settled in Ancona, Italy (latitude: 43°35′15″N; longitude: 13°31′01″E; altitude: 140 m). The location is characterised by a hot summer Mediterranean climate, according to the Köppen Climate Classification System [37].

The building has a centralised heating system with at least one fan coil unit per room. Since neither conditioning nor mechanical ventilation systems are present, only natural ventilation (i.e., window opening) can be used for air exchange.

Three multioccupied offices (2–3 persons) have been selected as case studies to survey occupants behaviours. The rooms are usually occupied from Monday to Friday and from 9 a.m. to 7 p.m., with some variations according to personal tasks. The age of the occupants is about 30 years and they are equally distributed between male and female.

3.2. Measurement Campaign. A one-year monitoring campaign has been performed from May 2016 to May 2017. Such long-term approach allows obtaining environmental and behavioural data from all seasons. A dedicated sensor network was implemented to measure and collect data from the three rooms (Figure 4). The network is based on an IoT gateway communicating with deployed sensor nodes through 802.15.4 protocol. The gateway stores data locally on MySQL database and remotely through the internet connection for continuous processing. Two different sensing nodes were implemented in each room: one measuring air temperature, relative humidity, and occupancy; another one measuring CO_2 concentration, indoor illuminance, and window opening.

Table 1 illustrates the recorded parameters and the characteristics of the sensors installed in the rooms. A time step of 10 minutes has been set for all the probes. In particular, people presence has been identified as cumulative frequency during each time interval, while the window status was provided by contact sensors, placed on the top of the casements, through a Boolean output (i.e., 0 = window closed and 1 = window open). The outdoor temperature has been detected from a public weather station (property of the Marche Civil Defence), located approximately 2 km from the surveyed building. Further information regarding the building and the monitoring approach can be accessed in a previous study [28].

3.3. Characterization of the Thermal Environment. This paragraph aims at providing a brief overview of the thermal environment from both an objective and subjective point of view.

The environmental data have been statistically analysed and reported in Table 2. The table summarises the parameters monitored in the three rooms only during the occupied periods. The table is split up into three sections according to different seasons to underline the climatic differences. The analysis concerns nearly 200 working days, with about 100 days of both heating and nonheating season.

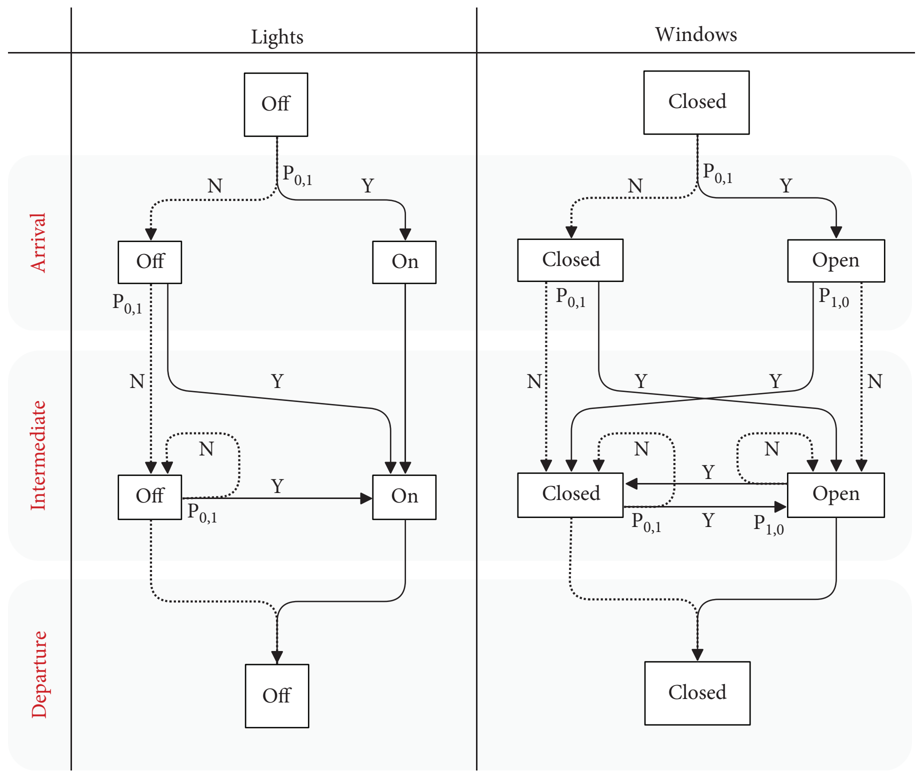


FIGURE 3: The general workflow of the behavioural models.

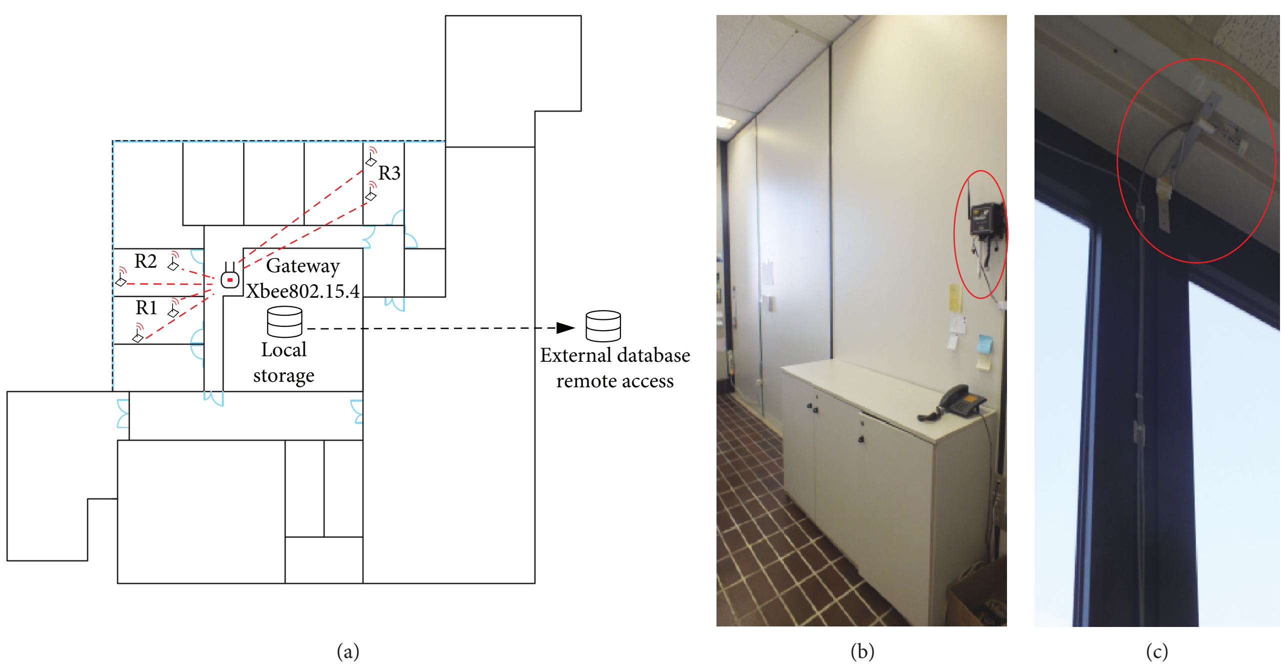


FIGURE 4: (a) Description of the sensor network, (b) the sensing node, and (c) detail of the window-opening sensors.

The mean winter indoor temperature is slightly higher than the recommended value (20°C) while the summer one is slightly lower than the suggested threshold (26°C). During the summer season, very high values (up to 34°C) have been recorded in the room facing east. The analysis of the CO_2 concentration shows that the mean is rather acceptable (650 ppm), even if values overcoming the International Guidelines [38] limits have been recorded too. In relation to the work-plane illuminance, it can be noted that the mean value is about 360 lx, which is quite lower than the threshold recommended by the EN 12464 [39]. Despite slight variations in relation to guidelines and standards, the outcomes suggest that the occupants should be quite satisfied with the working environment.

Table 1: Key features of the probes in the sensor network.

Sensor	Acquired parameter	Accuracy	Range	Number
Thermistor (SHT75)	Air temperature (°C)	±0.4°C	0 ÷ 70°C	1 per room
Capacitive (SHT75)	Relative humidity (%)	±1.8%	0 ÷ 100%	1 per room
NDIR	CO_2 (ppm)	±50 ppm	0 ÷ 2000 ppm	1 per room
Photodiode Si	Light (lx)	±3%	0.02 ÷ 20 klx	1 per room
PIR	Occupancy (num.)	n/a	12 m	1 per room
Magnetic	Window status (num.)	n/a	n/a	4 per room

Table 2: Statistical analysis of the monitored variables during the heating season, the nonheating season, and the total period (only occupied periods).

Season		Indoor temp. (°C)	Outdoor temp. (°C)	Indoor humidity (%)	CO_2 (ppm)	Work-plane illuminance (lx)
Total	Max	34.1	34.6	77	1660	2000
	Min	15.4	−2.7	21	363	0
	Mean	23.9	17.3	44	650	357
	St. dev.	2.6	7.5	10.5	186	196
Heating season	Max	28.6	23.8	65	1543	944
	Min	15.6	−2.7	21	375	0
	Mean	22.7	11.7	37	713	336
	St. dev.	1.1	5.0	7.6	150	142
Nonheating season	Max	34.1	34.6	77	1660	2000
	Min	15.4	8.4	24	363	0
	Mean	24.9	22.5	50	593	376
	St. dev.	3.1	5.2	8.6	198	235

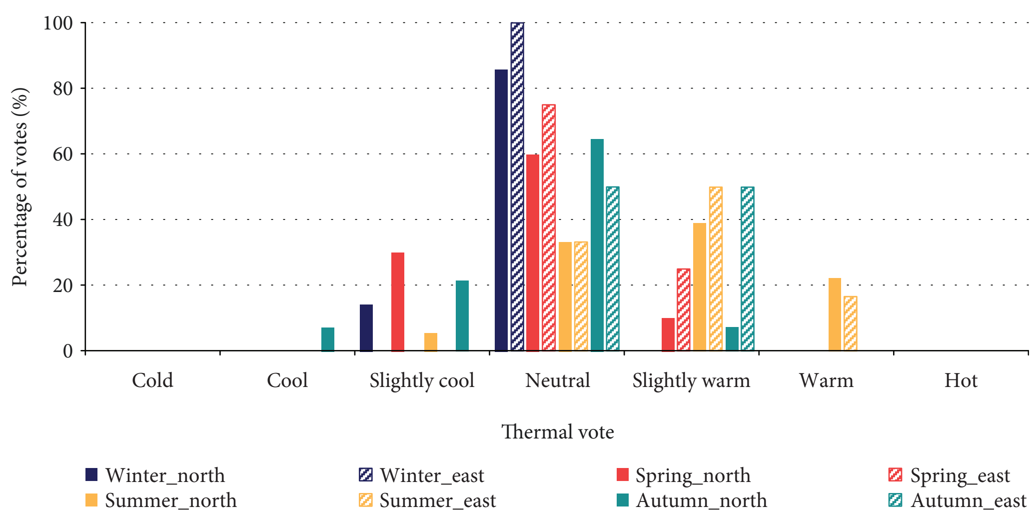


Figure 5: Mean thermal vote during the different seasons according to the exposure.

To have a comprehensive evaluation of the thermal environment and investigate the degree of satisfaction of the users, anonymous questionnaires have been distributed to the occupants once a month. The structure of the questionnaire has been set up to collect personal information (e.g., age and gender), room features (e.g., exposure and nr. of colleagues), and comfort sensations (i.e., thermal vote). The gathered information allows investigating the thermal perceptions for both the whole sample and according to the different orientations. Figure 5 displays the thermal vote in relation to the four seasons and separated for the north- (solid filling) and east-oriented (dashed filling) rooms. In general, the occupants felt a neutral sensation (i.e., PMV = 0) along the whole year, except during the summer where they frequently experienced warm perceptions. Intermediate seasons (autumn, in particular) show the greatest

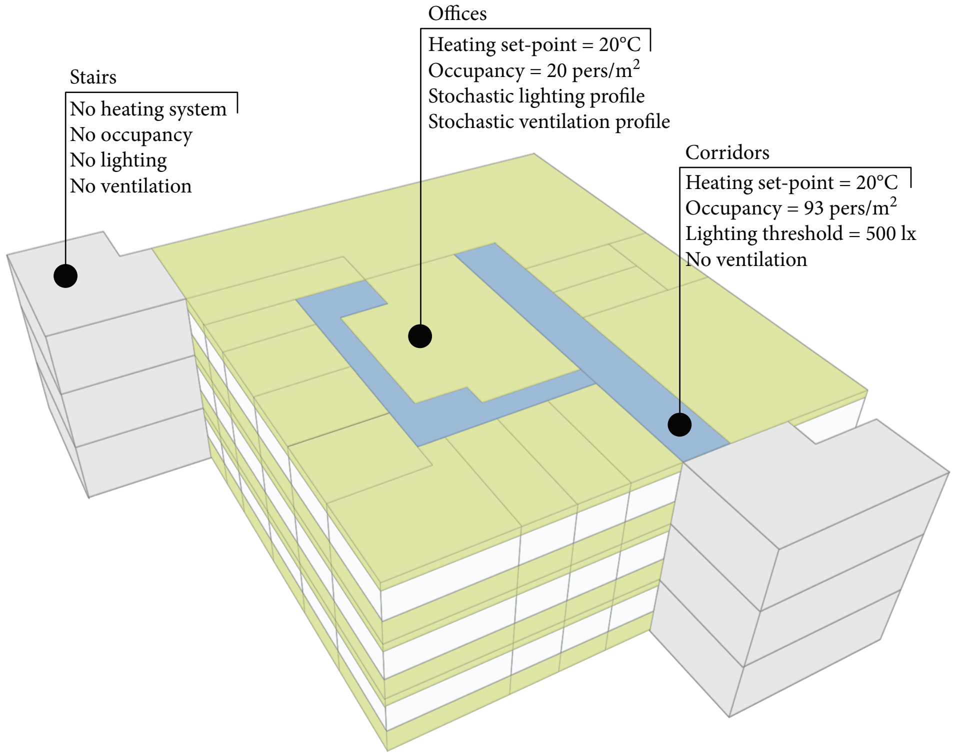


Figure 6: The building energy model developed in the IESVE environment.

variability (from cool to slightly warm) as a consequence of the wide outdoor fluctuations. The exposure affects the thermal sensation over the whole year. In fact, 18% of the votes, collected in the offices facing north, are connected to cooling sensations (i.e., votes −1 and −2), against 0% of the east side. On the contrary, the percentage of votes related to warm sensations (i.e., votes 1 and 2) is 23% for the north side and 36% for the east one. It is evident that the users working in the north side of the building suffer more often for cooling, especially during the autumn.

These analyses give a useful representation of the indoor thermal conditions and of users' perceptions in their working environment. However, it should be noted that the answers collected in the questionnaires are representative of an entire month. Along such period, many different situations could have been occurred, and so the occupants reported just the prevalent perception. This time span has been chosen targeting at performing a long-term seasonal analysis to support and complete the environmental monitoring. Therefore, this monthly data collection did not allow deriving neither hourly nor daily correlations to be implemented in the behavioural models.

3.4. Building the Energy Model. This section describes the virtual model created to test the workflow detailed in the previous section (Materials and Methods). The IESVE energy simulation software has been adopted to create the energy model.

The sketch, depicted in Figure 6, represents three floors of the case study building consisting of 12,183 m^3. The heating surface is about 1150 m^2 for each of the three floors. Offices (green), corridors (blue), and stairs (grey) have been set according to rooms' real properties both in terms of materials and schedules.

The heating system, set at 20°C, is active from the beginning of November to the mid of April, following the directives of Italian regulations [40]. As for the actual building, the cooling system and the mechanical ventilation are not included.

Table 3 summarises the settings of the profiles (i.e., occupancy, lighting, heating, and ventilation), which have been applied considering both the rooms end-use and the guidelines of ASHRAE 90.1 [41] and ISO 13790 [42].

A one-year baseline simulation has been run using standard and fixed schedules with the settings recapped in Table 3. After that, the behavioural models have been employed for a stochastic variation of lighting and ventilation profiles during the simulation runtime in the office rooms. The baseline simulation has been used for comparing deterministic and stochastic results.

The main aim of this study is to provide a methodology to include the human component within the entire design process. To provide a concrete application of this methodology, the connection to a real case study is essential. As a consequence, the behavioural models presented in this paper are strictly connected to the context in which they have been developed. In these terms, they can be defined as "calibrated models" since they are tailored on a specific and detailed case study. The models should be applied without changes in buildings which have similar

Table 3: Summary of the energy settings according to the different end-use.

Settings	Room type		
	Office	Corridor	Stairs
Occupancy profile	Mon–Fri/8–19	Mon–Fri/8–19	—
Lighting threshold	500 lx	500 lx	—
Lighting profile	Mon–Fri/8–19	Mon–Fri/8–19	—
Heating profile	Mon–Fri/6–23 Sat/6–19	Mon–Fri/6–23 Sat/6–19	—
Ventilation threshold	24°C	—	—
Ventilation profile	Mon–Fri/8–19	—	—

boundary conditions of the surveyed building (e.g., settled in the Mediterranean climate, office buildings, free human-building interaction).

Applications in contexts with dissimilar features could be possible but the uncertainty of the results would increase. One of the key points in extending the models to different contexts is the identification of the trigger parameters for users' behaviours and the tuning of the coefficients of the equations. Model adjustments require experimental data that can be collected not only with long-term monitoring but also performing spot campaigns along the different seasons. Moreover, the mathematical approach adopted in this research has been derived from previous studies which already provide behavioural models for applications in different contexts (e.g., use of air-conditioning units in homes).

4. Results and Discussion

Starting from presenting the developed behavioural models, this section offers a critical comparison of the predicting capabilities using the behavioural approach and the standard simulation approach, also in relation to real actions. A further analysis concerns the evaluation of the most influencing action on the energy consumptions to assess which behaviour mainly leads to a variation of building performances. Finally, simulations' repetition has been investigated using an uncertainty analysis.

4.1. Behavioural Models. The human-building interactions recorded during the monitoring have been analysed to identify the triggers for users' behaviours. Window opening and closing actions are mainly driven by thermal comfort preferences. In naturally ventilated buildings (as for the case study), ventilation patterns are strictly connected to indoor and outdoor temperature trends [43–45]. Light-switching behaviours are related both to visual comfort and habits. In particular, the lights are more likely to be turned on at the decrease of the indoor illuminance [46, 47], while switch off actions occur almost only when the occupants leave the room [34, 47].

According to these patterns, the regression analysis for window opening and closing has been carried out in relation to indoor and outdoor temperature, while light switching (i.e., turn-on behaviours) has been correlated to work-plane illuminance.

In reference to the numerical approach explained in the previous section (Measurement and Fitting of Human Behaviour), Table 4 reports the constant coefficients u, l, and k for each correlation. It also includes R^2 and RMSE, which highlight the quality of the fits on the experimental data. It can be noted that all correlations are statistically significant since both GOF estimators are of good quality. The best fit is the one relating the work-plane illuminance to light-switching behaviour, while indoor temperature and window closing are linked with a less robust correlation.

Table 4: Coefficients of the behavioural models and goodness-of-fit estimators.

Correlation	u	l	k	R^2	RMSE
Window open-indoor temp.	18	8.6	3.9	0.96	0.07
Window open-outdoor temp.	0.1	25.1	8.9	0.98	0.05
Window close-indoor temp.	31.5	8.7	3.1	0.71	0.15
Window close-outdoor temp.	31	18.9	3.5	0.93	0.04
Light switching-illuminance	360	269.4	12.6	0.99	0.01

Figure 7 graphically shows the behavioural models for window opening (Figure 7(a)), window closing (Figure 7(b)), and light switching (Figure 7(c)). The probability functions for window opening present a monotonically increasing trend, with a very similar shape. They show a significant probability when the temperatures overcome about 25°C, with T_{50} (i.e., the temperature at which half of the occupants open a window) around 30°C. The models for predicting the closing actions, characterised by a decreasing trend, significantly differ. The one linked to the indoor temperature reaches a closing probability of 50% at 19°C, while that driven by the outdoor temperature arrives at 60% at 0°C. The light-switching probability function is almost flat until 130 lx; then, it rapidly increases reaching 100% for 0 lx.

4.2. Behavioural Approach vs. Standard Approach. This paragraph presents a comparison between the stochastic approach and the deterministic approach.

A baseline scenario has been achieved running a one-year simulation with static settings. The profiles from standards (Table 3) have been applied in all the rooms, according to their specific end-use. Then, the profiles regulating the "office" rooms (see Figure 6) have been linked to the behavioural models for a stochastic adjustment of ventilation and lighting schedules.

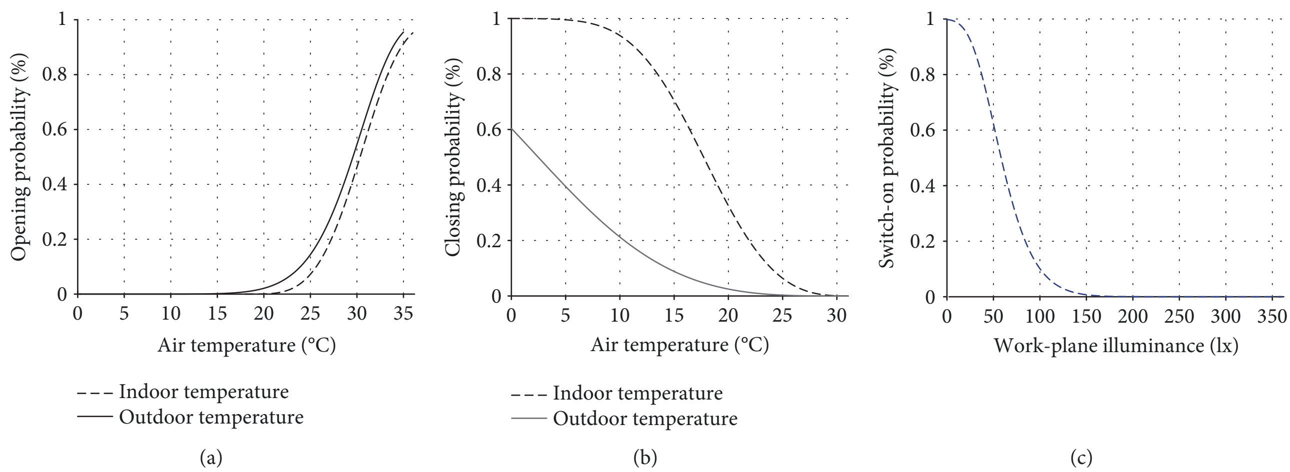


Figure 7: Behavioural models for the (a) opening probability; (b) closing probability; (c) switch-on probability.

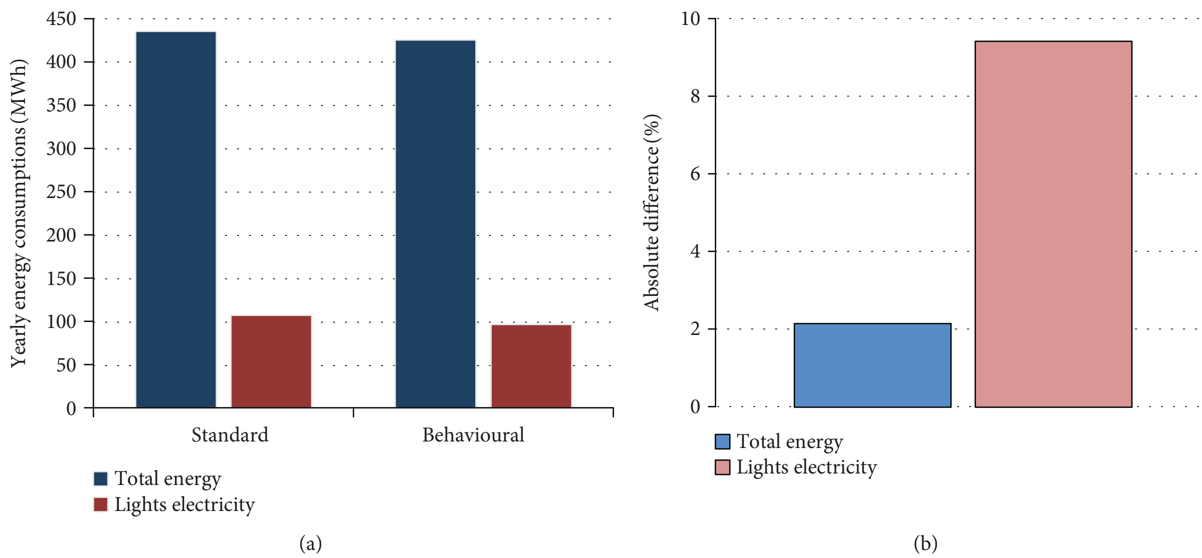


Figure 8: Differences in using a standard approach and behavioural approach in (a) absolute and (b) percentage difference terms.

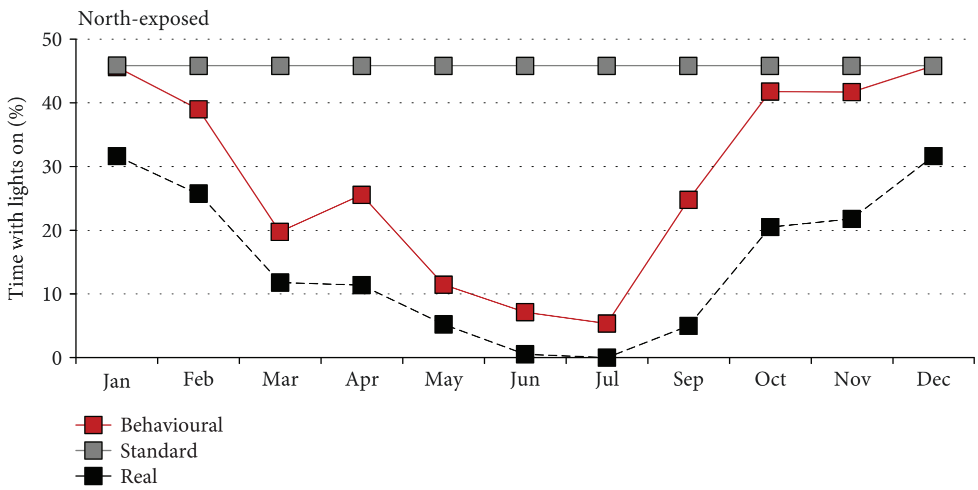
The computation time to perform one-year simulation using the behavioural functions is about 1 minute, for the current model. This new functionality increases the duration of the simulation of few seconds in comparison to the traditional settings.

The total energy performance (MWh) and the lighting consumptions (MWh) have been selected as key indicators to compare the two approaches.

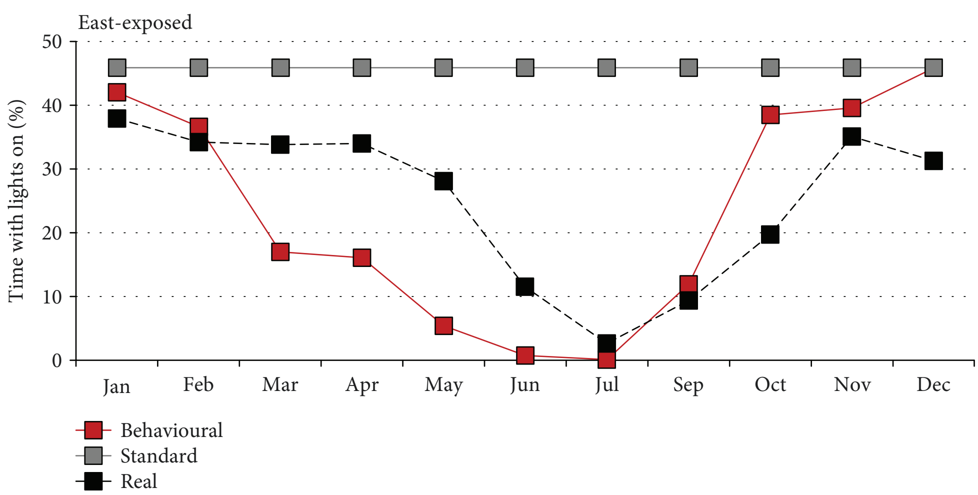
Figure 8(a) highlights that the standard approach provides a higher energy use than the behavioural one for both the two indicators. Figure 8(b) reports the percentage absolute difference between the two approaches. The variation of the overall energy consumptions is minimal since it is roughly 2%. This result is mainly a consequence of several building features and modelling settings. In fact, the window use is minimal during the winter season, when the consumptions are mainly a consequence of the heating system. Conversely, during the nonheating season, window adjustments are extremely frequent but no building system consumes fuel (i.e., neither cooling nor mechanical ventilation systems are present).

In comparison to consumptions related to the whole buildings, those related to lighting use show a much bigger variation. The difference up to 10% is mainly affected by the profile settings. According to the behavioural model shown in Figure 7(c), the light-switching probability starts for values lower than 360 lx but provides more consistent probabilities from 130 to 0 lx. Differently, the standard schedules consider the lights switched on when the indoor illuminance is lower than 500 lx, as stated in the prescriptions for office buildings.

4.3. Comparing Behavioural and Standard Profiles to Real Behaviours. The comparisons between simulated and real data give a concrete idea of the predicting capabilities of a model. In general, such observations are made at the building level, especially using energy consumptions as indicators. In the case study, it was not possible to record or derive this



(a)



(b)

FIGURE 9: Comparison between standard (grey), behavioural (red), and real (black) light-switching monthly behaviours in a north-exposed room (a) and an east-exposed room (b).

information both because of privacy issues and systems' configuration (the building has a very complex centralised system with central heating). To overcome these limitations and, in parallel, provide a realistic comparison between predicted and actual data, the analysis has been performed on the lighting and ventilation profiles. In detail, simulated profiles, both using the behavioural and standard approaches and real patterns, have been examined to assess the percentage of occupied time with lights on and the window open. The analysis has been performed for each month, except August since the case study building was almost always closed for the summer vacations.

Figures 9 and 10 show the results of this comparison for two rooms with a different orientation (i.e., north-exposed on the top and east-exposed on the bottom) in relation to lighting and ventilation profiles, respectively.

The behavioural profiles present a better prediction of the real patterns, in all the cases. The greatest difference between the standard approach and the behavioural approach can be appreciated for the light switching (Figure 9). Standard profiles present a constant trend along the year. The lights are always switched on during occupied hours since the simulated indoor illuminance never overcomes the threshold of 500 lux. The greatest discrepancies are related to the summer season (especially July), during which real lighting events are very rare. On the contrary, during wintertime, the gap is substantially shrunk because the occupants are more likely to work with lights turned on. Tuned on real users' preference, the behavioural model provides a much greater accuracy for both the orientations. In the north-exposed room, the behavioural profiles tend to overestimate real interactions. However, the difference is very little for most of the year (especially from March to September). The east-exposed room presents a real profile characterised by much more hours with lights turned on. The behavioural model provides better predictions for most of the year, except from March to May where the standard approach performs better.

The difference between actual and simulated ventilation patterns presents fewer differences for most of the months (Figure 10). The behavioural and standard

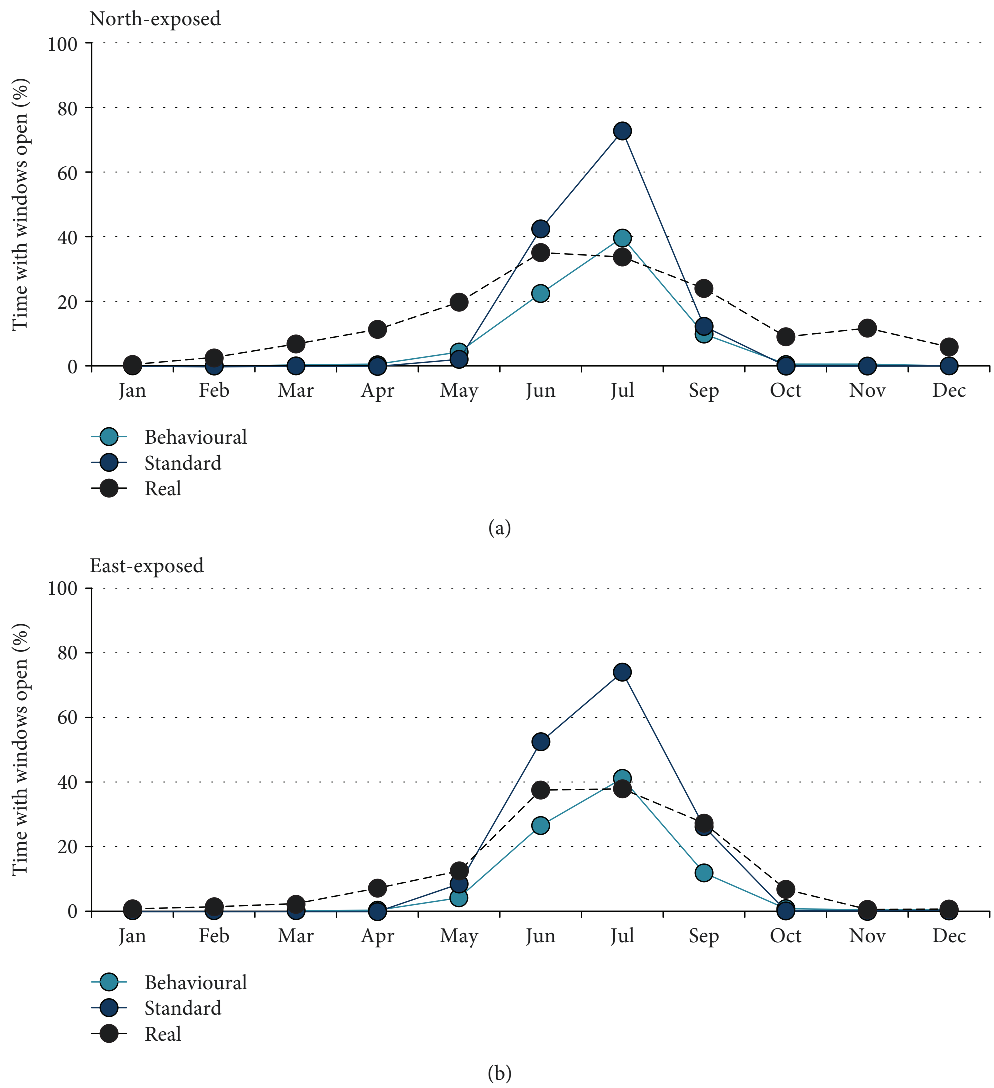


Figure 10: Comparison between standard (dark blue), behavioural (light blue), and real (black) window-opening monthly behaviours in (a) a north-exposed room and (b) an east-exposed room.

approaches follow a very similar trend during the heating season (i.e., from October to April). Predicting almost no hour with the window open, they slightly underestimate real behaviours. The gap is lower than 10%. In fact, in winter, occupants are unwilling to ventilate the offices to avoid thermal discomfort.

During the nonheating season, the two rooms behave similarly. They present an increase in the opening percentage until July when it reached the maximum. Then, the ventilation decreases due to thermal issues. During this period, the behavioural model provides more accurate predictions than the standard one. In particular, in July, the standard profiles show an overestimation of about 30% against the 5% of the behavioural ones.

The overall accuracy of the behavioural and standard approaches in reproducing the real actions has been assessed considering their predicting capabilities along the whole year. In detail, the percentage of hours with lights turned on and the window open has been calculated for the three patterns (i.e., the behavioural model, the standard approach, and the real behaviours). Then, the percentage difference (in absolute terms) between the two simulated patterns and the real one has been calculated to estimate the overall discrepancy. The results of this analysis are presented in Figure 11. It reports the differences for the lighting and ventilation profiles determined in the north-exposed (Figure 11(a)) and east-exposed (Figure 11(b)) rooms.

The greatest divergences are observed in the north-exposed room for both the patterns. In relation to the two approaches, the adoption of standard profiles (grey histogram) would lead to discrepancies between 230% and 340% when simulating light switching and to gaps of 70–120% for the ventilation pattern. The behavioural approach (red histogram) is related to much lower differences. The discrepancy for the lighting patterns is similar in both the rooms and it is about 130%. The divergence of the ventilation profiles ranged between 50% (east-exposed) and 90% (north-exposed).

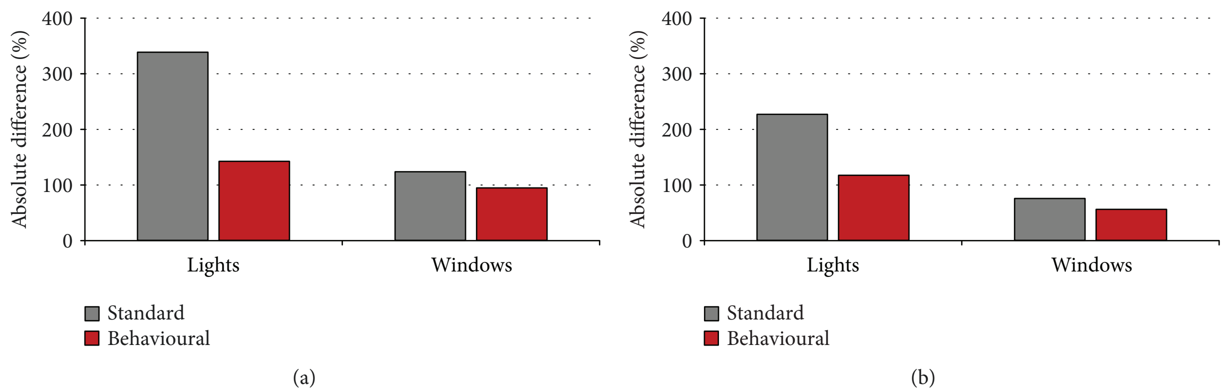


Figure 11: Absolute error in predicting light-switching and window-opening patterns for the standard approach and the behavioural approach for (a) a north-exposed room and (b) an east-exposed room.

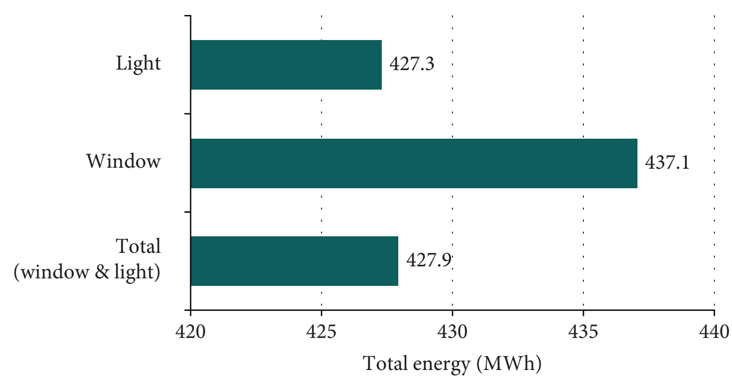


Figure 12: Preliminary analysis on the most influencing action on overall energy consumptions.

In summary, the adoption of behavioural rather than standard profiles reduces the discrepancy of 58% for light switching and 23% for the ventilation pattern in the north-exposed room, while the reductions related to the east-exposed room are 48% and 26% for the two profiles, respectively.

It should be noted that, despite the important reduction of the discrepancy achieved with the proposed methodology, the difference between the real and the behavioural profiles remains relevant, and it is caused by further important factors that were not taken into account during the simulation process. Influencing physical variables (e.g., wind speed, rainfall), occupancy patterns, and individual psychological features are key aspects affecting human-building interactions. Thus, the inclusion of those factors could make the discrepancy with the reality negligible.

Despite the difference between real and simulated conditions, the results presented in this section are very promising. The implementation of behavioural models in BPS is a key step to enhance simulation results. In fact, the improvement of predictions would provide more accurate energy and comfort assessments until the early design stages of the building.

4.4. The Most Influencing Action on Energy Consumptions. The modelling of multiple stochastic actions allows investigating which one has the greatest impact in energy terms. To perform this evaluation, it is necessary to perform $n + 1$ runs (with n being the number of probabilistic behaviours). For the case study, three simulations have been separately run. In the first one, only the lighting profiles have been modelled stochastically; in the second, only the windows, while in latter, both the actions.

Figure 12 shows the total energy consumptions derived from the three scenarios. It clearly appears that light switching is the most influencing behaviour on the building performance.

This result is strictly connected to the features of the simulation model. In fact, the interaction with the lights occurs almost along the whole year, affecting constantly the energy demand. Conversely, window opening is frequent only during the nonheating season, when no system requires energy.

This evaluation has the aim to underline potentialities of the behavioural modelling. In fact, recognising which action mainly leads to the building performance, the designers would focus their attention on that specific pattern to reduce energy use.

4.5. Evaluation of Standard Uncertainty due to the Number of Runs. Considering that the behavioural-based simulation follows a probabilistic approach, each simulation provides unique results, derived from the calculation of the probability that a certain action has been done at each step. Figure 13 highlights that both deterministic (e.g., internal loads) and

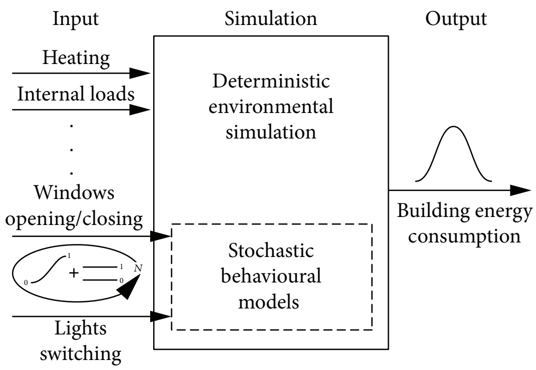


Figure 13: Description of the uncertainty evaluation applied to the behavioural-based simulation model.

probabilistic inputs (i.e., lighting and ventilation profiles) affect the simulation process proposed in this study. The inclusion of stochastic components (even if limited) creates variability in the final outcomes (i.e., the building energy consumptions). The main consequence is that each run produces different outcomes and not fixed results. Thus, a number of runs should be necessary to provide an accurate estimation of the energy consumption even if it would produce a probability distribution. However, an elevated number of simulations would not be feasible in terms of computational and time requirement. The uncertainty analysis is a valuable method to assess the uncertainty linked to models' stochasticity [48]. For this reason, an uncertainty evaluation has been performed to estimate the coverage interval achievable running one single simulation. The uncertainty can be evaluated from N independent observation obtained under the same conditions [49]. The uncertainty is then estimated from the standard deviation calculated on residuals, where the average observation is considered as the expected value. This standard deviation characterizes the dispersion about the expected value.

In this case, $N = 10^3$ runs of cosimulation were performed to generate a population of observations. One observation is the energy consumption calculated with a run. During each run and at each time step, the behavioural model calculates the probability of an action that is to be used by the simulation core engine. Thus, a distribution of energy consumptions is generated and used to calculate the coverage interval. The uncertainty due to the running of one simulation is then considered as the deviation achieved by 99.7% of distribution samples, applying a coverage factor of 3 (3σ). Figure 14 shows the distribution of energy consumption residuals obtained with the analysis.

A standard deviation of ±0.1 MWh was found on an average energy consumption of 426.6 MWh. This turned out to provide that running one simulation the uncertainty on the energy consumption would be ±0.3 MWh (3σ), confirming the feasibility of running one simulation.

5. Conclusions

This paper presents a methodology for the human-in-the-loop design applied to building retrofit and renovation. It started from the target of measuring, fitting, and including the behavioural component in the simulation environment to enhance the predictions of building performance. To reach this aim, three steps have been carried out: (1) measurement of users' behaviours and physical parameters; (2) the data fitting for the development of stochastic and data-driven behavioural models; and (3) the coupling of behavioural functionalities and energy engine to improve simulation outcomes. Such general workflow has been experimentally applied to investigate its capabilities. A one-year monitoring in a demo site allowed the development of data-driven behavioural models to predict light-switching and window-opening behaviours in offices. The models have been coupled with the IESVE energy simulation software through a cosimulation approach. The outcomes achieved using the behavioural approach have been compared to those obtained from a baseline simulation, performed using profiles from standard and deterministic rules. A variation up to 10% has been observed for lighting energy consumptions, while a minimal difference (about 2%) is related to the total energy. Due to missing information about real building performance, the comparison between simulated and actual behaviours has been performed on lighting and ventilation profiles. The behavioural approach, showing lower discrepancies, provides more accurate outcomes in representing users' actions than the standard approach. In fact, the behavioural models reduced the discrepancies of light-switching and ventilation profiles up to 58% and 26%, respectively. The inclusion of several behavioural features allows the identification of the most influencing action on energy consumptions. For the case study, light switching has been recognised as the behaviour which plays a crucial role in energy assessment.

Since the behavioural models follow a probabilistic approach, each simulation gives a peculiar result. A number of runs would be required to provide accurate estimations of the outcomes. For this reason, an uncertainty analysis has been adopted to estimate the coverage interval achievable running one single simulation. Reducing the runs to one, an uncertainty of ±0.3 MWh (3σ) on the building energy consumption has been reached.

The behavioural algorithms embedded in the simulation software are representative of a specific and precise context since they have been obtained from a homogeneous sample (i.e., three offices settled in the Mediterranean climate). The adoption of specific behavioural models is one of the main reasons for the slight deviations between different stochastic simulations. Increasing the availability of the experimental data is one crucial step to generate models that could be applied to broader contexts. This objective can be reached using different kinds of data sources and especially those provided by IoT devices. This approach can enhance the robustness of the behavioural models and, in parallel, simplify the overall procedure for the model development since the long-term environmental monitoring phase could be considerably reduced or avoided at all. The increase of data availability would also multiply the number of possible stochastic inputs (e.g., stochastic occupancy patterns) and so affect the variability of the simulation results.

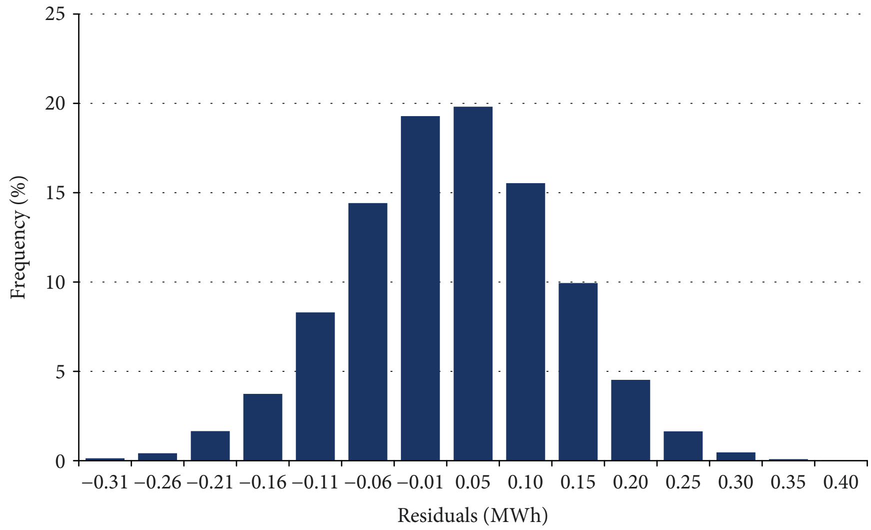


FIGURE 14: The frequency of energy consumption deviations obtained running 10^3 simulations.

In this perspective, future studies will be directed in investigating further probabilistic features and in testing the methodology in different contexts. These next steps will be targeted at increasing the applicability of the approach, covering more behavioural components. This comprehensive methodology can be a useful aid during the building design, retrofit, or renovation phases. The building control and management can be improved too. In particular, the embedding of behavioural models inside model-predictive-control (MPC) processes and within building management systems (BMS) would support the control of the energy flows. In parallel, the adoption of machine-learning algorithms and model training would evolve the behavioural models adapting them to specific comfort preferences of the users, which could change along time (e.g., different exposure, change of the occupants).

Data Availability

The monitoring and simulation data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

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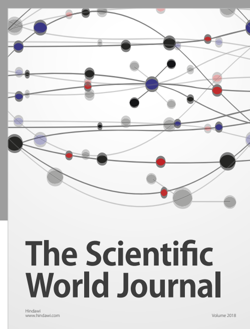

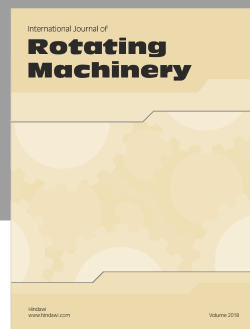

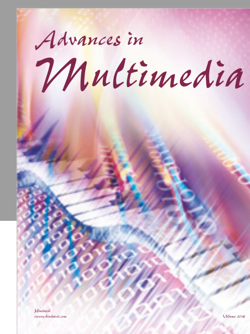

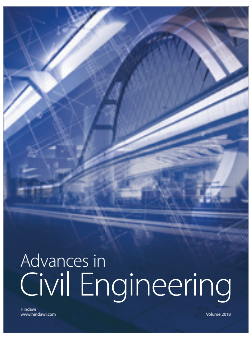

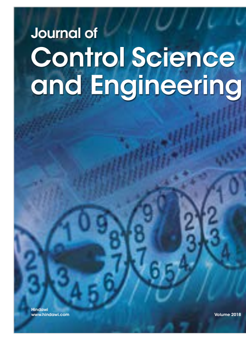

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