Probabilistic behavioral modeling in building performance simulation: A Monte Carlo approach

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The increased awareness on sustainability matters is contributing to the evolution of energy and envi-ronmental policies for the building sector at the EU level, oriented toward resource efficiency. There exist today several possible strategies to model building performance through the life cycle. The increase of available computational capacity and of data acquisition capability is opening new scenarios for practical applications, which can contribute to the reduction of the gap usually encountered between simulated and measured energy performance. This article aims to investigate an approach for probabilistic building performance simulation to be used across life cycle phases, employing reduced-order models for perfor-mance monitoring and energy management. The workflow proposed aims to establish a continuity among design and operation phases. Design phase simulation is generally subject to relevant temporal and economic constraints and a successful workflow should incorporate elements from current design practices but should also add new features, which have to be reasonably automated to reduce additional effort. Therefore, the workflow proposed is automated and tested for robustness using Monte Carlo technique. In the design phase, the approach can be used for identifying probabilistic performance bounds suitable for risk analysis in energy efficiency investments, employing cost-optimal or life cycle cost accounting methodologies. In the operation phase, it can be used for performance monitoring and energy management based on daily energy consumption analysis, similarly to other multivariate regression-based methods at the state of the art, addressing the problem of maintaining energy consumption and related costs constantly under control.

Keywords:
Probabilistic modeling
Behavioral modeling
Behavioral learning
Building performance simulation
Uncertainty propagation
Energy efficiency
Energy management

1. Introduction

We can identify a path of awareness increase on sustainability matters on global scale, starting from the Brundtland Report "Our Common Future" in 1987 [1], passing though Kyoto Protocol stipulation in 1997 and arriving today at the UN Climate Conference of Parties (COP) 21 of 2015. EU environmental and energy policy in the building sector has evolved over time embodying progressively the concepts of sustainability and resource efficiency [2]. European Commission established a long-term objective of decreasing the CO_2 emission levels for the building sector by 88–91% in 2050, compared to 1990 levels [3,4].

Built environment "decarbonization" has to go necessarily through increased penetration of renewable energy sources and increased efficiency in end-uses. Energy efficiency practices are relevant today for economic development at the EU level [5] and can determine several additional benefits [6]. Building renovation strategies [7,8] can potentially act in synergy with new economic [9,10] and technological [11–14] development paradigms, matching short-term goals (i.e. economic growth and employment) and long-term goals (i.e. sustainability).

An essential element for the deployment of these paradigms is the increase of "intelligence" of equipment and assets [15]. Therefore, digitization is a necessary step and, more in general, the availability of data appears to be crucial today for research in the energy field [16]. The presence of an uninterrupted information chain [17] between BIM, documental management [18,19] and BEM [20] is among the key factors which can contribute to the achieve-

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ment of high efficiency levels in buildings, although this issue is not completely solved at present [21,22]. The evolution of semantic web technologies and linked open data schemes can give a fun-damental contribution [23–26] in this sense. However, the large variability of technological solutions, end-uses and behavioral pat-terns [27] within the built environment makes it very difficult to define a unified and, at the same time, flexible performance model-ing approach, able to guide practitioners and stakeholders involved in multiple decision-making processes across building life cycle phases. It is worth noticing that the role of people is central both in the Internet of Things paradigm [11,12] and in the reduction of the gap between simulated and measured performance [28,29], considering the potential conflicts between internal environmen-tal quality (e.g. air quality, thermal comfort, visual comfort, etc.)[28,30], energy consumption and cost [31,32]. Excessive comfort expectations can cause an “economic rebound effect” [33], lim-iting the energy saving potential of efficiency practices. This can become an issue in terms of risk, for example, when predicting performance in techno-economic evaluations using cost-optimal analysis [34–36] and life cycle cost (LCC) accounting methodologies [37–39], reducing the credibility of energy efficiency projects. In this sense, the use of probabilistic behavioral modeling can be seen as an “occupant proofing” process from building simulation stand-point. The deterministic, code compliance based, way to model occupancy patterns in energy modeling is not sufficient, because it does not give enough information with respect to performance variability determined by occupants and, for this reason, interna-tional normative initiatives [40,41] are proposing more detailed approaches.

Design assumptions, modeling tools characteristics, occupants’ behavior, control and management represent relevant elements to be investigated already in the design phase. In this phase, errors are mostly connected to generally optimistic assumptions on building components and technical systems performance, together with an inadequate understanding of occupants’ behavior, as indicated before.

Despite the large effort in disciplines such as building physics, building science and energy management [42–46], an overall coherent, reliable, robust and interoperable model-based approach for performance optimization across all building life cycle phases, is still currently missing while there exist relevant environmental and energy policy issues connected to built environment [47,48]. If we analyze the state of the art of building modeling [49–52], optimiza-tion [53], calibration [54,55], control [56,57], occupants’ behavior [58,59] and comfort [60], we can see how a unifying feature of many researches is the use of reduced-order models developed for specific applications. This is, of course, not a solution in itself and further research should be oriented to the appropriate parametriza-tion and calibration of modeling approaches [61]. Nonetheless, it is necessary today to address in a flexible and effective way multiple issues such as techno-economic optimization at different scales, from buildings to districts [62,63], technology assessment at the local/regional level [64] and management of dynamic interaction with energy infrastructures and market [65–68], including load matching [69,70] and flexibility [71,72]. A synthesis of the relevant categories of building energy modeling approaches at the state of the art [49–52,54] is presented in Fig. 1.

In this article the research concentrates on the automation of the analysis of design phase simulation data, aimed at supporting performance monitoring and management across whole building life cycle. In order to perform these tasks effectively, a much tighter integration and comparability among models has to be present. In other words, we should be able to pass from model to simulated data (model output, forward approach) and from measured data back to model (model input, inverse approach). A synthetic scheme is reported in Fig. 2.

Further, with respect to design practices, in the traditional process there is a waste connected to project revisions and iterations: this can be overcome by introducing virtual prototyping based on parametric design, reported in Fig. 3.

The goal of parametric design is having more informed decision-making processes, avoiding useless project iterations by considering a more comprehensive spectrum of alternative scenarios from the beginning (multiple options are inherently part of a parametric strategies).

From a methodological standpoint, this information rich process is compatible with the state of the art procedures for uncertainty quantification in scientific computing [73,74], employing the con-cepts of aleatory and epistemic uncertainty. In the first case we can characterize our uncertainty with a probability distribution of val-ues (random process), while in the second case (lack of knowledge), we have to use interval data.

Probabilistic design and reliability-based design are well-known procedures applied in several engineering fields today [36]. How-ever, probabilistic design procedures aim primarily at producing safe and reliable design solutions, i.e. systems which perform correctly in nominal conditions, while for the built environment conditions can be so variable that systems have to be tested for robustness [36,75], i.e. they have to perform well enough also out-side nominal conditions, considered in the design phase.

The use of simulation data to train automated analysis tools aimed at energy management [76], together with the current use of state of the art model calibration techniques [54,55,61] highlight a possible path of continuity in this sense [77], which at present is exploited only partially. Continuous performance monitoring is necessary to ensure adequate performance [43,78,79]. Further, it is possible to validate design phase assumptions [80,81], giving an essential feed-back for the evolution of design practices [82] by ana-lyzing critically real operating conditions. In behavioral modeling in particular, occupancy-related parameters, such as air change rates and internal heat gains (i.e. due to people, lighting and appliances), can be determined by means of data-driven modeling approaches when sufficient measured data are present [83–85], but there is an inherent difficulty in the creation of general purpose models [58,59,86]. A possible solution could be that of testing the robust-ness of simulation outcomes with respect to empirical evidences from large-scale performance benchmarking studies [87,88]. The important role of large-scale data is underlined also by studies on the energy efficiency market [5] and on the future of energy research [16].

2. Methodological approach

The research aims to present a workflow employing both direct (forward) and inverse modeling techniques [89–92] to enable a continuity between performance analysis practices in design and operation phases, for the reasons outlined in the previous section.

The case study chosen to test the workflow is the eLUX Lab of the University of Brescia, Italy. The University Campus hosts a multi-disciplinary research initiative, whose goal is to bridge, on the one hand, the gaps traditionally separating design and energy simulation domains (i.e. promoting interoperability between BIM and BEM) and, on the other hand, the gaps between predicted and measured building performance (i.e. model calibration, supervisory control, energy management, etc.).

In particular, the workflow described makes use of a white-box building performance model (developed using EnergyPlus software) and a black-box reduced-order model (Artificial Neu-ral Network) trained on simulation data, following a possibility already highlighted in other studies [76,93]. The propagation of uncertainty [94,95] due to modeling assumptions is critical: the

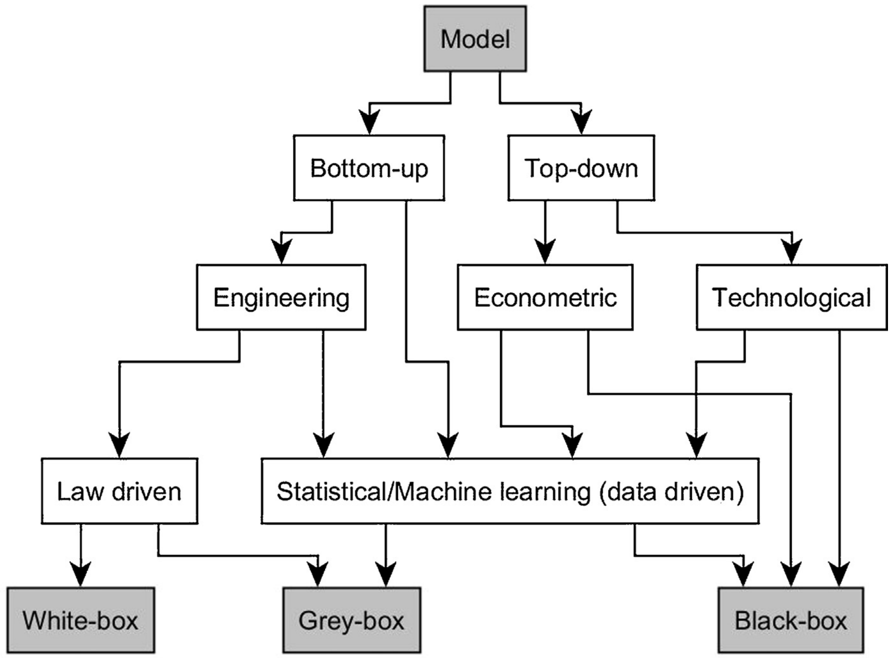

Fig. 1. Synthesis of the state of the art of building energy models.

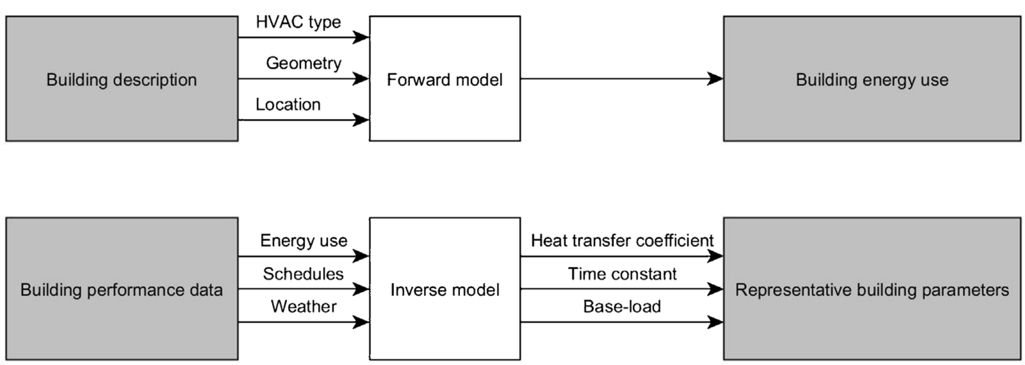

Fig. 2. Forward and inverse building energy models.

selection of appropriate combinations of simulation inputs [36,75] is a crucial point. Tools for parametric and probabilistic simulation are available today [96] but it is difficult to unveil the impact of uncertainty of assumptions [97] already in the design phase. This is evident, with respect to occupancy, in the methodological approaches used in recent research [98] and in normative initiatives [47,48]. Occupancy patterns' prediction is difficult [99–101] because of stochasticity [102,103], but appropriate techniques can be used to identify recurrent ones [104,105]. Measured data from sensors (e.g. CO_2 concentration, movement and presence, etc.) [106] can help tracking and reconstructing detailed dynamic operation profiles [98].

In the research work we use building survey and energy audit data together with probabilistic assumptions about build-ing occupancy, following the approach suggested in other studies [94,95,107,108]. For the reasons anticipated before, occupancy pro-files are among the most relevant elements to be studied in order to limit the "performance gap" [104,105] because they create direct internal gains (heat released by occupants) and they are partially correlated to electric appliances and lighting gains (dependent on the type of end-use and on occupants' behavior). Further, the internal air quality (IAQ) level depends on the pollutants released by occupants (as well as by other sources) within the internal environment. These elements inherently show the high degree of connection between energy balance components and behavioral issues.

The impact of occupancy on performance can be addressed by using a transparent physical and behavioral approach [98] with reasonable assumptions about the variability of occupancy levels [97]. Therefore, a parametric or probabilistic simulation strategy in the design phase could partially respond to the issues outlined in the introduction, coherently with the premises of retaining a physical interpretation of phenomena [42,54], rather than relying completely on data driven techniques.

In order to account realistically for the incidence of occupancy in multiple possible operation scenarios, a multi-layered supervised feedforward Artificial Neural Network (ANN) has been trained and used for Monte Carlo (MC) simulation [36], more details about these two techniques are explained later in the methodological section. The objectives of the simulation work performed were fundamen-tally three:

1. proposing a workflow that could be easily automated, but which could maintain a certain level of transparency with respect to key factors influencing performance;

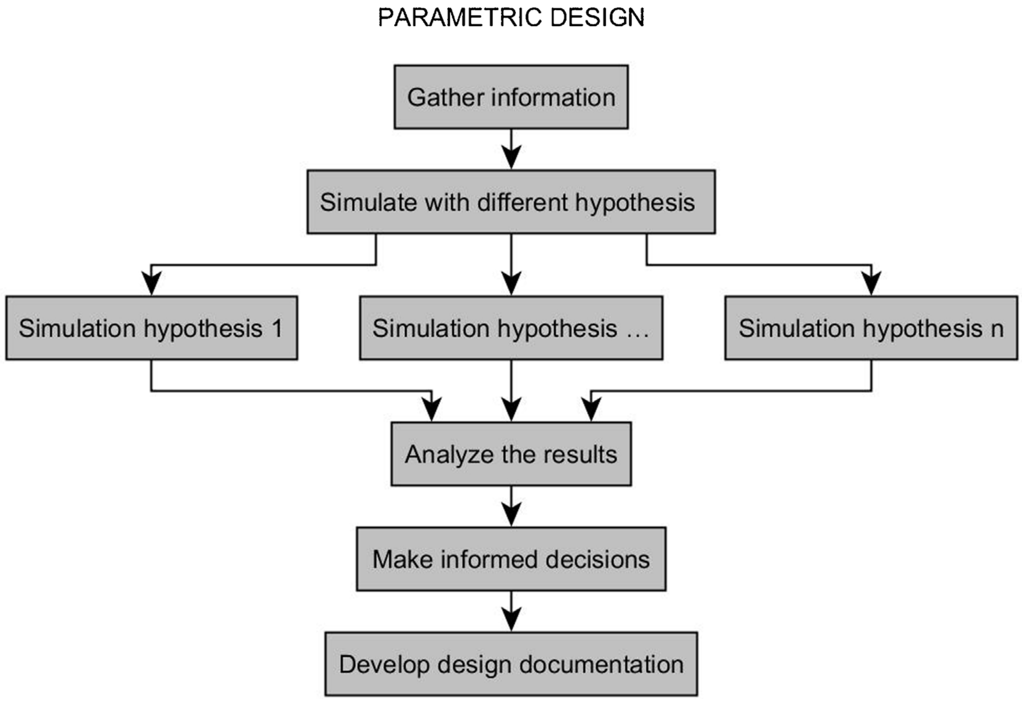

Fig. 3. Parametric design and virtual prototyping.

2. testing the feasibility of the approach under a large variability of occupancy conditions, considering the fact that the ANN is trained on a limited set of parametric data generated in the design phase;
3. verifying the numeric robustness of the approach with a large number of simulation runs.

These objectives do not imply necessarily the use of complex models, but rather the use of coherent assumptions in an appropriate methodological framework [98]. However, the Monte Carlo approach presented embodies a considerably more extensive application potential, related to the evaluation of variable conditions over time from different perspectives (e.g. occupants' comfort, thermal demand, electric demand, etc.) [109,110], by means of multiple reduced-order models, suitable for fault detection and diagnosis, supervisory building control [111,112] and operation management. Finally, the proposed approach could be used eventually also to extend the current deterministic design procedures to more effective ones, based on probabilistic criteria [113,114].

2.1. *Performance analysis in the design phase*

As introduced before, occupancy is one of the most relevant causes of uncertainty in building performance evaluation. For this reason, preliminary research work has been conducted on this topic for the case study [115]. It is possible to identify four main types of occupancy models in buildings at the state of the art [97], addressing respectively different levels of detail and different scales of analysis:

1. number of occupants at the building level in a certain period of time (building level);
2. occupied status of building zones in a certain period of time (building zone level);
3. number of occupants of building zones in a certain period of time (building zone level);
4. individual movement tracking (occupant level).

In the previous work on this case study [115] we combined approaches number two and three; the main variables in modeling of occupancy and related factors were:

1. presence/absence (occupied status) of people in a building zone (0–1, binary variable, e.g. a lesson in a classroom);
2. number of occupants within the building zone (from minimum to maximum value assumed, following a probabilistic distribution);
3. assumptions for the calculation of air change rates (CO_2 concentration due to occupancy);
4. internal gains dependent on occupancy (number of people, appliances, lighting);
5. internal gains independent on occupancy (appliances, lighting).

In the case study, a fixed internal distribution of functions was considered (i.e. fixed end-use for different zones) but the approach presented can be extended further accounting also for the variability of end-uses in zones across building life cycle phases (considering the issue of end-use flexibility). Of course, this can led to a large number of simulation scenarios generated either para-metrically (epistemic uncertainty) or probabilistically (aleatory uncertainty), or with a combination of both to explore uncer-tainty more appropriately [74]. Following the occupancy modeling approach described before, the choice of inputs for the building performance simulation model used in the preliminary work was related to:

1. operation schedules and occupancy patterns;
2. ventilation and internal air quality;
3. internal gains due to appliances.

With respect to occupancy patterns the choice was to use triangular probability distributions, similar to the ones used in other research studies on the uncertainty propagation in building simulation [95,107]. The ventilation settings were chosen following the requirements of Italian norms [116,117], considering a standard amount (minimum for IAQ) of outdoor fresh air per person,

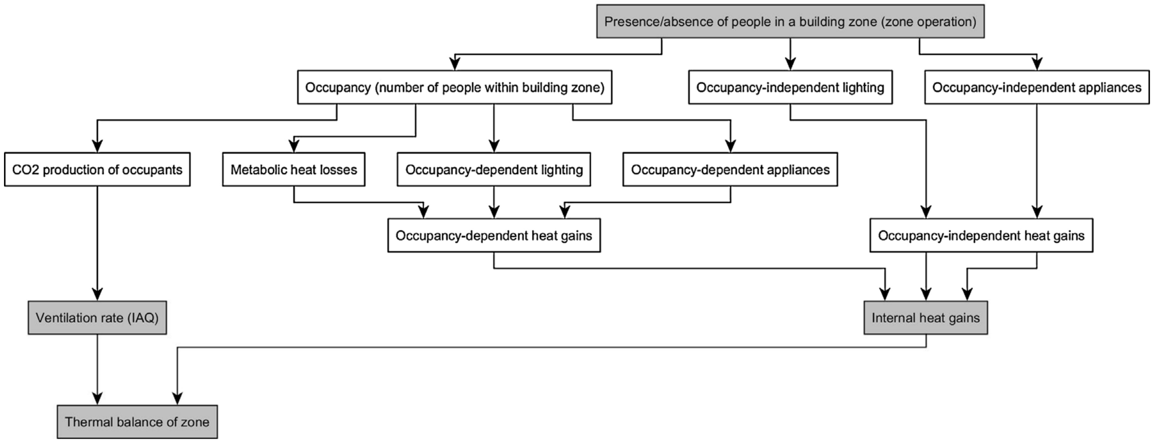

Fig. 4. Conceptual scheme of the correlation among the fundamental aspects considered in the input data to simulation model.

in order to maintain the level of pollutants and the concentration of CO_2 under acceptable limits. Finally, the total amount of internal gains used was related to the number of people (and their metabolic rate) and to the equipment (i.e. electric appliances and lighting), as explained more in detail in previous work [115]. The internal gains due to electrical appliances were considered to be partially dependent on occupancy, following the evidences collected in the energy audit. All these relevant components for the determination of building energy balance could be therefore subdivided into two main categories, based on their dependence or independence on occupancy. A conceptual scheme is reported in Fig. 4.

2.2. *Performance analysis in the operation phase*

Analysis of building performance in the operation phase is a potentially unifying feature of several practices (e.g. internal environmental conditions monitoring, fault detection and diagnosis, supervisory control, load forecasting, etc.) [104,118] which employ different types of models, tailored on the specific needs. In general, inverse models can contribute to the identification of relevant technical issues and to the calculation of multi-level metrics [54,55,61,108,119] and influential parameters [81,91,120], which are necessary for continuous performance benchmarking [121], following the line of thought reported in the introduction.

Examples of methodologically unified inverse modeling practices can be found in literature [104,118,122,123], and it can be noticed how regression-based models (energy signa-tures) represent a very effective and relatively simple solution [112,118,124,125] which can be used for automated model selection [120] and for supporting white-box models calibration, considering the identification of macroparameters [108]. However, multivariate linear regression models, in case of highly variable operating conditions (i.e. variable occupancy profiles), need a preliminary clustering work [104] aimed at identifying recurrent operating conditions, necessary for model construction (i.e. operation schedules). The selection of linear multivariate regression models can be potentially automated also in the case of multiple operating modes, by means of statistical ensembles [126,127], but the process is more challenging in terms of automation and requires additional research.

In our work, we tested the feasibility and robustness of prediction, in multiple operating conditions, of a single technique (ANN) instead of two combined techniques (clustering and multivariate linear regression). The feasibility of using ANN for dynamic building performance prediction has been addressed already in other research studies [93]. However, in our case study, we tested it with respect to a large set of hypothetical occupancy conditions.

In the ANN training and testing phases simulation data obtained by means of a forward (white-box) model, and predicted data obtained by inverse ANN model (black-box) were graphically compared [54,55,61], highlighting its predictive capabilities. Visual analytics is essential in the operation phase as it enables the identifica-tion of anomalies and malfunctioning, which can be highlighted, for example, by plotting the difference between predicted and measured data on a daily base and by calculating the cumulative sum of differences (CUSUM method and Shewhart chart) [54,128], or using weather-adjusted graphs (weather normalization) [129]. These practices can be employed along the whole building life cycle for periodic model calibration (retraining of reduced order models) [118,130–132], using long-term monitoring data at low frequency (e.g. monthly, daily) and short-term monitoring data at high frequency (e.g. hourly, sub-hourly) [118,130,133,134].

Further, visual analytics can be thought as a basic way to establish a continuity among performance analysis procedures in design and operation phases. Graphical methods are part of the current state of the art of model calibration [54,55,135] and simulation data themselves can be verified preliminarily using inverse modeling methods [136], by considering macroparameters and multi-level metrics [108,137].

Therefore, by generating in the design phase a large spectrum of possible operating conditions (considering the uncertainty in input assumptions) it is possible to reduce progressively the gap among simulated and measured data by means of semi-automated calibration workflows, employing reduced-order models, and visualization techniques to control the relevant parameters.

In the case study presented a monitoring system enables the determination of detailed occupancy profiles from measured data, using people counters is crucial to verify the real occupants' number during the different periods of the year. Additionally, CO_2 concentration sensors, connected to the direct digital control (DDC) of the mechanical ventilation system (e.g. modulation of airflow handled by AHUs), provide detailed information about actual indoor air quality, enabling the inverse estimation of the number of people within a certain zone. In this way, it is possible to use sensor data as input for the ANN created initially using design phase data and then retrained on measured data [79] for periodic calibration.

3. Description of the case study

As introduced before, the chosen case study is the eLUX lab building [115,138,139], used for the field testing of the multidisciplinary research initiative “Smart Campus School Project” carried out by the University of Brescia. The building has three floors, underground, ground and first floor, and it is characterized

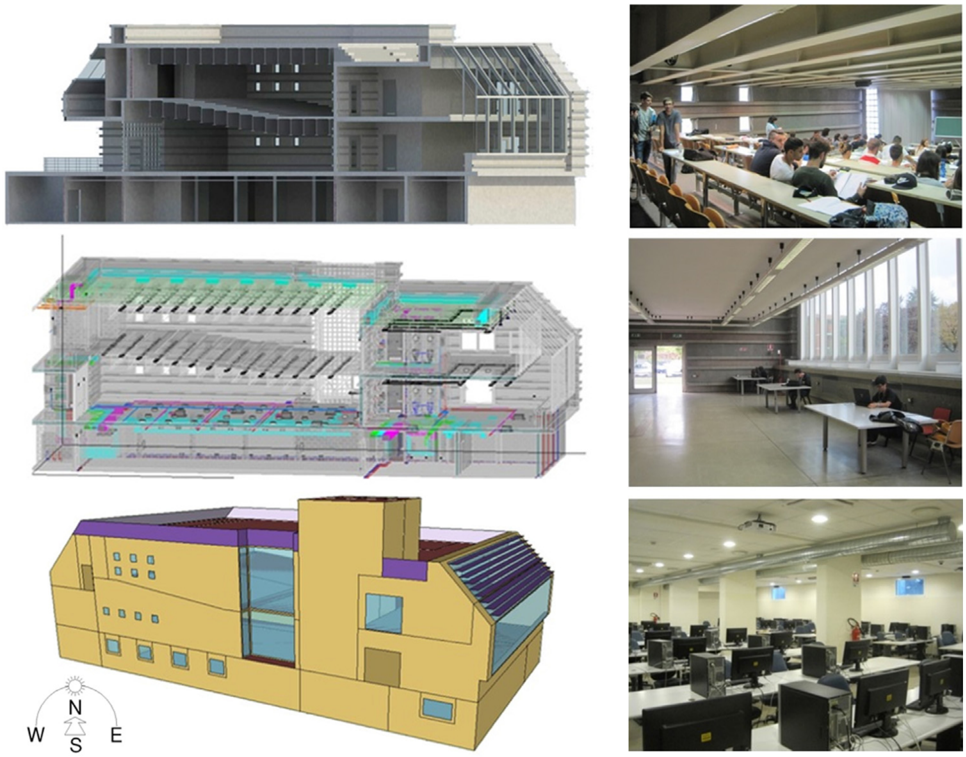

Fig. 5. Architectural, MEP (Autodesk Revit) models and energy model (SkecthUp/EnergyPlus) of the building and internal views of the aula magna (first floor), atrium (ground floor) and labs (underground).

Table 1
Description of the eLUX Lab rooms and thermal zones.

Location	Room	Space	Zone	Dimensions		Occupancy	
Floor	Name	Typology	N.	Area [m^2]	Volume [m^3]	N. users (survey)	N. users (standard assumption)
Underground	MLAB1	Computer lab	1	151.8	455.4	56	76
	MLAB2	Computer lab		207.9	623.8	82	104
Ground	MTA	Classroom	2	178.3	534.8	168	89
	MTB	Classroom		177.5	532.4	168	89
	Atrium	Common area	3	180.8	542.3	56	90
First	M1	Aula magna	4	337.5	1012.4	262	169

by the presence of an atrium (double height), lecture halls and computer labs. Internal and external views of the building and of the BIM and BEM models used are reported in Fig. 5. The building thermal zones considered are described synthetically in Table 1. As introduced before, the building has been previously simulated with a construction of model inputs according to the scheme in Fig. 4.

In the previous research work performed [115], probability distributions of occupancy were used to obtain probabilistic thermal demands and load profiles (heating and cooling). The distributions chosen were triangular, similar to the one used in other research studies on the uncertainty propagation in building simulation [95,107]. Results from previous simulation work were organized using a boxplot graphical method whose aim was visualizing the high variability of simulation output and, more specifically, highlighting the following quantiles of the statistical distributions of heating and cooling thermal demands and load profiles [135]:

1. lower bound (5% of data);
2. first quartile (25% of data);
3. median (50% of data);
4. third quartile (75% of data);
5. upper bound (95% of data).

In this research, the quantiles of the distribution of hourly heating load profiles were used to train the ANN whose scope was predicting probabilistic performance bounds suitable for use in operation, starting from the uncertainty in occupancy and the related factors. Clearly, the ANN model (black-box) is much faster than the original model (white-box) developed in EnergyPlus because it enables the automatic exploration of thousands of simulation scenarios without excessive computational effort. Our goal was testing its robustness using a Monte Carlo method, which generates samples of occupancy data according to chosen probabilistic distributions. In this research we concentrated on the analysis of thermal demand for heating, but the approach is flexible and could be easily extended to cooling and electricity demand. The work passages can be summarized as follows:

1. definition of input data and boundary conditions for energy simulation (i.e. climate, building technology, technical systems, etc.);
2. definition of characteristic occupancy patterns and settings (i.e. occupancy level, schedules, etc.);
3. parametric simulation using white-box model (EnergyPlus in this case);

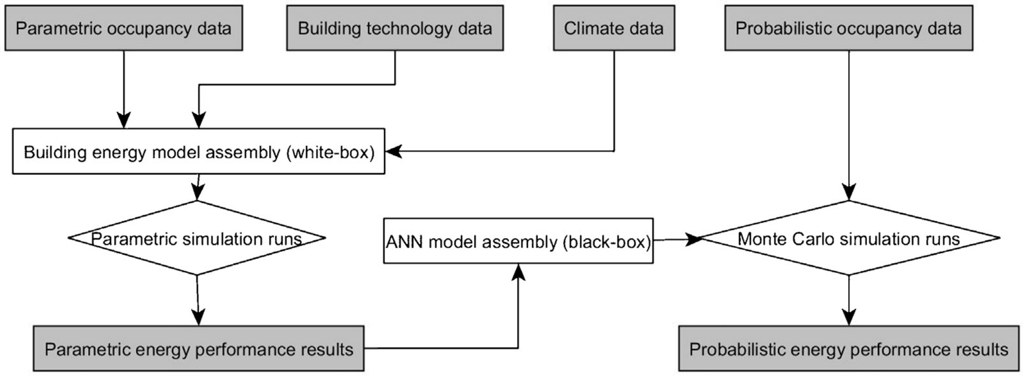

Fig. 6. Workflow of the research.

4. training of black-box, reduced-order, model (ANN) on parametric simulation data (heating demand data in this case);
5. definition of probabilistic occupancy patterns for Monte Carlo simulation employing reduced-order model (ANN);
6. simulation of statistical distribution of energy performance outcomes (heating demand in this case, generated by multiple runs of ANN according to Monte Carlo technique).

The workflow is also graphically depicted in Fig. 6, showing the relation between the original model, used in the design phase, and the one developed to perform Monte Carlo simulation. Details of training and testing of the ANN are reported in the following sections.

3.1. Training and testing of ANN

The ANN model chosen is a three-layer supervised feedforward network with linear input neurons, sigmoid hidden neurons and linear output neuron. The best performing architecture has been selected based on the lowest Mean Square Error (MSE). The network used to predict heating demand has a six input hourly dataset and one output hourly dataset:

- Input 1: outdoor air temperature;
- Input 2: global horizontal solar radiation;
- Input 3–6: occupancy data (i.e. number of users) of the four thermal zones;
- Output 1: thermal energy demand.

The output is the hourly energy demand. ANN was trained using the Bayesian regularization method and the split of the dataset between training and testing was 75 and 25%, respectively. An auto-mated process of model selection was used to determine the final number of neurons, 59, starting from a maximum limit set to 200. The automated model selection, considering MSE as a performance metric, is reported in Fig. 7 where it can be seen that the MSE falls when the number of hidden neurons goes from six to around 40 and then the MSE tendency is almost flat when the number of hidden neurons increases, with a minimum at 59.

The determination coefficient R^2 obtained by the final ANN model is 0.818, which represents the goodness of fit of the model (maximum R^2 value is 1, minimum 0). This value is in line with the ones found in other research studies on dynamic neural net-work used for heating prediction [93], which however makes use of additional pseudo dynamic parameter inputs (to improve computing performance) that require a priori knowledge of occupancy patterns. R^2 and regression lines are reported in Fig. 8, with similar values of R^2, namely 0.819 for the training set, 0.812 for the test set, 0.818 for the whole dataset.

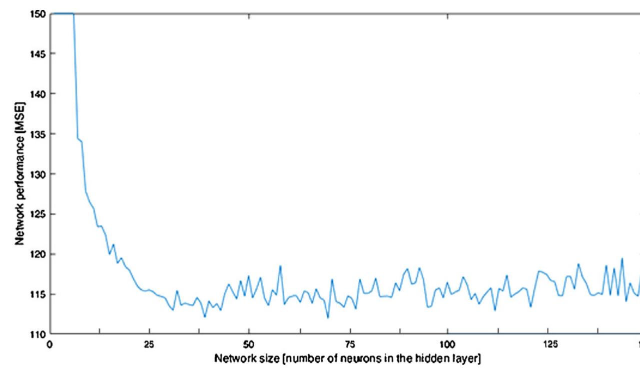

Fig. 7. ANN performance (MSE) according to the number of neurons in the hidden layer, numbers of input and output layer are fixed.

3.2. Monte Carlo simulation of ANN

As introduced before, we use Monte Carlo simulation to compute probabilistic thermal energy demand using the trained ANN on samples of occupancy patterns generated according to the selected distributions. We decided to use triangular probability density functions for occupancy, the most commonly used in literature [95,107]. However, considering the specific characteristics of the case study, a building for education with highly variable occu-pancy, the schedules have been constructed by differentiating the value of the triangular probability distributions in three time inter-vals, from 9 am to 10 am, from 11 am to 4 pm and from 5 pm to 7 pm, as indicated in Fig. 9. The values assumed in this research are narrower compared to the ones used in the preliminary exploratory work [115], trying to reproduce a variable but recurrent operational conditions.

As a result, the values assumed are based on the following assumptions:

1. from 9 am to 10 am:
   a minimum value, the corresponding minimum deterministic occupancy pattern;
   b mode, the corresponding 1st quartile of deterministic occupancy pattern;
   c maximum value, the corresponding maximum deterministic occupancy pattern;
2. from 11 am to 4 pm:
   a minimum value, the corresponding minimum deterministic occupancy pattern;
   b mode, the corresponding maximum deterministic occupancy pattern;

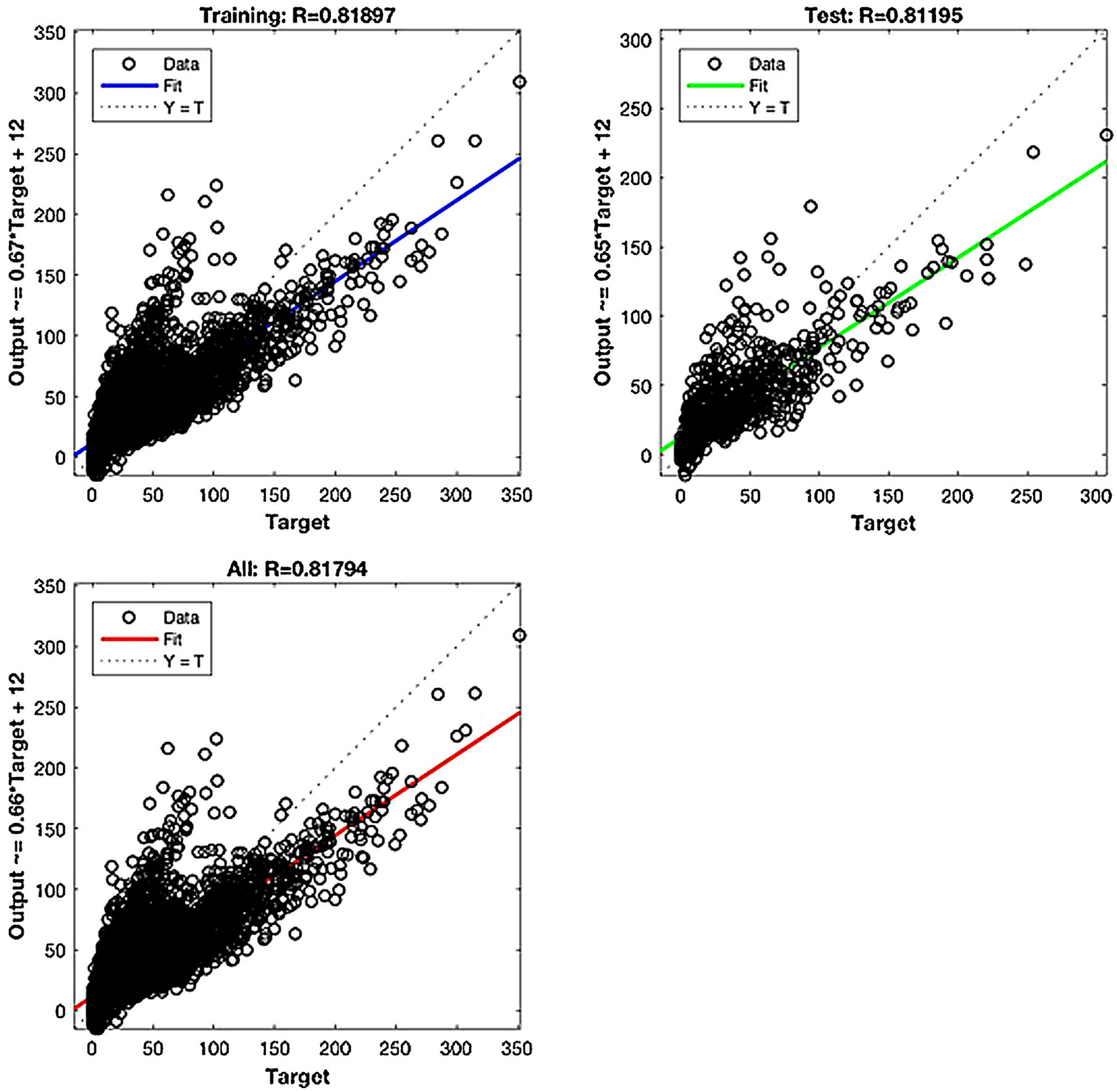

Fig. 8. R^2 and regressions of the ANN for heating demand on the different datasets.

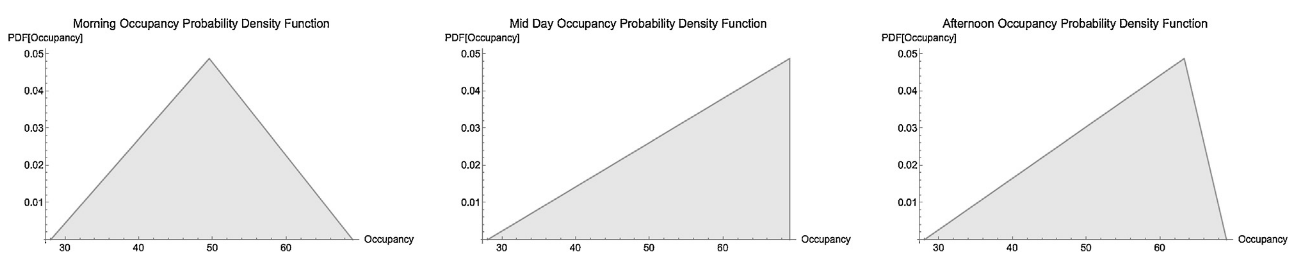

Fig. 9. Occupancy probability density functions used for Monte Carlo sampling in probabilistic simulation.

c maximum value, the corresponding maximum deterministic occupancy pattern;

3. from 5 pm to 7 pm:
   a minimum value, the corresponding minimum deterministic occupancy pattern;
   b mode, the corresponding third quartile of deterministic occupancy pattern;

Considering the fact that internal gains and ventilation rates to be provided to building zones are partially dependent on occupancy, as indicated in Fig. 4, it becomes clear how the results in terms of energy demand can be highly variable even with the same climatic conditions. For this reason, we decided to run five Monte Carlo simulations with 10.000 random occupancy patterns each, to derive five probability distributions of heating energy demand to be compared. The seed for the random numbers generator in each simulation is based on current time so to produce a different sequence of numbers in each simulation. The comparison among the results obtained from the five simulations is aimed at verifying the robustness of the approach, first of all with respect to the overall quantities obtained on a yearly base, reported in Fig. 10, where the numbers on the bars represent the frequency of occurrence.

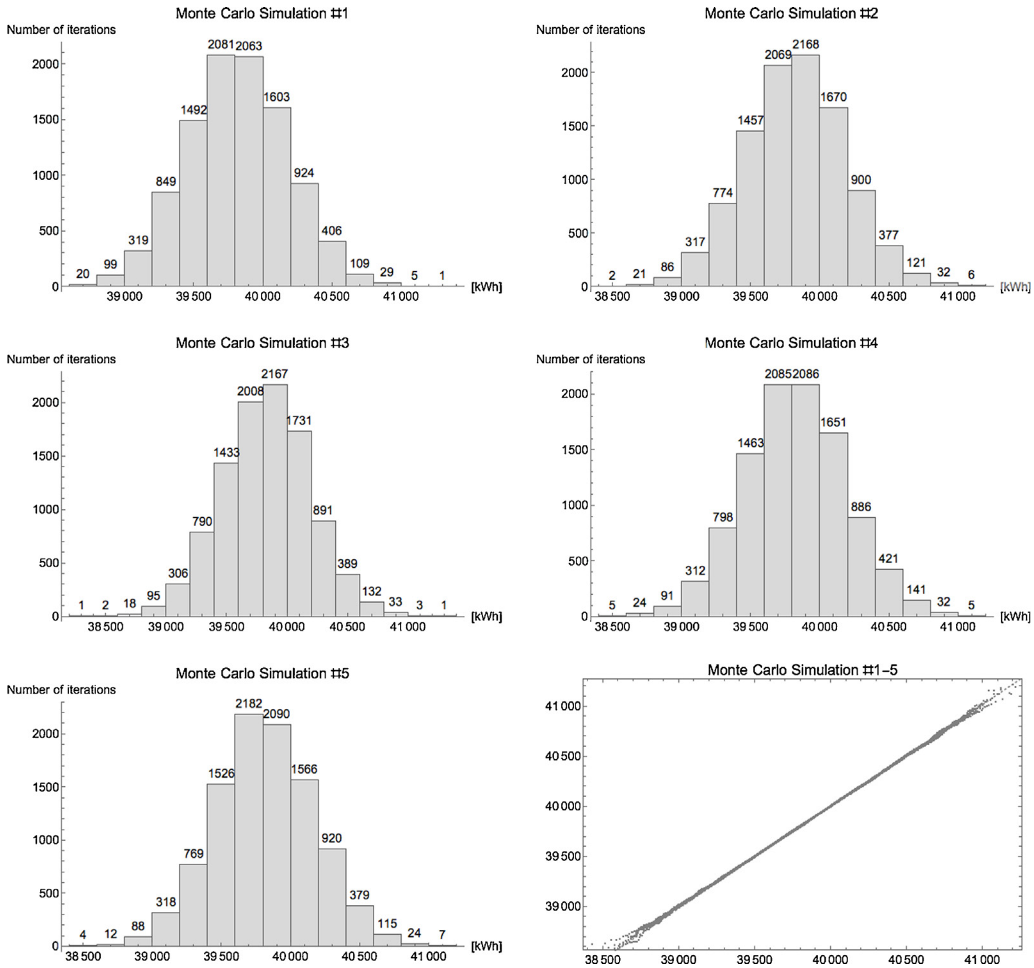

Fig. 10. Yearly heating energy demand calculated by five Monte Carlo simulation runs.

The results obtained are substantially uniform, as shown in the first five pictures of Fig. 10, while the sixth picture shows a plot of quantiles of the five Monte Carlo simulations against the quantiles of a normal distribution, highlighting the substantial normality of the data obtained.

After that, we wanted to verify the usability of the approach with respect to performance monitoring and diagnostic tasks, evaluating graphically the difference among deterministic and probabilistic simulation outcomes on a daily base (for operating days). Therefore, we plotted the five probabilistic simulation outcomes, represented as interval data, in the first five pictures of Fig. 11, to compare them with the mean value obtained by EnergyPlus simulation, reported in the sixth picture.

The gray dashed lines in the first five pictures correspond to the daily mean value computed by means of EnergyPlus, while the average values and standard deviations of Monte Carlo sim-ulation outcomes are reported with dots and error bars. Fig. 11 shows a deviation of MC mean energy demand from the one com-puted using EnergyPlus near the end of the heating season. This may be due to both a lower predictive ability of the neural net in that domain and to a choice made in making the comparison of MC and EP results. Although the probabilistic occupancy pattern used (functions in Fig. 9) is close to the maximum occupancy pat-tern used in EnergyPlus simulations for the most time of the day, the graphical comparison is made between MC probabilistic output and EP results computed with the mean occupancy pattern. Note-worthy, the deviation in the last part of the heating seasons (Fig. 11), i.e. when energy demand is low, does not affect substantially the overall ANN predictive ability (Fig. 8).

Finally, we reported in Fig. 12 the cumulative distribution function of yearly heating demand. The quantiles for each Monte Carlo simulation are presented in Table 2.

Starting from these values, it is possible to determine a probabilistic level of heating energy demand outcomes, which can be used, for example, to evaluate the risk of failure of an energy efficiency investment with respect to user behavior, represented in this case by highly variable occupancy patterns.

4. Discussion of results

As described in Section 2, the article aims to investigate an approach for probabilistic performance simulation to be used across building life cycle phases, employing reduced-order models for performance monitoring (i.e. surrogate models, meta-models) for specialized tasks. The workflow proposed aims to establish a continuity among design and operation phase practices, in order to reduce the performance gap, which is dependent, by a large amount, on the uncertainties caused by end-users' behavior.

Design phase simulation work is subject to relevant temporal and economic constraints and, therefore, a successful workflow should incorporate current design practices and, at the same time, should implement new features which should be reasonably auto-mated, to reduce additional modeling effort. For these fundamental reasons, we considered as a starting point the parametric simulation data generated in the design phase by means of a detailed

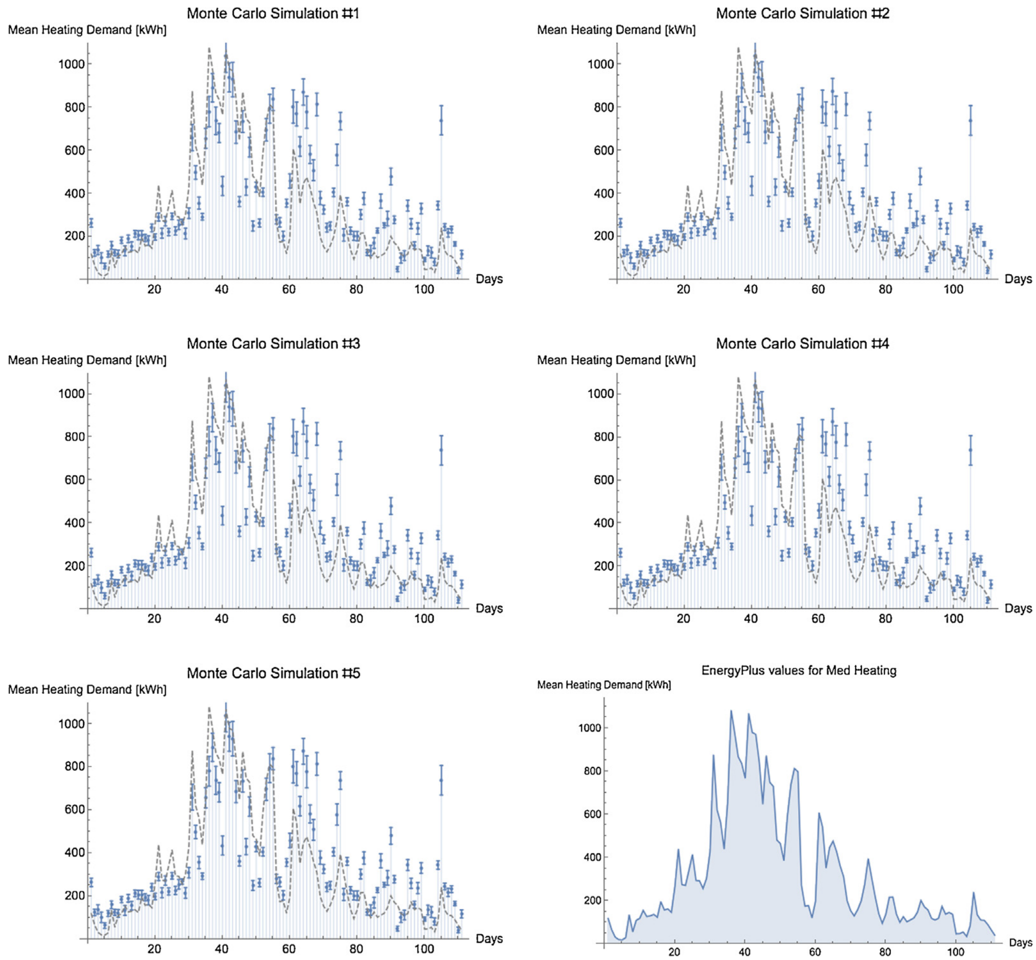

Fig. 11. Daily heating demand from Monte Carlo simulation compared to EnergyPlus (white-box model) results.

Table 2
Table of quantiles of probabilistic distributions of heating energy demand.

Monte Carlo simulation runs	Heating energy demand								
	Quantiles of probability distribution								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
	[kWh]	[kWh]	[kWh]	[kWh]	[kWh]	[kWh]	[kWh]	[kWh]	[kWh]
1	39,352	39,505	39,624	39,721	39,814	39,910	40,008	40,128	40,287
2	39,356	39,522	39,637	39,733	39,823	39,914	40,010	40,124	40,280
3	39,358	39,521	39,638	39,741	39,831	39,920	40,018	40,128	40,281
4	39,357	39,514	39,636	39,728	39,822	39,918	40,015	40,127	40,295
5	39,366	39,520	39,628	39,723	39,810	39,907	40,001	40,120	40,276

building energy simulation model (white-box) [115]. After that, we trained an ANN on hourly data to create a reduced-order model (black-box) to be used for predicting building energy demand at hourly intervals. The construction of the datasets for model training and testing embodies the selection of the most relevant variables involved in determining the energy demand, namely outdoor air temperature, solar radiation, occupancy level for every hour of the day and for every zone. In the specific case study building, the simulation of realistic profiles of internal gains, together with the presence of a ventilation control based on CO_2 concentration, highlighted a large dependence of the performance on occupancy rate.

The goodness of fit of the dynamic ANN model ($R^2 = 0.818$ in the whole dataset) is in line with values from other research studies in literature, but computational performance can be improved by reducing the size of the network: this remains an open problem in the design phase as the introduction of pseudo-dynamic transition inputs requires a priori knowledge of occupancy patterns [93].

On the other hand, while the architecture selected enables auto-mated processing of simulation output, the time required to train it is larger than in the case of a simpler one. This can become an issue because of the necessity of periodically retraining the network, but the recent developments in the field of deep learning are showing the possibility of using more complex architectures for networks, overcoming current limitations.

The current efforts in creating a unified framework for analyzing building energy data can be complemented by the advances in multi-level model calibration, to exploit "structural" properties in inverse models selection, for example by means of regression trees [140], and to identify different operating modes automatically,

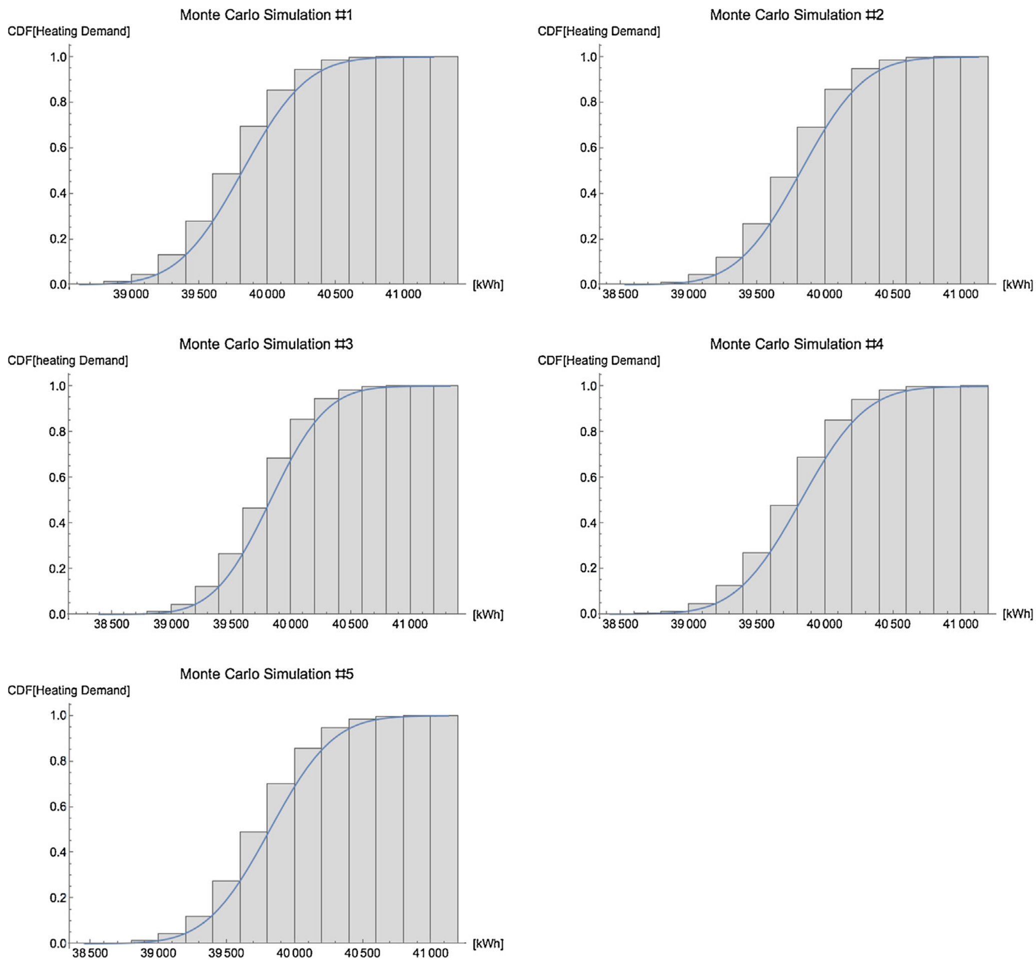

Fig. 12. Cumulative distribution function of yearly heating demand.

using statistical ensemble methods [126,127]. Therefore, it will be possible to improve the capabilities of inverse models to identify relevant physical quantities [141] and remain flexible enough for an automated implementation.

The outcomes of the Monte Carlo simulation runs highlighted the robustness with respect to multiple occupancy patterns. Therefore, the model can be used to obtain weather-adjusted daily thermal energy demand (similarly to regression models) for heating including boundaries of probabilistic daily energy consumptions, as shown in recent research [118,133,134].

The automated daily control of building energy consumption is not particularly data intensive and can be introduced in a cost-effective way for energy management [80,81,120,129,142,143] and anomaly detection in operation [129], using simple and intuitive visualization strategies. In the case study building, it will be possible to compare graphically predicted data and measured data in operation (real occupancy can be estimated by means of presence and CO_2 concentration sensors) and to characterize the thermal gains related to people occupancy. A day to day automated control is necessary to ensure adequate performance during building life cycle and, even though black-box models have to be necessarily retrained periodically on measured data, they can help identifying useful insights, including behavioral issues, if they are conceived to act in a synergic way with other tools (e.g. detailed white-box or gray-box building models, periodically recalibrated).As a conclusion, we would like to stress the fact that paths of integration among different modeling strategies (across building life cycle phases) are possible and cost effective. This is crucial from two points of view: first because it is necessary to provide reliable performance estimation in the design phase considering multiple hypothesis, second because it is necessary to maintain performance within acceptable boundaries in the operation phase, acting in a predictive and corrective way when necessary. These two elements can contribute to the reduction of the risk inherently present in energy efficiency investment, which is today a relevant barrier to deep retrofit practices in building renovation [8], by ensuring an appropriate control of operating costs from the very beginning and during the whole life cycle.

5. Conclusions

The effort to bridge the gap between simulated and measured performance determines the need for a synergic use of modeling tools available at the state of the art for simulation and for performance monitoring. These two needs can be satisfied in a cost-effective manner by automating the performance analysis workflows (generally time consuming and error prone), where different software applications can work together as smart computing "objects". These "objects" should be fed by measured data, acquired by building monitoring and automation systems and could, in turn, display useful analytical performance insights visually to practitioners and stakeholders.

The possibility to create unified workflows from forward to inverse models in buildings is confirmed by recent research, but there are relevant unsolved problems.

First, with respect to design phase correct assumptions remain a critical issue for practitioners and this is particularly evident for occupants' behavior. We can overcome this problem by considering several occupancy scenarios, within a general uncertainty analysis framework, able to encompass both epistemic and aleatory uncertainties. The appropriate balance between time and effort in modeling with respect to the effectiveness of the approach on the field could be identified by means of a performance benchmarking, based on large-scale data. For example, IEA Annex 70 "Building Energy Epidemiology: Analysis of Real Building Energy Use at Scale" is going in this direction, following other research initiatives focused on automated data analysis for performance benchmarking in the building stock. Further, IEA Annex 58 "Reliable Building Energy Performance Characterization Based on Full Scale Dynamic Measurements" illustrates the use of different and potentially scalable techniques for dynamic building performance analysis.

The advances in building performance modeling highlight the need for calibrated reduced-order models, suitable for multiple tasks in the operation phase, in particular environmental conditions monitoring, fault detection and diagnosis, supervisory control and energy management. A unified workflow should aim at integrating different types of models, from white-box ones (e.g. EnergyPlus) to gray-box and black-box ones, which can be more easily used (and customized) for specialized applications. The additional modeling effort put in the design phase, and the related costs, could be compensated if the outcomes were exploited successfully (e.g. in terms of energy and cost savings) also in the operation phase. Naturally, calibrated models have to be re-trained on measured data periodically during building life cycle to fit real building behavior, but the scenarios generated during the design phase can nonetheless give a realistic spectrum of performance variability, to be compared possibly with performance data collected on a large scale and analyzed by means of unified and scalable techniques, as indicated before.

With respect to operation phase, today our research efforts should orient not merely on technological learning, but also behavioral learning. Internal environmental quality and energy consumption (and the related costs and environmental impact) are potentially conflicting objectives. By properly addressing behavioral change we can contribute to soften the performance boundaries usually assumed in design, thereby exploiting also the adaptability and flexibility potential determined by people. At the same time, we can critically question the reliability and robustness of results obtained with conventional modeling and simulation approaches, based on standard assumptions, which drive today technological change and policy.

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