Surrogate Models to Cope With Users' Behaviour in School Building Energy Performance Calculation

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Abstract

The paper investigates the use of surrogate models for probabilistic building performance simulation that can be used for multiple applications across life cycle phases. The workflow presented aims to highlight a possible continuity among design and operation phase practices, in order to contribute to the reduction of the gap between simulated and measured performance, considering in particular the uncertainties caused by users' behaviour. Design phase simulation work is generally affected by relevant temporal and economic constraints and, consequently, a successful approach should enhance current design practices and implement new features which have to be automated, to decrease additional modelling effort. The parametric data obtained in the initial design phase by means of a detailed model are used to train an Artificial Neural Network model. The results obtained by this model are the compared with the ones obtained with a Resistance-Capacitance model. The approach is automated and tested for robustness using Monte Carlo simulation technique. This technique is used to identify, already in the design phase, probabilistic performance boundaries. The case study chosen is the eLUX Lab building at the Smart Campus of University of Brescia, in which highly variable occupancy patterns are present.

Introduction

The 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 (COM, 2011). This target represents also a prerequisite for meeting other EU economic and climate goals and energy performance in the whole life cycle of buildings becomes a relevant matter in terms of sustainability and resource efficiency at the EU level. Actual energy performance often differs from predicted one due to simplifications and approximations normally associated with modelling approaches (De Angelis et al., 2015) and uncertainty in modeling assumptions. The impact of end-users' behaviour is surely among the most important factors to be considered (Menezes et al., 2012;Tagliabue et al., 2016)**.** Further, the deployment of new economic (i.e. circular economy) and technological (i.e. Internet of Things) paradigms is routed on the digitization of equipment and assets, including buildings. The role of people is crucial also in the sense and determines the necessity to address appropriately the incidence of people behavior on energy performance. For this reason it is necessary to identify a reasonable compromise between time and computational effort in modelling and simulation of performance variability determined by people behavior, and to create a "continuity" in the use of models for multiple applications across life cycle phases (i.e. from design to operation).

Methodology

The increased awareness on sustainability matters is contributing to the evolution of energy and environmental policies for the building sector at the EU level, oriented toward resource efficiency. This evolution is challenging as it claims for an overall coherent, reliable, robust and interoperable model-based approach for performance optimization across building life cycle phases. In fact, while there exist today several possible strategies to model building performance from the energy and environmental standpoint, the relevant gap usually encountered between simulated and measured performance is clearly connected to biased assumptions in modeling, especially in the design phase, and to lack of performance monitoring, in the operation phase. The state of the art of building energy modelling is exhaustively discussed in literature (Zhao and Magoules, 2012; Harish and Kumar, 2016; Fumo, 2014; Foucquier et al., 2014; Coakley et al., 2014; Henze, 2013; Shaikh et al., 2014; Yu et al., 2015). Models used to simulate building energy performance should be aimed at maximizing the value of information, unveiling synergies across multiple processes and scales of analysis. There exists multiple potential feedbacks that can be exploited to improve performance (Fabrizio and Monetti, 2015; Evins, 2013; Nguyen et al., 2014). The first relevant distinction that can be made is among top-down (econometric, technological) and bottom-up (engineering) models (EN 16212, 2012). After that, an important subdivision is related to the different modelling strategies that can be applied in buildings: white-box, grey-box and black-box (Manfren et al., 2013). White-box models are detailed physics-based models, grey-box models are simplified physics-based models and black-box are data driven models based on little or no physical knowledge of the system. The

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choice of the modelling approach is determined by the specific objectives and by the required level of detail, accuracy, precision and computational effort. In this research we start from a white-box model and we develop two surrogate models, a grey-box and a black-box one for performance modeling and energy management. The two surrogate modelling approaches selected are respectively a Resistance-Capacitance (RC) model and Artificial Neural Network (ANN), trained on parametric simulation data (Tagliabue et al., 2015). The objective of the research work is assessing the feasibility, reliability and robustness of these two types of surrogate models to compute the energy performance of a case study building in which highly variable occupancy patterns are present, ensuring a more efficient use of the simulation data generated in the design phase. The probabilistic simulation of energy demand is performed by means of Monte Carlo (MC) technique, as indicated in Figure 1.

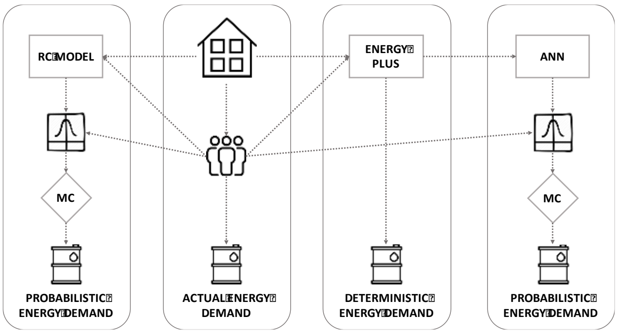

Figure 1: Graphical scheme of research

The overall methodology presented aims at enhancing current practices in performance simulation, highlighting the possibility of using semi-automated/automated approaches to analyze design-phase data, therefore establishing a continuity among design phase tasks (such as design optimization) and operation phase tasks (such as performance monitoring and energy management). The methodology presented is general and an overview of the potential applications using surrogate models in buildings is described in the following section.

Applications of surrogate models in buildings

The models generally used to simulate building energy behaviour (white-box, physics-based models) present several limitations with respect to automated applications (Hazyuk et al., 2012; Oldewurtel et al., 2012; Prívara et el., 2013; Afram and Janabi-Sharifi, 2015). The basic conditions that a model for automated applications should satisfy are reasonable simplicity, enough accuracy in the estimation of system dynamics, usability for prediction in real time operation (Maasoumy and Sangiovanni-Vincentelli, 2012; Hazyuk et al., 2012).

On the one hand, white-box models generally need detailed information and are non-linear problem while linearity (more in general convexity) is an important feature to obtain easily solvable optimization problems (Oldewurtel et al., 2012; Morari and Lee, 1999; Široký et al., 2011). On the other hand, black-box models, have been widely used in optimal control applications because they can deal efficiently with non-linear problems (Wang S, Jin, 2000). However, they are obtained by means of statistical/machine learning algorithms and, consequently, the identified parameters don't have a physical interpretation, losing a substantial part of the useful information that can be extracted by measured data (Oldewurtel et al., 2012; Afram et al., 2015; Zavala et al., 2011; Zacekova and Privara, 2012; Ferkl and Privara, 2010). In order to overcome these issues, grey-box models, mixing knowledge-based (physics-based) and statistical techniques are used in several applications (Afram and Janabi-Sharifi, 2015; Zacekova and Privara, 2012; Mahdavi, 2001; Jiménez and Madsen, 2008; Bacher and Madsen, 2011). In grey-box modeling the size of the problem is reduced using lumped parameters (Hazyuk et al., 2012; Foucquier et al., 2013; Kramer et al., 2013). The structure of the model (i.e. the reduction strategy) is found by applying basic physical principles (e.g. energy and mass balance) and the parameters can then be estimated both a priori or calibrated on measured data by using identification techniques (Hazyuk et al., 2012; Afram and Janabi-Sharifi, 2015; Hazyuk et al., 2012; European Commission, 2007; Froisy, 2006). The feasibility of integrated and automated performance modeling approaches is confirmed by different international studies on model predictive control (Gwerder et al., 2013) and on building performance characterization based on full-scale dynamic measurement (IEA-EBC). Considering these elements, it is possible to envision a path for the creation of synergies in research field such as design optimization, energy management, diagnostics, and automatic control.

Case study: the eLUX Lab of Brescia University

The case study presented is the eLUX Lab of the University of Brescia in Italy. The University Campus hosts a multi-disciplinary research initiative focused on Smart technologies (Unibs, 2014; Unibs, 2016). The research, involves multiple topics ranging from BIM (Building Information Modelling) to BEM (Building Energy Modelling), performance optimization, performance monitoring, energy management, user behavioral modeling. In particular, the research on behavioral modeling aims to improve the knowledge of user behavior from a cognitive stand-point, using multiple information sources. In the starting phase of the research activity, prior to refurbishment, a building survey and an energy audit have been conducted. The building has three floors, underground, ground and first floor, with lecture halls and computer labs, and a glazed atrium in which the students can conduct their individual studies, as shown in Figure 2.

Figure 2: External and internal views of the case study building.

The building zones considered for modeling and their net floor surfaces, together with the maximum allowable number of people, are reported respectively in Table 1 and Table 2. The operating schedules of the building are highly variable, due to the different uses of internal spaces.

Table 1: Use of the internal spaces.

Floor	Name	Type of use	Zone
Underground	MLAB1	Computer lab	1
	MLAB2	Computer lab	
Ground	MTA	Classroom	2
	MTB	Classroom	
	Atrium	Common area	3
First	M1	Aula magna	4

Table 2: Size and maximum number of people of the internal spaces.

Floor	Name	Surface	People $n_{o,max}$
		m^2	-
Underground	MLAB1	151.8	56
	MLAB2	207.9	82
Ground	MTA	178.3	168
	MTB	177.5	168
	Atrium	180.8	56
First	M1	337.5	262

Detailed building energy model

A detailed (white-box) building energy model has been created in EnergyPlus, starting from building survey and energy audit data. The model has been used initially for the generation of probabilistic energy demand scenarios, considering the use of a Demand Controlled Ventilation (DCV) system, using CO_2 concentration data to control the outdoor fresh airflow rate. In order to generate coherent scenarios, operating schedules and simulations settings have been defined according to the scheme reported in Figure 3 and described in detail in previous research work (Tagliabue et al., 2015). Parametric simulation data obtained from this model have been used to train the ANN model, as explained before.

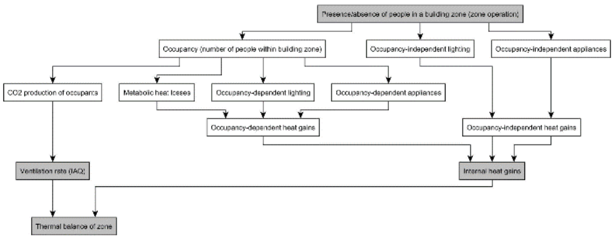

Figure 3: Scheme of the correlation among occupancy schedules and relevant factors affecting thermal balance.

A south-west facing external view of the detailed building energy model is reported in Figure 4.

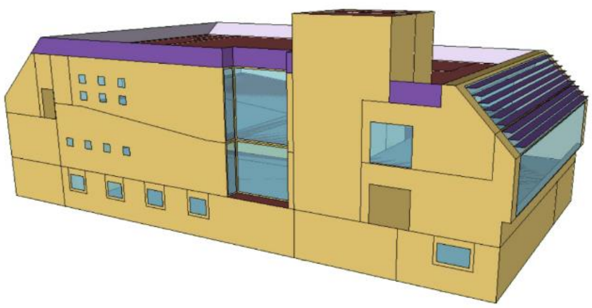

Figure 4: Building energy model in EnergyPlus.

Resistance-Capacitance (RC) building energy model

The simplified (grey-box) model is based on Resistance-Capacitance approach (RC), exploiting the electrical analogy for thermal modeling. Therefore, the model is a lumped parameters model for dynamic hourly simulation and optimization.

The building energy model is formulated following the indication given in international standards (UNI EN ISO 13790; UNI EN ISO 13791; UNI EN ISO13792; UNI EN 15255; 24 ISO 52000). The essential elements of the model are nodes (i.e. temperatures), resistors (i.e. thermal resistances) and capacitors (i.e. thermal capacities). The resistors are necessary to account for heat transfer through construction components and for ventilation. The capacitors are necessary to account for the inertia of construction components. A graphical representation of the model is reported in Figure 5.

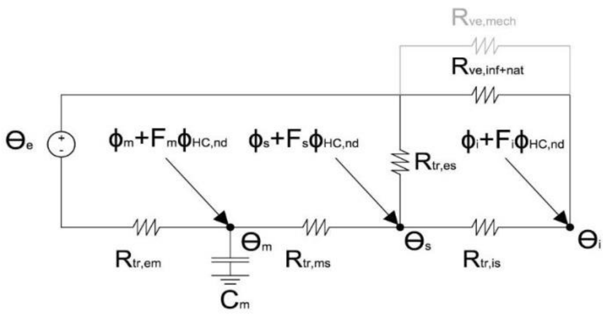

Figure 5: Graphical representation of RC model.

In the graphical representation:

- nodes are:
  - the external air temperature θ_e;
  - the internal air temperature θ_i;
  - the surface temperature θ_s;
  - the mass temperature θ_m.

- resistances are:
  - the mechanical ventilation $R_{ve,mech}$;
  - the natural ventilation and infiltration $R_{ve,nat}$;
  - the transmission due to no inertia elements $R_{tr,es}$;
  - the transmission due to massive elements $R_{tr,em}$ and $R_{tr,ms}$;
  - the transmission due to heat exchange between internal air and the internal surface $R_{tr,is}$.

- capacity is:
  - the global thermal capacity C_m

- heat fluxes are:
  - the solar and internal gains fraction on the internal air node Φ_i
  - the solar and internal gains fraction on the surface node Φ_s
  - the solar and internal gains fraction on the mass node Φ_m
  - the heat flow fraction due to heating/cooling system on the internal air node $F_{i\Phi HC,nd}$
  - the heat flow fraction due to heating/cooling system on the surface node $F_{s\Phi HC,nd}$
  - the heat flow fraction due to heating/cooling system on the mass node $F_{m\Phi HC,nd}$

Generally windows elements are considered to have negligible inertia and the related heat transfer coefficient $H_{tr,es}$ connects directly the external node θ_e to the surface node θ_s. The heat transmission through the massive elements is divided into three parts, respectively $H_{tr,em}$, $H_{tr,ms}$ and $H_{tr,is}$:

- from the external node θ_e to the mass node θ_m;
- from the mass node θ_m to the surface node θ_s;
- from the surface node θ_s to the internal air node θ_i.

The main capacitor of the network represents the lumped global thermal capacity, indicated with Cm. The total solar Φ_{sol} and internal gains Φ_{int} are distributed on the internal air node θ_i, surfaces node θ_s and mass node θ_m using coefficients to account for conductive and radiative heat transfer components; the conductive part is assigned to the internal air node θ_i while the radiative one to the surface θ_s and to the mass θ_m nodes. Similarly, the heat flow due to heating and cooling plant $\Phi_{HC,nd}$ is split into a conductive component, applied to the internal air node θ_i, and a radiative component, distributed to the surface θ_s and mass nodes θ_m according to other factors that are respectively called F_i, F_s and F_m as suggested by the standards (UNI EN ISO 13792; UNI EN 15255). However, these coefficients can be considered as tunable parameter, within certain limits, for example in a model calibration process. The simulation with the RC model requires the construction of coherent operating schedules and settings, similarly to the detailed model and differently from the ANN model, which directly learns from data generated by simulation.

Artificial Neural Network (ANN) model

ANN models for dynamic building performance prediction have already been successfully used in several studies (Paudel et al., 2014; Khayatian et al., 2016). The ANN model used is in this case is a three-layer (input layer-hidden layer-output layer) supervised feedforward network with 59 sigmoid hidden neurons and linear output neurons. The best performing layout has been selected based on the lowest Mean Square Error (MSE) in an automated way. The network used to predict heating demand has a 6 input hourly dataset and 1 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 ANN was trained using the Bayesian regularization method and the split of the dataset between training and testing was respectively 75% and 25%. The determination coefficient R^2 obtained by ANN is 0.819 for the training set, 0.812 for the test set, 0.818 for the whole dataset, as reported in Figure 6. R^2 coefficient represents the goodness of fit of the model (maximum value is 1). These values are in line with the ones found in other research studies on dynamic neural network used for heating prediction (Khayatian et al., 2016), which however use additional pseudo dynamic parameter inputs (to improve computing performance and reduce network dimension) that require a priori knowledge of occupancy patterns, while in this case we consider a training process directly on simulation data.

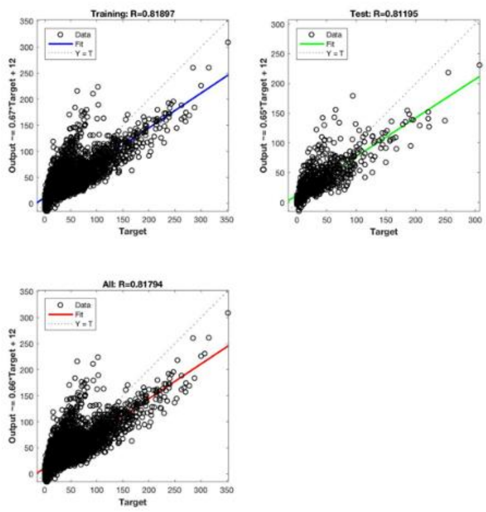

Figure 6: Training and testing of ANN for heating demand prediction

Monte Carlo simulation of RC and ANN models

Monte Carlo (MC) simulation is one of the most powerful techniques in modern probabilistic analysis. MC methods rely on repeated random sampling to obtain numerical results. By means of MC simulations it is possible to:

1. define a domain of possible model inputs;
2. generate inputs randomly from a probability distribution over the domain;
3. perform a deterministic computation of model outputs;
4. aggregate results and analyze their statistical distribution.

In this research MC simulations have been used to measure how the uncertainty in users' behavior (occupancy patterns) affects heating energy demands calculate by means of RC model and ANN.

Following case studies in literature and previous research work (Tagliabue et al., 2015) we decided to use triangular probability density functions for occupancy. However, differently from to the original simulation work, aimed at exploring highly variable occupancy scenarios, the schedules have been constructed by differentiating the value of the triangular probability distributions in three time intervals, from 9am to 10am, from 11am to 4pm and from 5pm to 7pm. The values assumed in this work are based on the following assumptions:

1. from 9am to 10am:
   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 11am to 4pm:
   a. minimum value, the corresponding minimum deterministic occupancy pattern;
   b. mode, the corresponding maximum deterministic occupancy pattern;
   c. maximum value, the corresponding maximum deterministic occupancy pattern;
3. from 5pm to 7pm:
   a. minimum value, the corresponding minimum deterministic occupancy pattern;
   b. mode, the corresponding 3rd quartile of deterministic occupancy pattern;
   c. maximum value, the corresponding maximum deterministic occupancy pattern.

The results obtained by using MC technique with RC and ANN models are described in the following section.

Results and discussion

MC simulations have been used to compute a probabilistic distribution of energy demand, using both RC and ANN models, as a function of uncertainty in occupancy patterns, The relation among occupancy patterns and energy balance is described in Figure 3. Both models proved to be suitable in MC simulation because they are much less computational time than detailed energy simulations and provide reliable results if compared to the ones given by Energy Plus.

Main results are shown in Figure 7 (RC as surrogate model) and in Figure 8 (ANN as surrogate model) where the Cumulative Distribution Function (CDF) of heating demand computed with MC simulations is depicted and compared with a Gaussian distribution having the same mean and standard deviation of MC results.

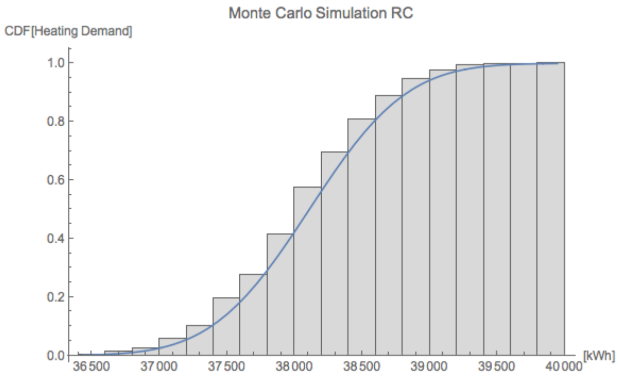

Figure 7: Cumulative Distribution Function of heating demand computed with MC simulation using the RC model compared to a Gaussian with the same mean and standard deviation (blue line).

The small difference in the mean value between the two MC simulations is due to the overestimation of heating energy demand when the demand is small (at the very beginning or at the end of the heating period) made by the ANN. A better tuning of the RC model parameters may also reduce the difference between the two means.

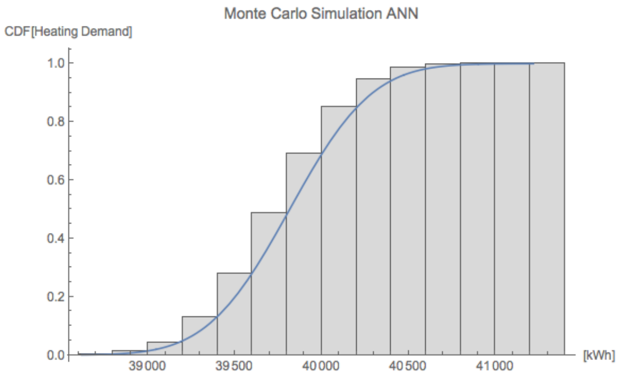

Figure 8: Cumulative Distribution Function of heating demand computed with MC simulation using the ANN compared to a Gaussian with the same mean and standard deviation (blue line).

The quantiles of the results of MC simulation are reported in Table 3 and compared in Figure 9. This figure highlights the fact that while ANN can be used effectively to reproduce the results of a detailed dynamic model (EnergyPlus) and RC can be used to calculated dynamic performance producing a similar interval of results, the assumptions on model parameters can produce a misalignments in the data. It is therefore necessary to define strategies to improve the alignment of results computed by the different models, using appropriate data parametrization and metrics (Yang and Becerik-Gerber, 2015).

Table 3: Heating Demand Quantile computed using ANN and RC model

	RC	ANN		RC	ANN
	kWh	kWh		kWh	kWh
5%	37,156	39,221	**55%**	39,863	38,166
15%	37,513	39,435	**65%**	39,954	38,315
25%	37,745	39,568	**75%**	40,067	38,485
35%	37,892	39,673	**85%**	40,195	38,713
45%	38,039	39,766	**95%**	40,418	39,009
50%	38,095	39,813			

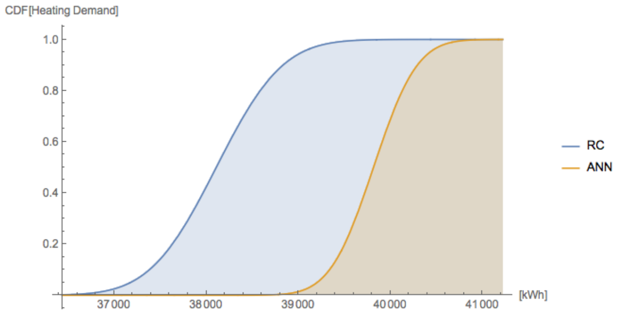

Figure 9: Comparison between heating demand CDF computed with Monte Carlo simulation using RC model and ANN

Conclusion

The objective of the research work was assessing the feasibility, reliability and robustness of the use of surrogate models to compute energy performance in highly variable conditions. In the research presented, surrogate models have been used to compute efficiently the dynamic energy performance of buildings in presence of highly variable occupancy patterns. These techniques are therefore suitable for the analysis of the impact of end-users' behaviour already from the design phase, identifying probabilistic performance boundaries. The proposed approach aims to ensure a more efficient use of the parametric simulation data generated in the design phase by means of semi-automated/automated modeling tools. Despite the similar ranges of results obtained by the two models, RC and ANN, the research highlighted how further work should be oriented to the definition of appropriate strategies for the alignment of results computed by different models, potentially suitable for multiple applications across building life-cycle phases. These strategies could be based on the definition of macro-parameters and multi-level metrics, as shown in recent research work in the field of model calibration.

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