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TUNING ENERGY PERFORMANCE SIMULATION ON BEHAVIOURAL VARIABILITY WITH INVERSE MODELLING: THE CASE OF SMART CAMPUS BUILDING

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Abstract
In order to establish a reliable model of occupants' interactions with indoor environment, a method accounting for stochastic factors is used. The result is no more a "single value" for the system performance, but a probability to fulfil a certain performance over time. In this way, occupant behaviour is not deterministic (e.g. the opening of windows when indoor temperature exceeds a threshold value) but coupled with a probability to perform an action.
The proposed approach is built upon continuous measurements of both indoor environmental parameters and external climate conditions along with the behaviour of the building occupants (such as window opening, thermostat radiator valve, set point temperatures, occupancy sensors, etc.), performed in a sufficient number of areas and rooms representing different interaction zones in the case study. The monitoring period can range from medium (i.e. one week better if repeated in different seasons) to long-term periods (i.e. a year). The simple measurement of time series of physical quantities (such as relative humidity, temperature, pollutant concentrations, luminance, etc.) generates huge amounts of data that can be hard to "translate" directly into a behavioural model. In order to overcome these barriers, different suitable models can be defined using statistical techniques such as logistic regression and Markov chains.
The various occupancy profiles are then inserted into the chosen dynamic simulation software. A monitoring and control scheme that detects users' occupancy, lighting levels, temperature, humidity, CO_2 and manages HVAC system settings has been designed and installed. This system has been design to enable a faster "as-built" energy model calibration, using data from commissioning and early occupancy phases.
Therefore, the actual measurement in the building will give the possibility of extracting useful information to calibrate the building energy model with a probabilistic behavioural model fitted to real metered data through inverse modelling.

Keywords:
Probabilistic approach, behavioural variability, energy performance, inverse modelling

1 INTRODUCTION

The relevant gap between simulated and measured energy performance can be fundamentally caused by design phase, construction phase, commissioning and operational phase errors [1]. In the design phase, on the modelling side, errors are mostly connected to biased assumptions (generally optimistic) on building components and subsystems. Further, the large variability of technological solutions, end-uses and behavioural patterns [2] within the built environment makes it very difficult to define a unified and yet flexible modelling approach. With respect to behavioural patterns in particular, the

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relation among parameters related to occupancy, such as air change rates and internal heat gains (i.e. due to people, lighting and equipment), can be determined by means of statistical modelling approaches when sufficient data are available [3-5]. It is thus necessary to unveil, even in the design phase, the potential impact of the variability of occupants' behaviour on energy performance [6]. This can be seen as an "occupant proofing" process from building performance simulation standpoint, able to clarify the role of occupants in gaining a high level of energy performance. In fact, modelling assumptions can become an issue (in terms of robustness and risk) when predicting future performance, especially in techno-economic feasibility evaluations such as cost-optimal [7] and life cycle cost (LCC) analyses, which are crucial for the definition of energy efficiency investments, or energy performance contracting (EPC). These issues can be uncertain thermal characteristics of the building fabric, of the technical systems, variable operational patterns, uncertain level of internal environmental quality (e.g. indoor air quality), etc. In a general sustainability perspective, the environmental and economic impacts related to energy demand, although described with different performance indicators, are strictly correlated with the social (and behavioural) dimension of the problem (environment, economy and society are the three pillars of sustainability). This dimension is represented by the type of activities within the built environment and by the internal environmental quality (e.g. air quality, thermal comfort, visual comfort, etc.), perceived by the occupants [8], that ultimately determines the "success" or "failure" of a built environment itself with respect to its scope.

2 METHODOLOGY

The methodological approach is applied to the initial energy modelling phase (design phase for the building refurbishment) and is conceived to be extended and validated during building operation, by means of a performance monitoring system aimed for detailed data acquisition; data that will be analysed to address relevant technical issues, generally encountered in model calibration [9-13]. The research work aims, in general, at integrating direct and inverse modelling techniques [14-16] (i.e. establishing a continuity between modelling practices used in the design phase and model calibration techniques in the building operation phase). Actually, the availability of validated and calibrated building energy models is fundamental to explore accurately efficiency measures and optimized operational strategies during the whole building lifecycle, considering also the economic counterparts in terms of investment and operating costs (either for new construction or refurbishment), which can determine whether a project is feasible or not. The probabilistic modelling approach starts from basic building survey and energy audit data, together with assumptions about building occupancy similar to other studies [17-19].

3 THE SMART CAMPUS BUILDING

The ongoing multidisciplinary research on the Smart Campus Building of the University of Brescia, Italy [20-21], involves several topics ranging from BIM (Building Information Modelling) to BEM (Building Energy Modelling), performance optimization, performance monitoring/tracking and optimal control. In this paper, the focus is the probabilistic modelling of occupancy within the building, considering the effects in terms of energy performance and the problem of model calibration and anomaly detection in the early monitoring phase, after the refurbishment. The building is used as a field testing of the multi-disciplinary research initiative "Smart Campus School Project" carried out by the University of Brescia to show the potential for building refurbishment with smart technologies, considering technological and behavioural learning problems. 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 (Fig. 1).

Fig. 1: Interior views of the building.

The considered building zones are described synthetically in table 1.

Floor	Name	Typology
Underground	MLAB1	Computer lab
	MLAB2	Computer lab
Ground	MTA	Classroom
	MTB	Classroom
	Atrium	Common area
First	M1	Aula magna

Table 1: Use of the internal spaces.

A south facing external view of the building and of the BEM model are reported in Fig. 2 and Fig. 3.

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Fig. 2: Brescia Smart Campus Building, Italy.

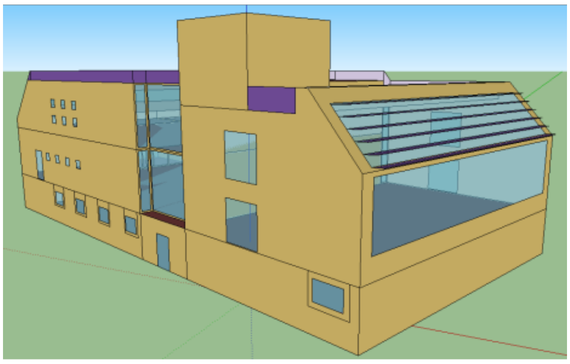

Fig. 3: Building energy model in EnergyPlus.

After zoning, we determined the operational state and the occupancy of the zones on the basis of a sample weekly operation schedule. The use of the lecture halls is intensive but the actual attendance to the lectures hasn't been measured continuously up to now, but it will be monitored by person counters and data collected in the next weeks.

4 RESEARCH METHODOLOGY

4.1 Building spaces and users

In the starting phase of the research activity, a building survey and an energy audit have been conducted, to identify the maximum allowable people occupancy for the different zones. Data is reported in table 2.

Floor	Name	Surface [m^2]	Users $n_{o,max}$
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

Table 2: Size and users of the internal spaces.

4.2 Probability distribution

The maximum people number $n_{o,max}$ has been considered for the generation of occupancy scenarios, using a triangular probability distribution (min = 0,3 $n_{o,max}$, mode = 0.6 $n_{o,max}$, max = 1.0 $n_{o,max}$).

In synthesis, while the standard simulation assumes a fixed people density, the probabilistic one simulates the profiles generated by means of a triangular probability distribution and sets the user dependent parameters accordingly. Given the probabilistic nature of the outcomes, the results will be represented by (similarly to a boxplot graphical method):

- minimum
- first quartile (25% of simulation data)
- median (50% of data)
- third quartile (75% of simulation data)
- maximum

The results are compared to a standard calculation (with standard data for the educational use of the building).

4.3 Monitoring and inverse modelling

A continuous monitoring phase (started recently) and the following analysis will be carried out in the next months and years. However, criteria to enable a methodological continuity between direct and inverse modelling are provided in this research stage (Fig. 4). The sensor data will enable the calibration of the building energy model, including occupant's behaviour. In the case study considered, the people counters will be crucial to verify the real occupants' number during the different periods of the year and CO_2 concentration sensors will be used for the control of the mechanical ventilation system (e.g. modulation of airflow handled by AHUs by means of a stepped or continuous control logic). Further, the CO_2 sensors will provide detailed information about actual indoor air quality, enabling the inverse estimation of the number of people within a certain zone. Another inverse modelling strategy will be based on multiple linear regression model, used to estimate influential parameters [22,23] and to calibrate progressively the building energy model by estimating inversely macro-parameters. The starting point can be considered the use of weather-adjusting visualization [24].

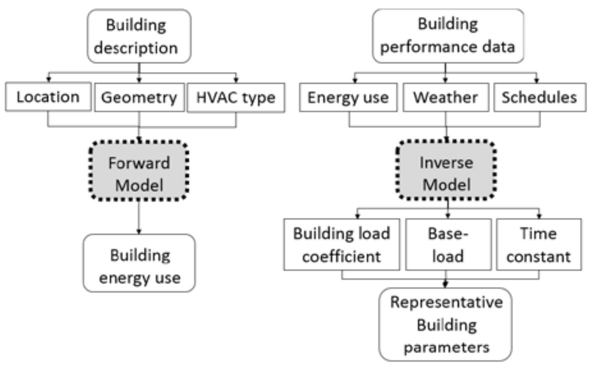

Fig. 4: Basic approach of a typical forward energy analysis model (left) and of a typical inverse energy analysis model (right).

The list of installed sensors is reported in table 4.

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Con trol	Function	Sensor typology	Type	N.
Lighting	Presence	Presence	L_1	24
	Daylighting control	Luminance	L_2	4
Ventilation	Air control	Inlet air temperature	V_1	15
		Outdoor air temperature	V_2	8
		Relative humidity	V_3	9
Heating	Emission control	Presence, CO_2, ventilation and conditioning damper	H_1	18
Cooling	Emission control	Presence, CO_2, ventilation and conditioning damper	C_1	18

Table 4: Installed sensors: Typology.

4.4 Modelling approach

The used modelling approach considers the strict interaction between occupants' behaviour and building performance, focusing primarily on the following fundamental aspects:

- thermal comfort (i.e. set-point for heating and cooling)
- internal air quality (e.g. CO_2 concentration)
- internal heat gains (i.e. occupancy, equipment and lighting)
- electricity consumption

This does not imply the use of complex models, but rather the use of simple but coherent assumptions in a probabilistic framework. The number of occupants, appliances and lighting power are generated according to a probability distribution. The main variables are:

- presence/absence of people in a building zone (0-1, binary variable, e.g. a lesson in a classroom)
- variable percentage of occupants within the building zone (from minimum to maximum value assumed, following a probabilistic distribution)
- assumption for the calculation of air change rate (CO_2 concentration due to occupancy)
- internal gains dependent on occupancy (number of people, appliances, lighting);
- internal gains independent by occupancy (appliances, lighting)
- electricity consumption dependent/ independent on occupancy (appliances and lighting)

The proposed probabilistic simulation approach aims to extend the current design procedures for energy simulation, based on deterministic criteria, to more general stochastic ones [25,26]. In the research, a fixed internal distribution of functions (fixed end-use for different zones) is assumed (given the characteristics of the case study).

5 RESULTS

The variability of the daily thermal energy demand for heating and cooling is reported in Fig. 5 and Fig. 6. The results show the potentially large variability in the daily energy need for heating and cooling in the different operating scenarios and the difference from the standard calculation that underestimates the cooling demand and overrates the heating demand (due to internal gains and ventilation rates). The variability considered in internal operation patterns is particularly large and is aimed at exploring also pessimistic operation scenarios. Starting from this data, it will be possible in the operation phase to compare graphically simulated data and measured data and to characterize the average thermal gains due to people occupancy (knowing also the amount of electricity demand for different uses within the building) using multivariate regression. This strategy is simple compared to a detailed definition of occupancy probability distribution determined directly from data but can be very effective for performance control. In the envelopment of the simulation conditions considered (Fig. 7), the hourly consumption patterns, differently from the daily patterns, can show critical peak conditions, the potential for free-cooling and occupancy variability (graphical methods). The deterministic, code compliance based, way to account for occupancy patterns in energy modelling is not realistic, because it doesn't give enough information with respect to the variability of the performance determined by occupants.

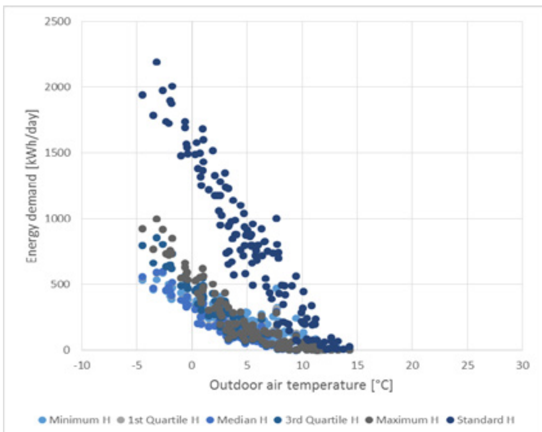

Fig. 5: Heating energy demand vs outdoor air temperature.

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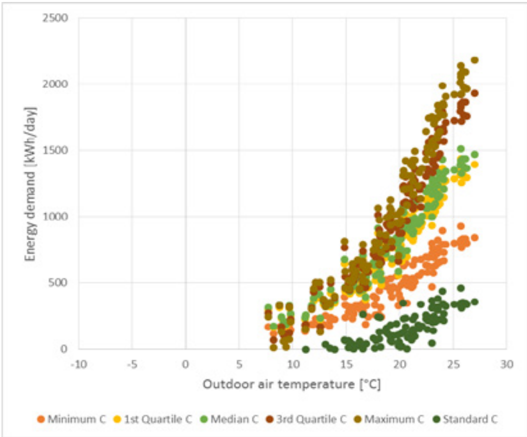

Fig. 6: Cooling energy demand vs outdoor air temperature.

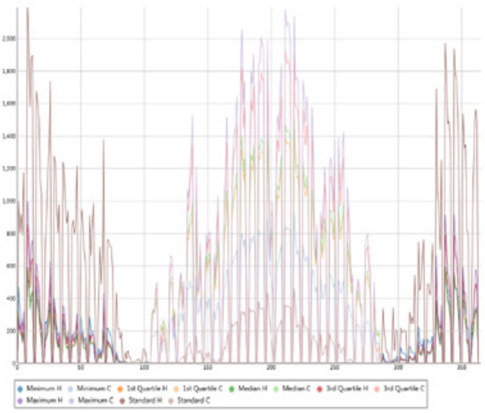

Fig. 7: Energy demand envelopment for the tested occupancy profiles.

6 DISCUSSION

Occupancy patterns' variability contributes (among other factors) to the wide performance gap between predicted and real conditions. A parametric or probabilistic simulation strategy could partially respond to the issue, coherently with the premises to adopt a more representative modelling strategy, suitable for design phase analysis. Subsequently, inverse modelling techniques should be used to calibrate the building model during building operation in order to progressively give more consistency to model output data, i.e. by reducing their gap with respect to measured data. For this reasons continuous monitoring is necessary to ensure adequate performance, and to validate the approach applied in the design phase [27], nonetheless the possibility to evaluate the impact of occupants from the very beginning constitutes an important improvement over current practices.

7 CONCLUSIONS

At the core of the research approach there is the effort to provide a continuity in the workflow among design phase, simulation models and procedures to tune energy models with data collected in the operation phase, i.e. calibration. More in general, the scope of the multidisciplinary research on the Smart Campus Building is to bridge, on the one hand, the gaps traditionally separating the design and energy simulation domains and, on the other hand, the gaps between simulated and measured building performance, in real time operation, for optimal control and energy management.

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9 REFERENCES

1. De Wilde P., The gap between predicted and measured energy performance of buildings: A framework for investigation, Automation in Construction, 41 (2014) 40-49.

2. Li C., Hong T., Yan D., An insight into actual energy use and its drivers in high-performance buildings, Applied Energy, 131 (2014) 394-410.

3. Zhao J., Lasternas B., Lam K.P., Yun R., Loftness V., Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining, Energy and Buildings, 82 (2014) 341-355.

4. D'Oca S., Hong T., Occupancy schedules learning process through a data mining framework, Energy and Buildings, 88 (2015) 395-408.

5. D'Oca S., Hong T., A data-mining approach to discover patterns of window opening and closing behavior in offices, Building and Environment, 82 (2014) 726-739.

6. Feng X., Yan D., Hong T., Simulation of occupancy in buildings, Energy and Buildings, 87 (2015) 348-359.

7. Corgnati S.P., Fabrizio E., Filippi M., Monetti V., Reference buildings for cost optimal analysis: Method of definition and application, Applied Energy, 102 (2013) 983-993.

8. Menezes A.C., Cripps A., Bouchlaghem D., Buswell R., Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap, Applied Energy, 97 (2012) 355-364.

9. Coakley D., Raftery P., Keane M., A review of methods to match building energy simulation models to measured data, Renewable and Sustainable Energy Reviews, 37 (2014) 123-141.

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DOI 10.3218/3774-6_23, ISBN 978-3-7281-3774-6, http://vdf.ch/expanding-boundaries.html

10. Fabrizio E., Monetti V., Methodologies and Advancements in the Calibration of Building Energy Models, Energies, 8 (4) (2015) 2548-2574.

11. Manfren M., Aste N., Moshksar R., Calibration and uncertainty analysis for computer models – A meta-model based approach for integrated building energy simulation, Applied Energy, 103 (2013) 627-641.

12. Rodríguez G.C., Andrés A.C., Muñoz F.D., López J.M.C., Zhang Y., Uncertainties and sensitivity analysis in building energy simulation using macroparameters, Energy and Buildings, 67 (2013) 79-87.

13. Yang Z., Becerik-Gerber B., A model calibration framework for simultaneous multi-level building energy simulation, Applied Energy, 149 (2015) 415-431.

14. Krarti M., Weatherization and energy efficiency improvement for existing homes: an engineering approach, CRC Press (2012).

15. Reddy T.A., Applied data analysis and modeling for energy engineers and scientists, Springer Science & Business Media (2011).

16. Tronchin L., Manfren M., Tagliabue L.C., Multi-scale analysis and optimization of building energy performance–Lessons learned from case studies, Procedia Engineering 118 (2015) 563 – 572.

17. Macdonald I., Strachan P., Practical application of uncertainty analysis, Energy and Buildings, 33 (3) (2001) 219-227.

18. Macdonald I.A., Quantifying the effects of uncertainty in building simulation, University of Strathclyde (2002).

19. Hopfe C.J., Hensen J.L., Uncertainty analysis in building performance simulation for design support, Energy and Buildings, 43 (10) (2011) 2798-2805.

20. De Angelis E., Ciribini A., Tagliabue L.C., Paneroni M., The Brescia Smart Campus Demonstrator. Renovation toward a zero energy classroom building, Procedia Engineering, 118 (2015) 735-743.

21. Tagliabue L.C., Manfren M., De Angelis E., Energy Efficiency Assessment Based on Realistic Occupancy Patterns Obtained Through Stochastic Simulation, in: M.R. Thomsen, M. Tamke, C. Gengnagel, B. Faircloth, F. Scheurer (Eds.) Modelling Behaviour, Springer International Publishing (2015) pp. 469-478.

22. Masuda H., Claridge D., Estimation of building parameters using simplified energy balance model and metered whole building energy use, Proceedings of the Twelfth International Conference for Enhanced Building Operations, (2012) Manchester, UK, October 23-26.

23. Paulus M.T., Claridge D.E., Culp C., Algorithm for automating the selection of a temperature dependent change point model, Energy and Buildings, 87 (2015) 95-104.

24. Lin G., Claridge D.E., A temperature-based approach to detect abnormal building energy consumption, Energy and Buildings, 93 (0) (2015) 110-118.

25. Parys W., Saelens D., Hens H., Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices – a review-based integrated methodology, Journal of Building Performance Simulation, 4 (4) (2011) 339-358.

26. Parys W., Souyri B., Woloszyn M., Agent-based behavioural models for residential buildings in dynamic building simulation: state-of-the-art and integrated model assembly, in: M.R. Thomsen, M. Tamke, C. Gengnagel, B. Faircloth, F. Scheurer (Eds.) Modelling Behaviour, Springer International Publishing (2015) pp. 339–358.

27. Bynum J.D., Claridge D.E., Curtin J.M., Development and testing of an Automated Building Commissioning Analysis Tool (ABCAT), Energy and Buildings, 55 (0) (2012) 607-617.

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