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Building performance monitoring: from in-situ measurement to regression-based approaches

Lamberto Tronchin[1,*], Massimiliano Manfren[2], Vincenzo Vodola[1], Benedetto Nastasi[3]

[1] Department of Architecture (DA), University of Bologna, Via Cavalcavia 61, 47521 Cesena, Italy
[2] Faculty of Engineering and Physical Sciences, University of Southampton, Highfield, Southampton SO17 1BJ, United Kingdom
[3] Department of Architecture Engineering & Technology (AE+T), TU Delft University of Technology, Julianalaan 34, 2628BX Delft, The Netherlands
[*] lamberto.tronchin@unibo.it

Abstract. Simple and robust data analysis methodologies are crucial to learn insights from measured data and reduce the performance gap in building stock. For this reason, continuous performance monitoring should become a more diffuse practice in order to improve our design and operation strategies for the future. The research presented aims to highlight potential links between experimental approaches for test-facilities and methods and tools used for continuous performance monitoring, at the state of the art. In particular, we explore the relation between ISO 9869:2014 method for in-situ measurement of thermal transmittance (U) and regression-based monitoring approaches, such as co-heating test and energy signature, for heat load coefficient (HLC) and solar aperture (gA) estimation. In particular, we highlight the robustness and scalability of these monitoring techniques, considering relevant issues in current integrated engineer design perspective. These issues include, among others, the necessity of limiting the number of a sensors to be installed in buildings, the possibility of employing both experimental and real operation data and, finally, the possibility to automate and perform monitoring at multiple scales, from single components, to individual buildings, to building stock and cities.

1. Introduction

Simple and robust data analysis methodologies are crucial to learn insights from measured data and reduce the performance gap in building stock [1], considering also the relevant impact of human behaviour [2]. For this reason, continuous performance monitoring should become a more diffuse practice in order to improve our design and operation strategies for the future [3, 4] and to handle the energy transition in existing buildings [5]. The research presented aims to highlight potential links between experimental approaches for test-facilities and methods and tools used for continuous performance monitoring, at the state of the art, considering also possible extensions with advanced computing tools [6]. Linking transparently design phase performance estimates and measured data in operation is a major challenge today [7], requiring a careful consideration of the underlying uncertainties. Furthermore, energy retrofitting strategies driven by detailed modelling and comparison with benchmarks is still not common practice, creating in some cases increased operation cost [8] and lack of trust in building performance simulation tools. Data analysis techniques can offer deeper insights of building performance and their effects on occupants [9] as well as indoor microclimatic conditions [10], including aspects such as lighting and acoustics [11], among others. In this paper we concentrate on energy monitoring, with respect to indoor/outdoor temperature and solar radiation conditions. At present Building Energy Management Systems (BEMS) can be used to evaluate building performance dynamically, acting when the control variables reach target values, and basically collecting data on a continuous base. A typical case is energy system control linked to external temperature to lower energy

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consumption by means of technologies such as heat pumps [12] or more complex hybrid systems [13]. Control logic behind BEMS is essential in managing renewable energy effective integration in terms of direct use [14] or when interacting with storage facilities to achieve optimal operation strategies [15]. In all these cases, the ability to define a robust underlying model for optimization is crucial. While black-box approaches are possible [16], we consider more appropriate the choice of grey-box (i.e. physical-statistical) approaches, to learn useful insights from data and to link current state of the art approach for component scale [17] and building scale analysis [18].

2. Overview on building performance monitoring techniques

In this research we aim to explore in particular the relation between ISO 9869 [19] method for in-situ measurement of thermal transmittance (*U*), as well as its extensions [20], together with regression-based monitoring approaches, such as co-heating test [21] and energy signature [22, 23], for heat load coefficient (*HLC*) and solar aperture (*gA*) estimation [24, 25]. All these approaches are already consolidated at the state of the art but further efforts are necessary for their seamless integration, in particular with respect to the comparability of measurements with design phase simulations. The importance of creating standardized procedure for large scale statistical analysis of building data has been stressed by institutions such as NIST (National Institute of Standards and Technology) in the US [26]. In fact, in the next few years, the possibility of collecting and processing data at large scale will be crucial for informing future policies for built environment [27].

3. Modelling research developments

In the previous Section we highlighted a certain degree of continuity in the monitoring approaches for buildings, basically following a bottom-up logic, from individual construction components (U value), to building fabric assembly (HLC), up to the meter level (energy signature). In the following sections we will describe first (Section 3.1) the analogies among methods from U value estimation up to energy signature, including some potential advances to enhance comparability of results across multiple scales of analysis. After that (Section 3.2) we will present an example of visual representation of the integration of different monitoring methodologies. The general goal of this discussion on modelling research developments is highlighting the potential scalability of monitoring techniques and the need for harmonization of experimental procedures to increase robustness of estimates (which dependents critically on the amount and quality of data collected) and reduce cost. In fact, modelling research developments can help limiting the number of sensors to be installed in buildings, and can exploit the possibility of employing both measurements in experimental phase (production/commissioning) and operation (continuous commissioning).

3.1. From in situ measurement to regression-based approaches

In this section briefly the steps necessary to link U value estimation, HLC estimation and energy signature. First of all we consider the averaging method proposed by the standard is reported in Equation 1:

$$U = \frac{\sum_{t=0}^{n} q_{in,n}}{\sum_{t=0}^{n} \Delta T_{n}} \tag{1}$$

where U (W/m^{2}K) is thermal transmittance experimentally determined using ISO 9869, q_{in} (W/m^2) is the heat flux entering in the wall, n is the number of data points, $\Delta T = T_i - T_e$, T_i (°C) is internal air temperature, T_e (°C) is external air temperature.

If we consider then the daily average heat flux (instead of instantaneous measurements for a single component) to maintain a thermal zone in constant internal temperature conditions, we can formulate a simplified representation of the energy balance of the zone as shown in Equation 3. This equation corresponds to simplification used in co-heating test method [21]:

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$$q_h = HLC\Delta T - gA_{sol}I_{sol} - q_{int} \tag{2}$$

where q_h (kW) is average daily heat flux, *HLC* (W/K) is heat loss coefficient, gA_{sol} (m2) is solar aperture, I_{sol} is the average daily solar irradiation (on horizontal or south plane), q_{int} (kW) is average daily heat flux due to internal gains (people, light, appliances). gA_{sol} parameter is a very approximated estimation of the actual solar geometry of the building, as it is highly dependent on the orientation chosen for I_{sol} (horizontal or south).

Assuming the possibility of performing measurement without internal gain (q_{int}=0), we can reduce Equation 2 to Equation 3, which may be fit with a linear bivariate regression with intercept equal to 0.

$$q_h = HLC\Delta T - gA_{sol}I_{sol} \tag{3}$$

If we then divide both sides of Equation 3 by ΔT we obtain Equation 4, which represents an alternative formulation of co-heating test. The left side of this equation is similar in principles to Equation 1. This property has been exploited in recent research [24, 25] to estimate the value of *HLC* with a dynamic averaging method conceptually similar to the one proposed by ISO 9869 for individual components.

$$\frac{q_h}{\Delta T} = HLC - gA_{sol}\frac{I_{sol}}{\Delta T} \tag{4}$$

Finally, we can use the same measurements to obtain an energy signature model [22], represented in Equation 5:

$$q_h = a(T - T_{bp}) \tag{5}$$

where *a* is the slope of the linear regression (negative for heating), T_e represent daily average external air temperature and T_{bp} represent balance-point temperature (q_h = 0).

Energy signature uses regression, without assuming internal air temperature as an input, and can be used for inexpensive long term monitoring. For this approach also an approximated physical interpretation of the coefficients can be found in literature [18]. Therefore, energy signature can essentially complement (for long-term monitoring) co-heating test, which needs measures of indoor air temperatures as an input and short term measurements under controlled conditions. Further, extensions of this methodology can be achieved by means of integration with variable-base degree-days method, as shown in recent literature [28], potentially extending the applicability for large scale energy system planning [27].

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3.2. An example of visual representation of the integrated modelling methodology

In order to give a practical example of the integration of the different models reported above, we take simulation data of heating energy demand (energy needs) from a simulation model previously calibrated on measured data [7]. We use these data (daily average heat flux need to maintain the thermal zone in constant operating conditions) to create two plots against ΔT and I_{sol}, respectively in Figure 1 and 2, to highlight correlations. The range of daily average outdoor air temperatures consider is between 8 and 13 °C, with corresponding average daily solar flux data.

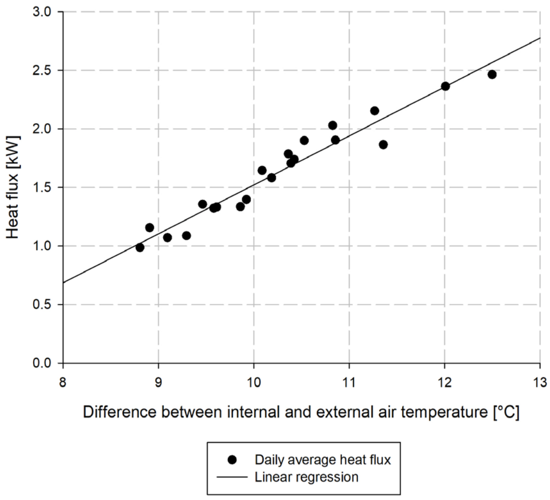

Figure 1. Daily average heat flux with respect to difference between internal and external air temperature

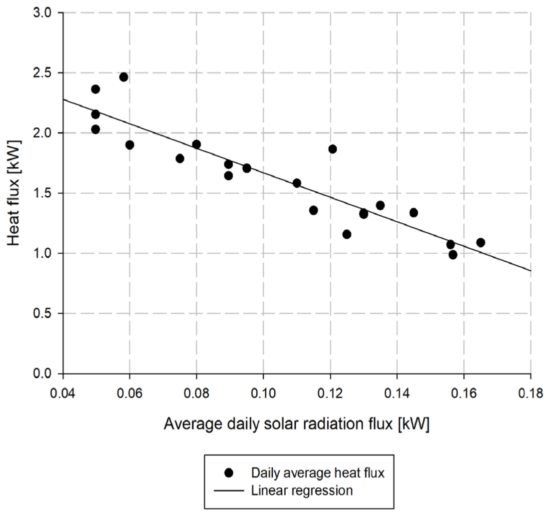

Figure 2. Daily average heat flux with respect to average daily solar radiation flux

This model representation corresponds to the simplified energy balance in Equation 3. In this case we consider two separate scatter-plots with a univariate regression to highlight the basic trends in data, but the actual model is a multivariate regression with q expressed as a function of ΔT and I_{sol}. Indeed, this model can represented with 3D graph as a plane. Finally, for the same data we plot daily average flux against external air temperature in Figure 3. This approach corresponds to Equation 5 where T_{bp} is the intercept on the x axis (daily average heat flux = 0).

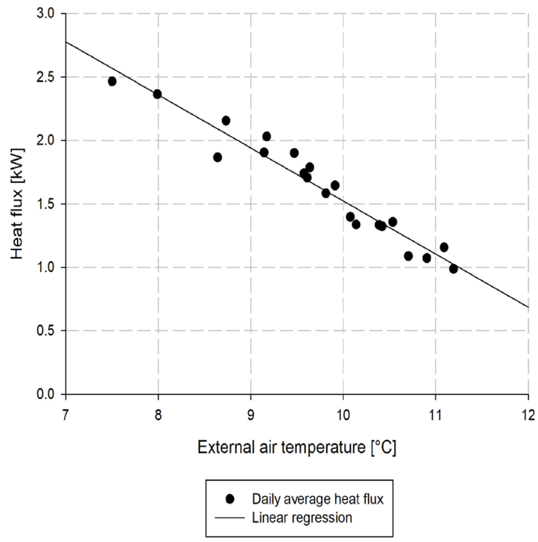

Figure 3. Daily average heat flux with respect to external air temperature

In this way, we can think about these modelling techniques as different steps of a unified approach for performance monitoring across life cycle phases. Of course, the approach proposed can be improved, in particular, in terms of identification of daily dynamic components of energy balance in regression formulations [29], extension to hourly regression models and, finally, by linking this approach transparently with surrogate modelling techniques to be used already in the design phase [7] to fit multiple possible building design and operation conditions.

4. Conclusion

In this research we presented an overview of building performance monitoring methodologies, following a bottom-up perspective, from individual components up to the system level. We highlighted a potential continuity among different methodological approaches acting on different scales. However, further research efforts should be devoted to harmonization and experimental analysis, as all these approaches depend critically on the quantity and quality of data, essentially providing boundaries for reliable estimation of design and operation performance. This can lead to an integrated strategy for continuous performance improvement based on a constant feed-back from data at multiple levels. Clearly, in order to exploit the potential advantages, it is necessary to automate data acquisition and processing procedures (in terms of computing tools and rules) at multiple scales, from single components, to individual buildings and to building stock and cities.

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