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Energy analytics for supporting built environment decarbonisation

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Abstract

The identification of techno-economically feasible decarbonisation paths and sustainability transitions for the built environment is a necessary task for research today and building stock renovation processes can act in synergy with innovative economic and technological development paradigms to achieve different types of benefits such as economic growth and employment, together with resource efficiency and sustainability for the whole sector. The research presented aims at selecting the most relevant data analysis processes and techniques to respond to practical technical questions and to support decision-making in the built environment, at multiple scales of analysis, from individual buildings, to building stock and urban environment. The research aims to indicate in this way the possibility to join the micro-scale view, involving technological and behavioral issues in buildings, and the macro-scale view, involving strategic problems at market and policy levels for energy and sustainability planning. Further, the combined use of modelling techniques with large scale data acquisition and processing could guarantee multiple feed-backs from measured data, useful for the evolution, first of all, of design and operation practices in building but also, more in general, of the whole value chain of the sector. A synthesis and integration of modelling methodologies is presented through case studies, showing a path to improve transparency of performance assessment across building life cycle phases. Finally, multivariate data visualization techniques are presented to ease wider applicability of the described numerical techniques.

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Keywords: parametric modelling; behavioural modelling; building performance simulation; energy efficiency; techno-economic optimization.

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1. Introduction

Buildings have a great impact in terms of carbon emission at the EU [1], US and global scale [2]. At EU level, for example, building accounts for approximately 40% of carbon emission, determined by their direct energy use, and a larger impact if we consider the direct and indirect use of resources. Different modelling approaches at the state of the art can be used for extracting useful insights for the support of building stock renovation processes, dealing with relevant technical issues. A detailed discussion on the suitability of energy modelling approaches with respect to multiple criteria can be found in literature [3]. Energy efficiency measures can create multiple advantages [4], but the increase of efficiency of energy systems strengthens the interdependency between design and operational optimization with an impact at multiple scales, from individual technologies, to single buildings, to building stock and infrastructures [5]. This higher interdependency determines the need for formalized rules in optimization based approaches for energy research and practical applications [6], as well as the need for larger quantities of specific data for effective deployment of innovative strategies for built environment [7]. For this reason, a tight integration and comparability among different models is the focus of research. We should be able to pass from models to simulated data (model output, forward approach) and from measured data back to models (model input, inverse approach), in multiple ways, implementing effectively cycles of continuous improvement as well as its cost-benefit tradeoff [8].

Nomenclature

Variables and parameters

A	average value	R^2	determination coefficient
a,b,c,d,e,f	regression coefficients	RD	relative deviation
$C_v(RMSE)$	coefficient of variation of $RMSE$	$RMSE$	root mean square error
g	solar gain factor	S	simulated
H	heat transfer coefficient	SS	sum of the squares
I	solar radiation	y	numeric value
$NMBE$	normalized mean bias error	Δt	time interval
q	specific energy transfer rate (thermal power)	η	heat sinks/source factor
Q	heat transfer	θ	temperature
R	regression value		

Subscripts and superscripts

–	average	sim	simulation
^	predicted value	$sink$	heat sink, loss
c	cooling	sol	solar gains
e	external side, outdoor conditions	$source$	heat source, gain
h	heating	tot	total
i	internal side, index	tr	transmission
int	internal gains (appliances, lighting, people)	ve	ventilation
res	residual		

2. Multi-scale analysis of building energy performance

Research should be oriented to the creation of a theoretically consistent framework matching indicators, technical issues (and related practical questions), actions and computational techniques to put continuous improvement in practice. What emerges from scientific literature is the necessity of standardizing building data in order to derive useful insights, for example by means of the reference building concept. Further, people behavior and comfort preferences constitute additional elements of uncertainty, even from the point of view of business models. All these factors can lead to a consistent gap between predicted and actual performance [9] and modelling methodologies should be able to deal with them as well. In this research we propose an integration and comparison among results obtained with dynamic simulations (forward models) and energy signatures analyzed by means of multivariate regression (inverse models).

2.1. Multivariate regression to link forward to inverse modelling

Simulation data are generated by means of a dynamic hourly simulation tool [10]. In order to develop a regression model starting from monthly data, we considered the simplified energy balance of the building, used in the semi-stationary calculation methodology defined in technical standard [10]. The heat flows in building zones can be subdivided in two categories, heat sources (e.g. heat input, heat gains) and heat sinks (e.g. cold input, heat losses). Heat sources and sinks are reported in Table 1 and subdivided according to the specific internal and external conditions.

Table 1. Heat sources/sinks definition.

Thermal balance component	Heat source	Heat sink
$Q_{tr+ve} = H\left(\theta_i - \theta_e\right)\Delta t$	$\theta_i < \theta_e$	$\theta_i > \theta_e$
Q_{sol}	always	-
Q_{int}	always	-

The thermal demand for heating and cooling (sensible heat demand, based on balance) is calculated using the following formulas, where a heat sinks/sources utilization factor is introduced, according to the standard previously cited.

$$Q_h = Q_{sink} - \eta_h Q_{source} \tag{1}$$

$$Q_c = Q_{source} - \eta_c Q_{sink} \tag{2}$$

The subdivision among heat sources and sinks specified in Table is useful because it enable partitioning with respect to external temperature data. By introducing the heat transfer coefficient H [11] and the notation used in Table 1 we can reformulate equation 1 and 2 respectively in equation 4 and 5.

$$H = H_{tr} + H_{ve} \tag{3}$$

$$Q_h = H_h\left(\theta_i - \theta_e\right)\Delta t - \eta_h\left(Q_{sol,h} + Q_{int}\right) \tag{4}$$

$$Q_c = \left(Q_{sol,c} + Q_{int}\right) - \eta_c H_c\left(\theta_i - \theta_e\right)\Delta t \tag{5}$$

The limitations of the semi-stationary method are mainly related to the hypothesis of a fixed and predetermined internal temperature θ_i and to the calculation of the utilization factors for gains η_h and losses η_c.

However, if we use this method for inverse modelling they are not constrained (in regression. models).

2.2. Inverse modelling by means of multivariate regression modelling

The monthly heating demand preliminary calculated is divided by the number of operating days and then by 24 hours (i.e. total operating hours) to derive an average thermal power for heating and cooling demand, called energy signature in technical standard [12].

$$q_h = H_h\left(\theta_i - \theta_e\right) - \eta_h\left(q_{sol,h} + q_{int}\right) \tag{6}$$

$$q_c = \left(q_{sol,c} + q_{int}\right) - \eta_c H_c\left(\theta_i - \theta_e\right) \tag{7}$$

$$q_{sol,h} = e_0 + e_1\theta_e \tag{8}$$

$$q_{sol,c} = f_0 + f_1\theta_e \tag{9}$$

In this case, the thermal power has been also divided by building volume, to enable a meaningful comparison among buildings with different sizes. Further, in formulas 8 and 9 the dependence on solar radiation is eliminated by introducing a simplification, using correlation between solar radiation and temperature. The regression models obtained are reported in Table 2 and 3 respectively for heating and cooling, considering only external temperature dependence (model type 1) and dependence on both external temperature and solar radiation (model type 2).

Table 2. Regression models for heating demand analysis.

Element	Model type 1		Model type 2	
Model	$q_{h,1} = a_0 + a_1\theta_e + \varepsilon$	(10)	$q_{h,2} = b_0 + b_1\theta_e + b_2 I_{sol} + \varepsilon$	(11)
Regression coefficients	$a_0 \cong H_h\theta_i - \eta_h\left(e_0 + q_{int}\right)$ $a_1 \cong -\left(H_h + \eta_h e_1\right)$	(12)	$b_0 \cong H_h\theta_i - \eta_h\left(q_{int}\right)$ $b_1 \cong -\left(H_h\right)$ $b_2 \cong -\eta_h g_h$	(13)

Table 3. Regression models for cooling demand analysis.

Element	Model type 1		Model type 2	
Model	$q_{c,1} = c_0 + c_1\theta_e + \varepsilon$	(14)	$q_{c,2} = d_0 + d_1\theta_e + d_2 I_{sol} + \varepsilon$	(15)
Regression coefficients	$c_0 \cong f_0 + q_{int} - \eta_c H_c\theta_i$ $c_1 \cong f_1 + \eta_c H_c$	(16)	$d_0 \cong q_{int} - \eta_c H_c\theta_i$ $d_1 \cong \eta_c H_c$ $d_2 \cong g_c$	(17)

In order to verify the goodness of fit of inverse model we use a calibration approach. A detailed description of metrics for model calibration R^2, *NMBE*, and *Cv(RMSE)* and acceptability criteria for calibrated models can be found in literature [13]. The threshold limits considered by different protocols are reported in Table 3.

Table 4. Threshold limits of metrics for model calibration with monthly data.

Metric	ASHRAE Guidelines 14 (%)	IPMVP (%)	FEMP (%)
NMBE	± 5	± 20	± 5
Cv(RMSE)	15	-	15

3. Results and Discussion

An example of application of this scalable data analysis technique is reported, employing a selection of 10 case studies out of a larger sample of case studies previously analyzed [14]. Multivariate linear regression models are used to compare design assumptions (forward model data) and inverse model parameters. This application is meant to validate simulation data and enable progressive model calibration. The case studies selected are 10 real Italian buildings previously simulated and their results are ranked with respect to the value of *H*, global heat transfer coefficient due to the sum of transmission H_{tr} and ventilation H_{ve} components, as explained before. The multivariate linear regression approach proposed is based on energy signature concept [12], where energy consumption is divided by the duration of the time interval of analysis to obtain an average power, plotted against the screening variable, in this case the external air temperature. The regression models used are reported in Table 2 and 3, where q_h, q_c are average heating and cooling thermal power, normalized by gross volume (to enable comparability across different scales), θ_e is the average external air temperature and I_{sol} is the global solar radiation on horizontal radiation divided by the time interval of analysis, monthly in this case. Finally, *a, b, c* and *d* are regression coefficients and ε

is an error term. The normalized energy demand for heating and cooling is summed up on a yearly based and compared with regression results in Table 5.

Table 5. Comparison of simulation and regression models for heating and cooling demand calibration.

Case study	Heating			Cooling		
	Simulation	Regression 1	Regression 2	Simulation	Regression 1	Regression 2
	kWh/m^3	kWh/m^3	kWh/m^3	kWh/m^3	kWh/m^3	kWh/m^3
1	5.2	5.3	4.8	5.1	5.4	4.9
2	9.4	9.4	9.4	1.8	1.8	1.8
3	7.8	7.8	7.8	7.4	7.4	7.4
4	10.4	10.5	10.4	3.9	3.9	3.9
5	15.4	15.4	15.4	5.4	5.5	5.4
6	9.7	9.7	9.7	2.9	2.9	2.9
7	11.7	11.6	11.9	4.2	4.2	4.2
8	16.8	16.8	16.8	12.0	12.2	12.0
9	36.1	36.1	36.1	3.7	3.7	3.7
10	36.9	36.9	36.9	3.6	3.6	3.5

It shows a good agreement between the result and, therefore, the suitability of regression for monthly based model calibration. Figures 1, 2, and 3 report respectively monthly energy demand normalized with respect to gross volume, related energy signatures and regression lines of model type 1.

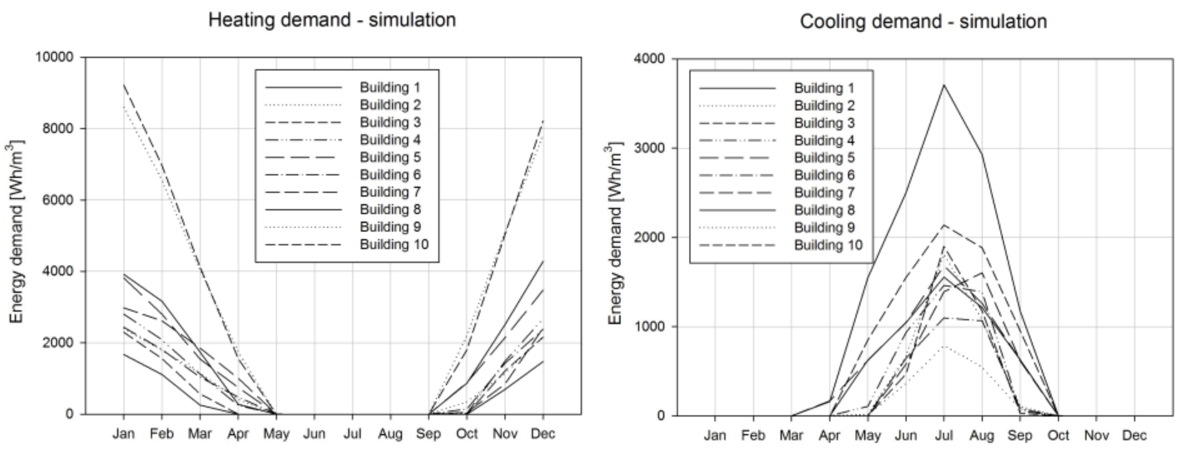

Fig. 1. Normalized monthly heating and cooling demand simulation.

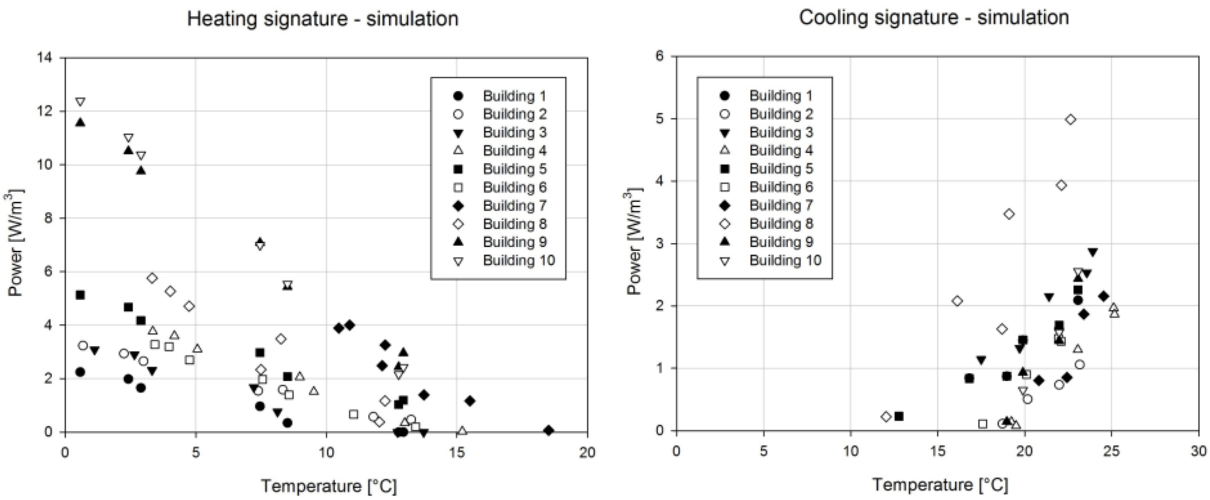

Fig. 2. Normalized energy signature data.

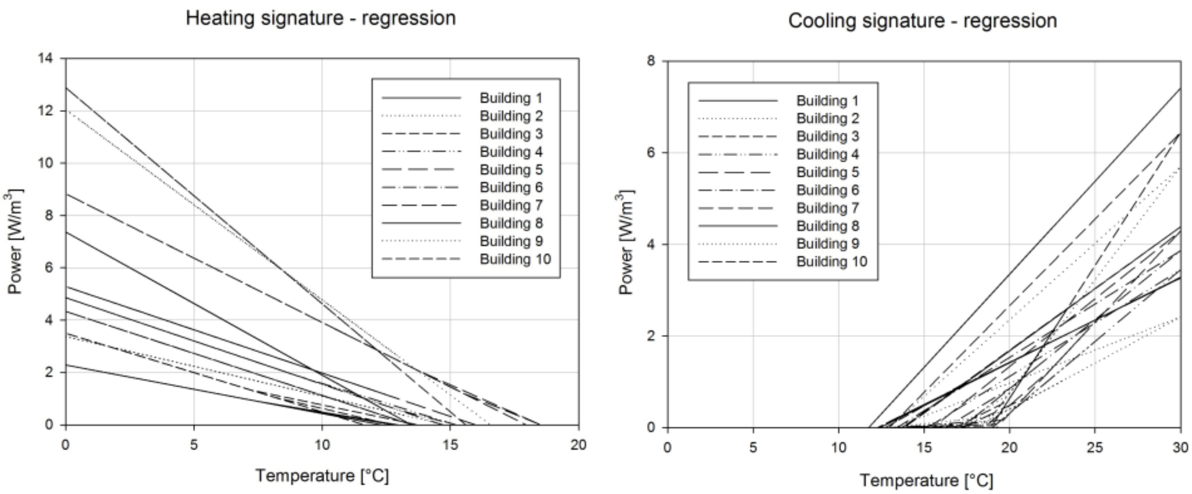

Fig. 3. Linear regression for heating and cooling demand - Model type 1.

Further, as shown in Table 2, $-a_1$ and $-b_1$ coefficients represent an estimate of H [14], later cited as $H_{h,sim}$ because, in this research, we start from simulated data of the heating season. A summary of the results obtained for heating regression models is reported in Figure 4 and Table 6, showing again, more in detail, the good agreement between simulation and regression results. Models can be further improved with respect to solar radiation, by introducing dummy variables to account for different periods of the year and multipliers to account for solar geometry and its impact on solar gains, depending on building geometry.

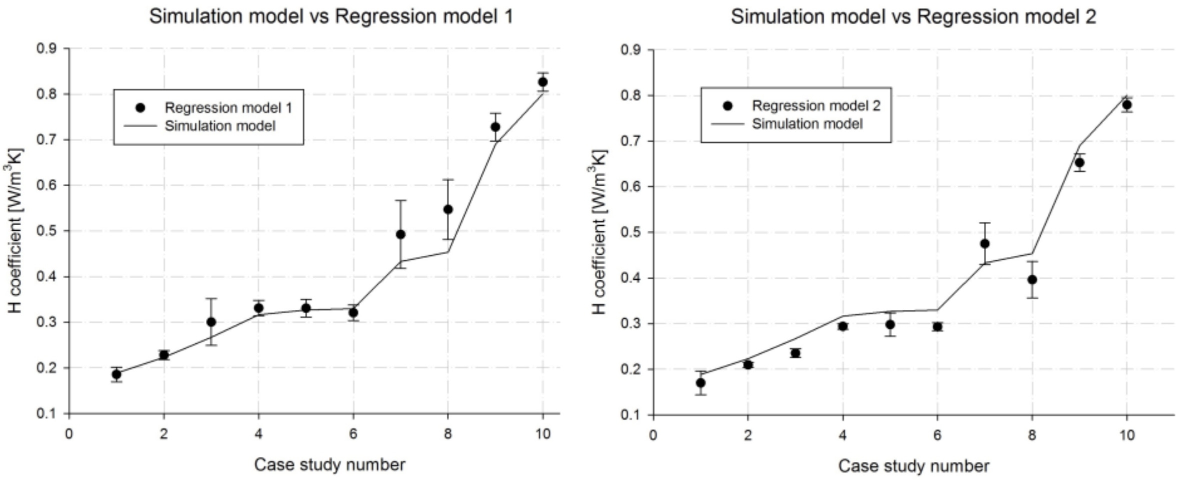

Fig. 4. Forward and inverse building energy models comparison, estimation of $H_{h,sim}$.

Table 6: Comparison of simulation and regression models for heating and cooling demand calibration.

Case study	Simulation	Regression model type 1				Regression model type 2			
	$H_{h,sim}$	$-a_1$	R^2	*NMBE*	$C_v(RMSE)$	$-b_1$	R^2	*NMBE*	$C_v(RMSE)$
	W/m³K	W/m³K	-	%	%	W/m³K		%	%
1	0.189	0.186 ± 0.016	0.978	2.7	12.9	0.170 ± 0.026	0.979	3.0	11.3
2	0.223	0.228 ± 0.010	0.991	0.0	5.2	0.210 ± 0.006	0.999	0.0	2.0
3	0.267	0.300 ± 0.051	0.920	0.0	15.7	0.235 ± 0.009	0.999	0.0	1.9
4	0.317	0.331 ± 0.017	0.987	1.4	7.3	0.294 ± 0.006	0.999	0.0	1.7
5	0.327	0.331 ± 0.019	0.983	0.0	6.6	0.298 ± 0.026	0.990	0.0	5.0
6	0.330	0.321 ± 0.017	0.986	0.0	6.9	0.293 ± 0.009	0.998	0.0	2.5
7	0.433	0.492 ± 0.075	0.704	2.6	23.2	0.475 ± 0.046	0.977	2.1	11.0
8	0.454	0.547 ± 0.065	0.933	0.0	15.1	0.396 ± 0.040	0.991	0.0	5.5
9	0.690	0.728 ± 0.030	0.991	0.0	4.4	0.653 ± 0.019	0.999	0.0	1.6
10	0.801	0.826 ± 0.020	0.997	0.0	2.8	0.779 ± 0.016	0.999	0.0	1.3

4. Conclusion

Energy use and technologies affect sustainability in all its fundamental components, society, environment and economy. Research and development in energy transitions should necessarily face techno and socio-economic problems. The synergy among recent developments in economic and technological paradigms, energy efficiency measures, and renewable energy technologies can constitute an important factor to promote renovation in the built environment, but it is necessary to propose market effective solutions that can minimize the life cycle economic and environmental impact. In this sense, the interplay among forward and inverse modelling approaches (e.g. using energy analytics techniques) is essential to improve both design and operation practices. Further, it is important to investigate simultaneously the spatial and temporal scalability of modelling approaches and the standardization of data structures, considering in particular performance metrics and calibration criteria for decision-making. The role of models in the energy field is cross-sectorial and the use of common principles and techniques could stimulate a rapid development of multi-disciplinary research, which is an essential part of innovation in the quadruple helix model, in which civil society organizations, industry, government and academia collaborate to share knowledge and data.

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