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Parametric energy performance analysis and monitoring of buildings—HEART project platform case study

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A R T I C L E I N F O

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A B S T R A C T

Building performance analysis changed the way in which buildings are designed and operated. The evaluation of different design and operation options is becoming more resource intensive than ever before. Although building dynamic simulation tools are potentially a suitable way for assessing energy performance of buildings accurately, they require adequate training and a careful evaluation of model input data. In Europe, the majority of buildings were constructed before 1990 and are in urgent need for a significant energy efficiency improvement, through deep renovation. In this respect, advanced renovation solutions are available, but costly and lengthy renovation processes and technical complexities hinder the achievement of a large scale impact. Energy refurbishment of buildings is an open challenge and essentially requires the adoption of a valid methodological approach to link design and operational performance analysis transparently, in order to address the potential gap between simulated and measured results.

The HEART project, funded in the EU Horizon 2020 program, aims to address the increasing need for deep retrofit interventions and to develop systemic strategies leading to high performance and cost effective solutions. The research for the cloud platform used in the project is based on two fundamental tools: parametric simulation to produce a large spectrum of possible building energy performance outcomes (considering realistically the impact of the user behaviour and variable operating conditions from the very beginning), and model calibration employing simple, robust and scalable techniques. In this paper we present the preliminary development and testing of the computational processes that will be implemented in the cloud platform, employing the first pilot case study of HEART Project in Italy, currently under refurbishment.

1. Introduction

Building performance analysis and standards (de Wilde, 2018) changed the way in which buildings are designed and operated. The evaluation of different design and operation options is becoming more time consuming and computationally intensive than ever before, following workflows that have to account for multiple interconnected aspects (Hayter, Torcellini, Hayter, & Judkoff, 2000). Although building dynamic simulation tools are potentially a suitable way for accurately assessing the energy performance of buildings, they require adequate training and a careful evaluation of model input data. Further, a discrepancy between simulated and real behaviour can be observed for new or existing building (Bordass, 2004; de Wilde, 2014; Demanuele, Tweddell, & Davies, 2010; Kampelis et al., 2017; Menezes, Cripps, Bouchlaghem, & Buswell, 2012). While this discrepancy can be acceptable within reasonable boundaries, this topic is highly debated (de Wilde, 2017; Imam, Coley, & Walker, 2017).

Additionally, the majority of buildings in Europe were constructed before 1990; and are in urgent need for a significant energy efficiency improvement, through deep renovation. Even though the research effort and the related scientific literature focusing on deep refurbishment have seen a steep increase in recent years (D'agostino, Zangheri, & Castellazzi, 2017; D'Oca & op't Veld, 2018; Fotopoulou et al., 2018; Salvalai, Sesana, & Iannaccone, 2017; Sebastian et al., 2018; Semprini,

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Nomenclature

Variables and parameters

A	Average value
a,b	Regression coefficients
$Cv(RMSE)$	Coefficient of variation of $RMSE$
E	Energy
I	Irradiation
H	Heat transfer coefficient (transmission and infiltration/ventilation)
M	Measured/simulated data
$MAPE$	Mean absolute percentage error
$NMBE$	Normalized mean bias error
q	Energy transfer rate (energy signature)
P	Predicted data
R^2	Determination coefficient
$RMSE$	Root mean square error
S	Simulated
SS	Sum of the squares
τ	Operating hours
U	Thermal transmittance
y	Numeric value
θ	Temperature
ε	Error term

Subscripts and superscripts

$-$	Average
$\hat{}$	Predicted value
e	External
h	Heating
i	Index
n	Number of points
res	Residual
sim	Simulation
sol	Solar

Gulli, & Ferrante, 2017), very few works address both the problem of ensuring the fulfilment of nZEB design standards while reducing the risk of performance gap. In particular, the few documented case studies (setting ambitious goals) are frequently related to custom made and costly interventions (Dodoo, Gustavsson, & Tettey, 2017; Ferreira & Almeida, 2015; Gustafsson et al., 2017).

The HEART (Holistic Energy and Architectural Retrofit Toolkit) project, funded in the EU Horizon 2020 program, aims to address the increasing need for deep retrofit interventions and to develop systemic strategies leading to high performance and cost effective solutions. HEART project employs a cloud-based platform that supports decision-making in the planning and design phase and optimizes energy performance in the operation phase.

More specifically, HEART platform enables the creation of a virtual model; the model indeed serves as a basis for an iterative evaluation procedure that simulates different possible combinations and compares them (as an example: thickness of the thermal insulation of envelope, heat pump and PV plant peak power, etc.). It should be noted that this procedure has the ability to significantly reduce the design effort. After performing a preliminary automatic check on the suitable technological options, HEART's cloud-based Decision Support System (DSS) selects within a predefined shortlist of subcomponents the ones that suit the retrofit intervention best. This procedure enables to streamline the design/decision making phase reducing the choices' processing time by at least 30 % (Karaguzel, Zhang, & Lam, 2014). The final design configuration is then used to initialize the Building Energy Management System (BEMS), which will be then progressively calibrated on measured performance. HEART calculation procedure is based on model calibration techniques, which are essential to link design and operational performance analysis. The research for the construction of the cloud platform is based on two fundamental tools: parametric simulation to produce a large spectrum of possible building energy performance outcomes (considering realistically the impact of the user behaviour and variable operating conditions from the very beginning), and model calibration employing simple, robust and scalable techniques. In this paper we present the preliminary development and testing of the computational process, employing the first pilot case study of HEART Project in Italy, currently under refurbishment.

2. Background and literature review

Today, the importance of parametric and probabilistic analysis of building performance is evident (Jaffal, Inard, & Ghiaus, 2009; Kotireddy, Hoes, & Hensen, 2018; Schlueter & Geyer, 2018; Shiel, Tarantino, & Fischer, 2018), both in new construction and retrofit interventions (EEFIG, 2015; Saheb, Bodis, Szabo, Ossenbrink, & Panev, 2015), and parametric performance data are used for exploratory analysis.

Despite the research efforts put in design tools and technical standards in the last decades, both "re-bound" (Herring & Roy, 2007) and "pre-bound" (Rosenow & Galvin, 2013) effects are generally present in buildings and the gap between simulated and measured performance has been widely investigated (and debated) in recent years (de Wilde, 2014; Imam et al., 2017).

Indeed, we have to consider the robustness of our assumptions and calculation methodologies from the early design phase, ideally learning from feedback during the design iterations and, finally, from measured performance (Coakley, Raftery, & Keane, 2014; Fabrizio & Monetti, 2015), using model calibration techniques in operation phase. Among other factors influencing performance (Yoshino, Hong, & Nord, 2017), the impact of occupants' comfort preferences and behaviour on performance is generally overlooked in the design phase (Cecconi, Manfren, Tagliabue, Ciribini, & De Angelis, 2017; Tagliabue, Manfren, & De Angelis, 2015; Tagliabue, Manfren, Ciribini, & De Angelis, 2016). However, occupants' comfort preferences and behaviour (Cecconi et al., 2017; Menezes et al., 2012; Tagliabue et al., 2016) can lead to a relevant gap (de Wilde, 2014), undermining the effectiveness of policies that have (necessarily) to confront with real behaviour (Herring & Roy, 2007; Imam et al., 2017; Sunikka-Blank & Galvin, 2012). This is particularly evident if we consider the issue of de-risking the investments in deep refurbishment, which have to guarantee, in principles, cost-optimal performance levels (Aste, Adhikari, & Manfren, 2013; Fabbri, Tronchin, & Tarabusi, 2014; Ferrara, Monetti, & Fabrizio, 2018; Tronchin, Tommasino, & Fabbri, 2014). In order to address this fundamental issue, a methodological continuity should be established

Table 1
Hierarchical organization of parametric building modelling data.

Category	Sub category
Location	Climate
Fabric	Archetype creation Geometry
Thermo-physical parameters	Envelope
Building operation	Activities Control and operation settings Operation schedules

Table 2
Parametric simulation data configurations – Level 1.

Category	Group	Type	Unit	Baseline	Design
Location	Climate	UNI 10349:2016	–		
Fabric	Archetype creation	Number of floor	–	3.00	
		Net height of each floor	m	2.70	
		Gross height of each floor	m	3.00	
		Length of the building (S/N orientation)	m	9.93	
		Aspect ratio (Width/Length)	–	2.75	
		Window to wall ratio (WWR) for building	–	16.00	
		Orientation angle	deg	−21.00	
	Geometry	Gross volume	m^3	2349	
		Net volume	m^3	1832	
		Heat loss surface area	m^2	1013	
		Net floor area	m^2	678	
		Surface/Volume ratio (S/V)	1/m	0.43	
Thermo-physical parameters	Envelope	U value external walls	$W/(m^2K)$	0.56[a]	0.18[a]
		U value basement	$W/(m^2K)$	0.46[a]	0.46[a]
		U value roof	$W/(m^2K)$	0.71[a]	0.29[a]
		U value transparent components	$W/(m^2K)$	3.30[a]	1.40[a]
		SHGC factor glass	–	0.60	0.60
Building operation	Activities	Internal gains (lighting, appliances and occupancy, daily average)	W/m^2	5[c]	5
	Control and operation settings	Heating set-point temperature	°C	20[c]	20
		Cooling set-point temperature	°C	26	26
		Air-change rate (infiltration and natural ventilation)	vol/h	0.8[c]	0.5
		Shading factor (solar control summer mode)	–	0.6	0.6
		Schedules – Option 1: IG/VE/H/C[b]	N. Table 2	0	0
		Schedules – Option 2: IG/VE/H/C[b]	N. Table 2	0/0/1/2	0/0/1/2

[a] Average U value determined considering calculation methodologies given in standards ISO 6946:2017, ISO 13789:2017, and ISO 13370:2017.
[b] IG: Internal gains, VE: ventilation, H: Heating, C: Cooling.
[c] Variations on these parameters are considered as specified in Table 9 in Section 4.2.

Table 3
Parametric simulation data configurations – Level 2.

Category	Group	Type	Unit	Baseline	Parametric
Location	Climate	UNI 10349:2016	–		
Fabric	Archetype creation	Number of floor	–	3.00	
		Net height of each floor	m	2.70	
		Gross height of each floor	m	3.00	
		Length of the building (S/N orientation)	m	10.95	
		Aspect ratio (Width/Length)	–	2.5	
		Window to wall ratio (WWR) for building	–	15.80	
		Orientation angle	deg	−21.00	
	Geometry	Gross volume	m^3	3923	
		Net volume	m^3	2746	
		Heat loss surface area	m^2	1300	
		Net floor area	m^2	898	
		Surface/Volume ratio (S/V)	1/m	0.47	
Thermo-physical parameters	Envelope	U value external walls	$W/(m^2K)$	0.56	0.115 − 1.37
		U value basement	$W/(m^2K)$	0.46	0.15 − 1.4
		U value roof	$W/(m^2K)$	0.71	0.156 − 1.67
		U value transparent components	$W/(m^2K)$	3.30	0.8 − 4.8
		SHGC factor glass	–	0.60	0.60
Building operation	Activities	Internal gains (lighting, appliances and occupancy, daily average)	W/m^2	4	1.0 − 6.0
	Control and operation settings	Heating set-point temperature	°C	20	18 − 24
		Cooling set-point temperature	°C	26	26 − 28
		Air-change rate (infiltration and natural ventilation)	vol/h	0.8	0.15 − 1.65
		Shading factor (solar control summer mode)	–	0.6	0.25 − 1
		Schedules – Option 1[a]: IG/VE/H/C	N. Table 2	0	0

[a] IG: Internal gains, VE: ventilation, H: Heating, C: Cooling.

between performance analysis practices across life cycle phases (i.e. model based analysis), using parametric simulation in design phase and progressively calibrating building models to measured data (lo learn from feed-back, as expressed before) (Tronchin, Manfren, & James, 2018). For this reason, in our research we addressed both design and operation phase performance issues through meta-models (Manfren, Aste, & Moshksar, 2013) (i.e. surrogate models, reduced-order models), which are considered among the most promising techniques to overcome the limitations determined by the dimension of parametric simulations and optimization problems. The choice of a specific technique can dependent on several factors (Koulamas, Kalogeras, Pacheco-Torres, Casillas, & Ferrarini, 2018). Meta-models can be very flexible (Østergård, Jensen, & Maagaard, 2018); however, the trade-offs between complexity, predictive ability and transparency have to be

Table 4
Parametric geometric configurations (archetypes) - Level 3.

Archetype number (ID)		0	1	2	3	4
Simulation dataset	Unit	Single-family buildings, villas, etc.		Terraced buildings, large residential buildings, etc.	Tower buildings	
		S/V > = 0.9	S/V > = 0.7	0.7 > S/V > 0.4	S/V > = 0.4	S/V > = 0.2
Number of floors	n.	1.00	2.00	3.00	4.00	7.00
Net height	m	2.70	2.70	3.00	3.10	3.10
Gross height	m	3.10	3.10	3.40	3.60	3.60
Length (S/N orientation)	m	12.00	7.90	8.50	11.50	24.90
Aspect ratio	–	2.00	2.00	2.00	2.00	2.00
Surface/Volume (S/V)	1/m	0.90	0.70	0.55	0.40	0.20
Geometry						
Gross volume	m^3	893	774	1474	3809	31,249
Net volume	m^3	664	576	1110	2801	22,977
Heat loss surface area	m^2	799	544	809	1523	6245
Net floor area	m^2	246	213	370	903	7412

Table 5
Schedules used in parametric simulation.

N.	Schedule name	Unit	Period [gg/month]	Hour of the day[(hours) value]
0	Constant	–	01/01–31/12	(1 – 24) 1
1	Heating set point (measured)	°C	01/01–15/04 15/10–31/12	(1 – 6) off, (7 – 9) 20, (10) off, (11 – 15) 20, (16) off, (17 – 22) 20, (23 – 24) off
2	Cooling set point	°C	16/04–12/10	(1 – 24) 26
3	Internal gains	%	01/01–31/12	(1 – 5) 10, (6) 20, (7) 80, (8) 20, (9 – 12) 10, (13) 80, (14) 20, (15 – 17) 10, (18) 20, (19) 80, (20) 100, (21 – 23) 20, (24) 10
4	Infiltration/Ventilation	–	01/01–31/12	(1 – 24) 1

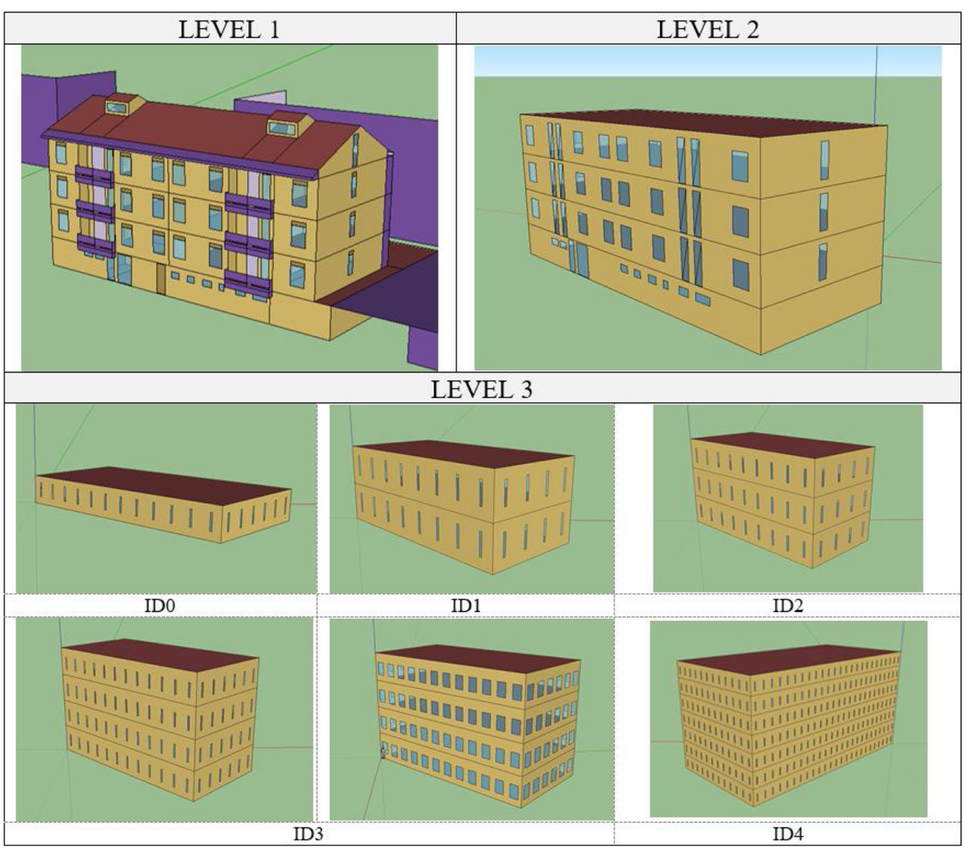

Fig. 1. 3D views of building models: on the top left Level 1, on the top right Level 2 and at the bottom Level 3 with 5 different archetypes.

Table 6
Regression models for heating demand analysis.

Demand	Model type 1	Model type 2
Heating	$q_{h,1} = a_0 + a_1\theta_e + \varepsilon$	$q_{h,2} = b_0 + b_1\theta_e + b_2 I_{sol} + \varepsilon$

Table 7
Threshold limits of metrics for model calibration with monthly data for different protocols.

Metric		ASHRAE Guidelines 14	IPMVP	FEMP
MBE	%	± 5	± 20	± 5
Cv(RMSE)	%	15	–	15

considered (i.e. black-box Vs grey-box models) (Koulamas et al., 2018). In this research we propose the use of linear multivariate regression as meta-modelling technique. This choice is determined by the analysis of several examples of multi-variate regression models to support design optimization (Al Gharably, DeCarolis, & Ranjithan, 2016; Asadi, Amiri, & Mottahedi, 2014; Catalina, Virgone, & Blanco, 2008; Hygh, DeCarolis, Hill, & Ranjithan, 2012; Ipbüker, Valge, Kalbe, Mauring, & Tkaczyk, 2016) found in recent literature. Further, regression models are used to address also topics such as performance robustness for energy performance contracting and cost-optimal analysis (Kavousian & Rajagopal, 2013; Ligier, Robillart, Schalbart, & Peuportier, 2017). Additionally, with respect to operation performance analysis, regression models are acceptable for calibration if they are able to satisfy the thresholds of measurement and verification (M&V) protocols (ASHRAE, 2014; EVO, 2003; FEMP, 2008), which constitute the minimal requirements. In particular, regression on energy signature data (ASHRAE, 2014; ISO, 2013) is largely used (and empirically tested) for M&V. Finally, in order to render these applications more transparent and semi-automated, further research should be oriented towards the definition of multi-scale and multi-level performance metrics (Tronchin, Manfren, & Tagliabue, 2016; Yang & Becerik-Gerber, 2015) and corresponding visualization techniques. In this paper we present the preliminary phase of a research aimed at addressing these issue.

3. Research methodology

The building presented in this research is the first case study of HEART project, which was built in 1985 in Bagnolo del Piano, in the Province of Reggio Emilia in Northern Italy. The building is a multi-storey residential building with 12 apartments.

Heating service is supplied by a hydronic centralized system with a natural gas boiler and radiators as terminal units. Instead, domestic hot water service is supplied by decentralized electric boilers in each apartment. While different performance indicators (e.g. energy demand for end-uses, primary energy demand, CO_2 emissions, cost of energy services, etc.) will be calculated in the HEART platform according to the methodology proposed in the standard ISO 52000-1 (ISO, 2017) (overarching framework for the Energy Performance of Buildings, or EPB), in this research we start from heating consumption analysis. In general, this component of energy consumption is the dominating one in this type of buildings. Therefore we organize our research methodology in this way:

1 in Section 3.1 we report data and describe assumptions for parametric performance analysis, organized according to three levels of detail in modelling;
2 in Section 3.2 we define regression models for the calibration process (energy signatures);
3 in Section 3.3 we define statistical indicators to track the goodness of fit and predictive ability of regression models, from design to operation phase.

Following this methodology, while we use parametric simulations (with different levels of detail in modelling, as specified before) for the creation of the data in the HEART platform, we need also medium/long-term performance data to define an energy model baseline for the existing building (i.e. the case study building in this research), using calibration techniques. In this sense, regression models are employed to link design and operational performance analysis, for the reasons expressed in Section 2. The changes of regression models are tracked by means of statistical indicators because (during the analysis process) we can find multiple different simulation configurations, which can give relatively similar energy demand results and corresponding regression models, which can fit the data with similar performance (i.e. statistical indicators). Finally, we use visualization techniques (i.e. scatterplots and parallel coordinate plots) to enable an effective comparison of design phase (simulation) and operation phase (measured) performance data, in multiple conditions. The ability to compare performance in multiple conditions and for multiple building configurations is a fundamental part of the development of the platform.

3.1. Parametric performance analysis for HEART data platform creation

As anticipated, in this research parametric simulation is used to generate data for the HEART data platform creation. The construction

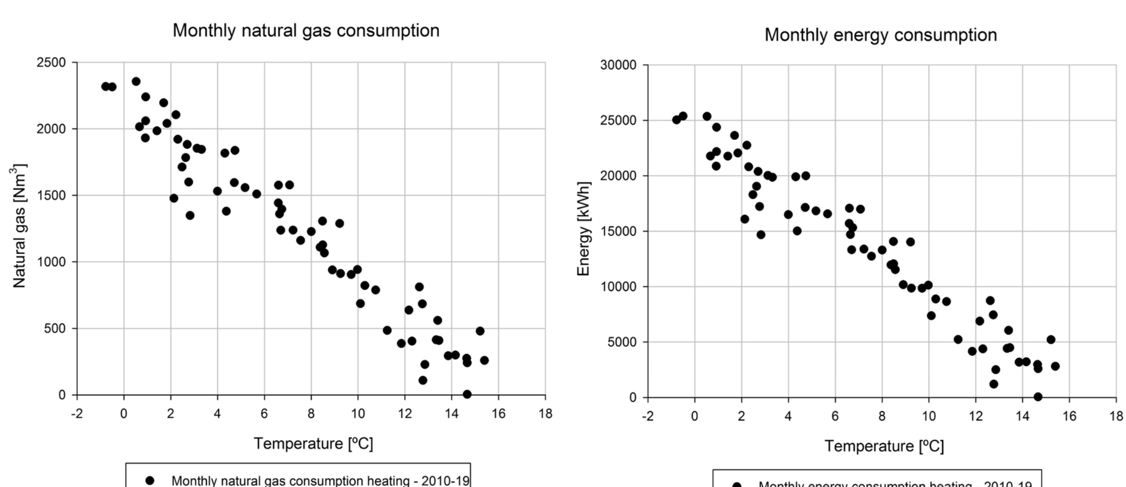

Fig. 2. Natural gas and energy signature for heating consumption at the meter level – Years 2010-2019.

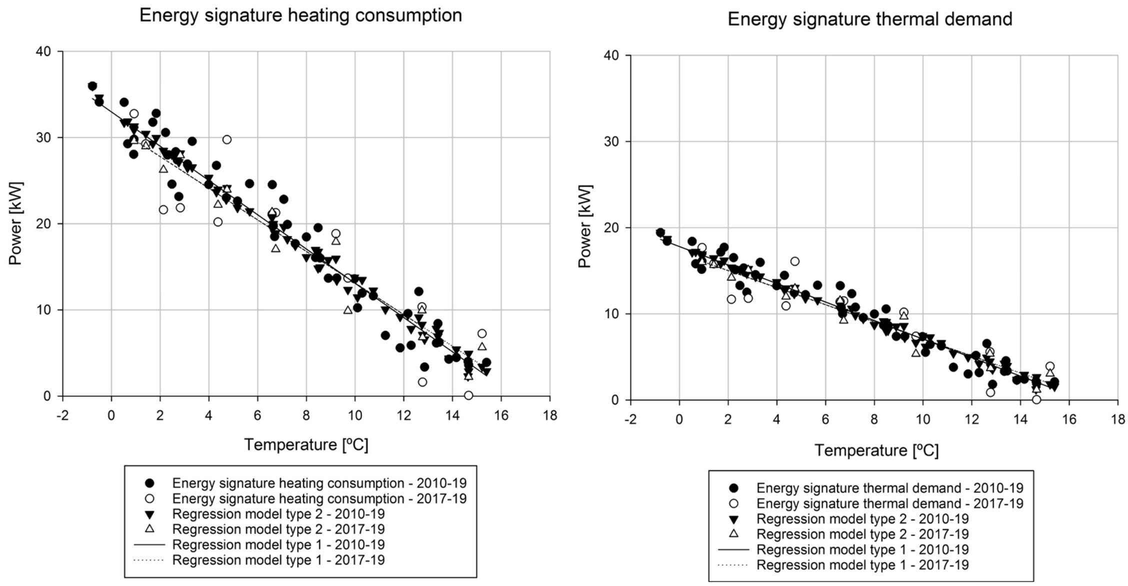

Fig. 3. Energy signature of heating consumption and thermal demand – Years 2010-2019.

Table 8
Comparison of statistical indicators of energy signature regression of thermal demand for heating.

Data	Regression model type 1				Regression model type 2			
	R^2 –	MAPE %	NMBE %	C_v(RMSE) %	R^2 –	MAPE %	NMBE %	C_v(RMSE) %
2010 – 19	0.923	13	− 0.18	14.7	0.929	15	− 0.15	14.1
2017 – 19	0.828	18	− 0.21	22.6	0.873	14	− 0.12	19.4

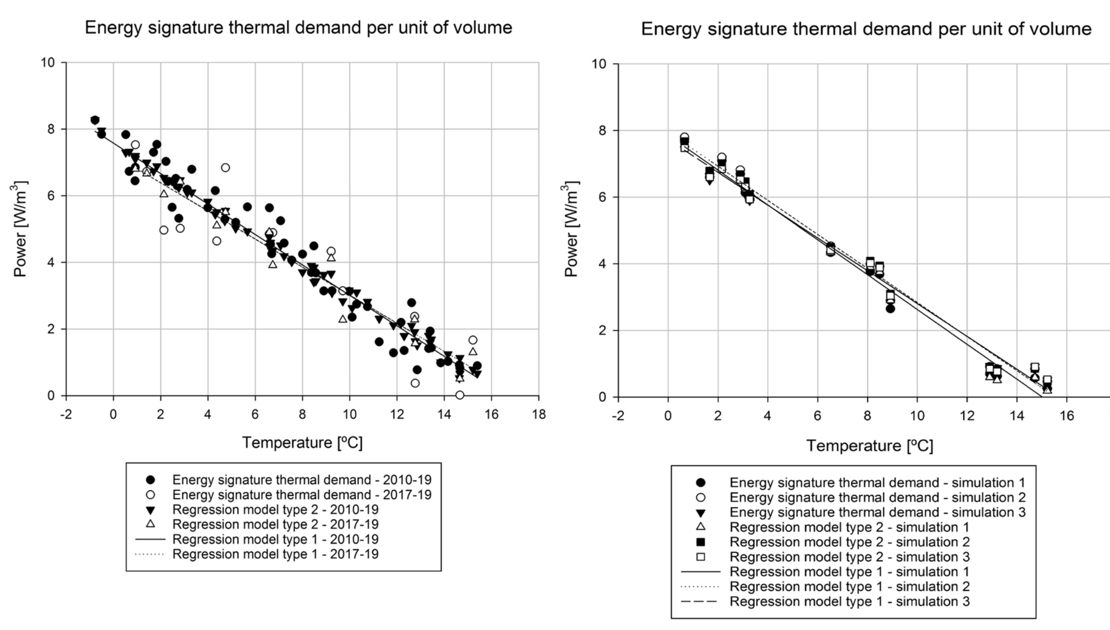

Fig. 4. Energy signature of heating demand per unit of gross volume – comparison between measured and simulated data.

Table 9
Variations in simulation input parameters considered to evaluate performance variability for Level 1 model – existing building (baseline).

Simulation runs	Internal gains (lighting, appliances and occupancy, daily average)	Heating set-point temperature	Air-change rate (infiltration and natural ventilation)
	W/m^2	°C	vol/h
Simulation 1	5	20	0.80
Simulation 2	5	21	0.70
Simulation 3	6	22	0.60

Table 10
Statistical indicators and regression coefficients of energy signature of thermal demand per unit of gross volume – intermittent operation.

Data	Simulation	Regression model type 1					Regression model type 2				
	$H_{h,sim}$ W/m³K	$-a_1$ W/m³K	R^2 –	*MAPE* %	*NMBE* %	C_v(*RMSE*) %	$-b_1$ W/m³K	R^2	*MAPE* %	*NMBE* %	C_v(*RMSE*) %
2010 – 19	–	0.46 ± 0.02	0.923	13	−0.18	14.7	0.49 ± 0.02	0.929	15	−0.15	14.1
2017 – 19	–	0.42 ± 0.06	0.828	18	−0.21	22.6	0.51 ± 0.07	0.873	14	−0.12	19.4
Sim1	0.60	0.52 ± 0.02	0.985	19	0.13	8.1	0.48 ± 0.01	0.997	6	0.02	3.4
Sim2	0.57	0.51 ± 0.02	0.984	18	0.12	7.7	0.47 ± 0.01	0.998	3	0.02	2.8
Sim3	0.53	0.49 ± 0.02	0.983	18	0.12	7.8	0.45 ± 0.01	0.998	3	0.02	2.8

Table 11
Thermal demand per unit of gross volume predicted with design weather data UNI 10349:2016 – intermittent operation.

Configuration	Thermal demand		
	Simulation kWh/m³	Regression 1 kWh/m³	Regression 2 kWh/m³
2010 – 19	–	21.2 ± 0.22	20.4 ± 0.38
2017 – 19	–	20.8 ± 0.76	18.5 ± 1.25
Sim1	20.1	20.1 ± 0.25	20.0 ± 0.23
Sim2	21.0	21.1 ± 0.25	21.0 ± 0.20
Sim3	20.6	20.7 ± 0.25	20.6 ± 0.20

of building simulation cases follows the hierarchical organization of information (using categories and sub-categories of inputs) reported in Table 1.

Three different levels of analysis have been defined to test the simulation and model validation and calibration process:

1 **Level 1,** detailed building energy model, baseline (existing) and design (retrofit) configurations;
2 **Level 2,** simplified building energy model, baseline (existing) and parametric configurations;
3 **Level 3,** five archetypal building energy models, parametric configurations.

We start our analysis from the most detailed model, Level 1. The input data are reported in Table 2.

After that, in Level 2 analysis we simulate baseline (existing building) and parametric configurations (using ranges for parameters and 11 steps) of a simplified energy building model derived by Level 1, with slightly different geometric characteristics. All assumptions are summarized in Table 3 and, in particular, the simplifications introduced are the following ones:

1 geometry simplification of the original building fabric;
2 single average representative construction technologies, one for each surface (vertical wall, floor, roof and windows), with parametric configurations from most to least insulated option;
3 operational settings with constant schedules for heating and cooling (24/24 h operation).

In Level 3 analysis, we maintain essentially the same ranges of variation of input parameters considered in Level 2 and a similar logic for the simplification of models, but we reduce the steps considered to 6 (in Level 2 steps are 11), to reduce computation time. However, we introduce a variability in terms of building geometry using five archetypes, reported in Table 4, from the least compact (ID = 0) to the most compact (ID = 4) in term of Surface/Volume (S/V) ratio.

Table 5 shows the data of the schedules adopted in the simulations across the different levels of detailed defined before. However, while Level 1 model has been simulated with real operational settings (identified during the energy audit), Level 2 and Level 3 models have been simulated (at this stage of development of the project) using constant operational settings to limit the amount of possible combinations. Finally, Fig. 1 show the different 3D views of models used for parametric simulations.

3.2. Regression analysis of simulated and measured energy signatures

The linear multivariate regression models used in this research are derived from scientific literature review (Section 2) and have been used

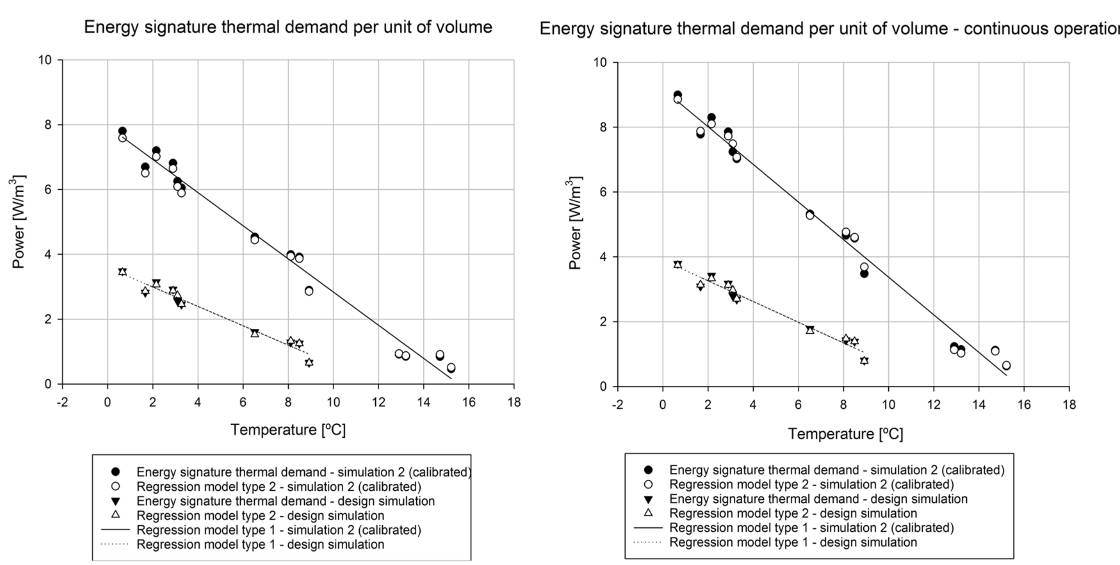

Fig. 5. Energy signature of thermal demand per unit of gross volume – comparison between simulated data for intermittent and continuous operation.

Table 12
Statistical indicators and regression model coefficients of energy signature of thermal demand per unit of gross volume – intermittent and continuous operation.

Data	Simulation	Regression model type 1					Regression model type 2				
	$H_{h,sim}$ W/m³K	$-a_1$ W/m³K	R^2 –	*MAPE* %	*NMBE* %	$C_v(RMSE)$ %	$-b_1$ W/m³K	R^2	*MAPE* %	*NMBE* %	$C_v(RMSE)$ %
Sim2 (intermittent	0.57	0.51 ± 0.02	0.984	18	0.12	7.7	0.47 ± 0.01	0.998	3	0.02	2.8
Sim2 (continuous)	0.57	0.58 ± 0.02	0.986	15	0.11	7.0	0.53 ± 0.01	0.998	3	0.02	2.6
Design (intermittent)	0.30	0.30 ± 0.02	0.963	10	0.14	8.0	0.27 ± 0.01	0.994	2	0.03	3.2
Design (continuous)	0.30	0.32 ± 0.02	0.966	9	0.14	7.4	0.29 ± 0.01	0.994	2	0.03	3.1

Table 13
Thermal demand per unit of gross volume predicted with design weather data UNI 10349:2016 – continuous operation.

Configuration	Thermal demand		
	Simulation 2 (Level 1) kWh/m³	Regression 1 kWh/m³	Regression 2 kWh/m³
Existing building (baseline)	24.60	24.70 ± 0.28	24.60 ± 0.22
Design	8.60	8.60 ± 0.17	8.60 ± 0.15

in previous research applications. The models are trained and tested on energy signature data (ISO, 2013). Energy signature is calculated as follows:

$$q = \frac{E}{\tau} \tag{1}$$

where q is the energy signature (energy transfer rate), expressed in kW, E is the energy demand, expressed in kWh, and τ is the number of operating hours. Energy signature data are then subdivided by building gross volume to enable the comparison across different building sizes and end-uses (Arregi & Garay, 2017; Tronchin et al., 2016; Tronchin, Manfren, & Nastasi, 2019) and plotted against average outdoor air temperature for the corresponding period of analysis, monthly in this case. As shown in Table 6, two types of models are considered:

1 type 1, accounting only for external air temperature dependence;
2 type 2, accounting for both external air temperature and solar radiation dependence.

External air temperature is the most important regressor (predictor variable) to be considered for weather normalization (Lin & Claridge, 2015). Solar irradiation is introduced as an additional regressor because of the relevant impact that solar gains may have in building with medium to high level of insulation. By formulating the models in this way, it is possible substantially to normalize energy consumption with respect to weather conditions (i.e. creating models independent on the specific weather data files used and suitable for performance comparison in multiple weather conditions). Beside weather normalization of energy performance, environment temperature is fundamental for exergy analysis methods (Meggers, Ritter, Goffin, Baetschmann, & Leibundgut, 2012; Tronchin & Fabbri, 2008), which may be applied, for example, to study the performance of heat pump systems. Further, energy consumption depends also on internal environmental quality (Fabbri & Tronchin, 2015) and, for this reason, the impact of operational settings and behaviour should be appropriately weighted (Ligier et al., 2017).

What we exploit in our analysis is an approximate physical interpretation of regression coefficients a_1 and b_1, that are substantially comparable to $-H_{h,sim}$ (heat transfer coefficient for simulation in heating mode), as shown in previous research (Allard, Olofsson, & Nair, 2018; Tronchin et al., 2016, 2019). Finally, while the focus of this research is calibrating the model considering heating demand, this regression approach is far more general and may be applied to other energy uses, e.g. including cooling and base load (DHW, appliances, etc.) (ASHRAE, 2014). In a general case, the overall predictive model will be the combination of linear submodels (Paulus, Claridge, & Culp, 2015; Paulus, 2017), respectively for heating, cooling and baseline demand, creating a piecewise linear multivariate model. In the next section we illustrate the statistical indicators used for model selection (based on its performance) and calibration.

3.3. Statistical indicators for model selection and calibration

In order to evaluate and compare properly simulation data in design phase and measured data in operation phase, we selected basic statistical indicators and specific indicators used at the state-of-the-art of model calibration procedures (ASHRAE, 2014; EVO, 2003; FEMP, 2008)). We illustrate first some basic statistical indicators, namely R^2 and *MAPE*. The determination coefficient R^2 can assume values ranging from 0 to 1 (or 0–100%, if expressed in percentage), where 1 means that the model fit perfectly data. R^2 is calculated as 1 minus the ratio between the sum of the square of residuals and total sum of the squares, with the Formula 2.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{2}$$

MAPE (Mean Absolute Percentage Error) can be used to account for the average absolute value of the difference among measured (or simulated, in design phase) and predicted data (by the regression models in this case), normalized with respect to measured data themselves. *MAPE* is calculated as shown in Formula 3.

$$MAPE = \frac{1}{n} \sum_i \left| \frac{M_i - P_i}{M_i} \right| \cdot 100 \tag{3}$$

We consider then two indicators for calibration, *NMBE* (Normalized Mean Bias Error) and *Cv(RMSE)* which the Coefficient of Variation of Root Mean Squared Error (*RMSE*). *NMBE* is the total sum of the differences between measured (or simulated, in design phase) and predicted energy consumption (by the regression models in this case) at the calculation time intervals (monthly in this case), divided by the sum of the measured (or simulated, in design phase) energy consumption. *NMBE* is calculated according to Formula 4. A positive value of *NMBE* indicates a model overestimation of energy consumption (a positive bias), vice versa a negative value indicates an underestimation (a negative bias).

$$NMBE = -\frac{\sum_i (M_i - P_i)}{\sum_i M_i} \cdot 100 \tag{4}$$

Cv(RMSE) represents a normalized measure of the variability among measured (or simulated, before operation) and predicted data. It is based on *RMSE*, which is a measure of the sample deviation of the differences between measured values and values predicted by the model, which is divided by A, which represents measured (or simulated, before operation) energy consumption. Lower *Cv(RMSE)* values indicate a better calibrated model. *Cv(RMSE)* calculation is illustrated

Table 14
Parametric analysis of building configuration – ranges of data for parallel coordinate plot analysis.

Category	Sub category	Type	Unit	Configuration	
				Existing	Design
Fabric	Archetype	Orientation angle	deg	−45-+45	−45-+45
	Geometry	Surface/Volume ratio (S/V)	1/m	0.40 − 0.70	0.40 − 0.70
Building operation	Activities	Internal gains (lighting, appliances and occupancy, daily average)	W/m^2	4 − 6	4 − 6
	Control and operation settings	Heating set-point temperature	°C	18 − 22	18 − 22
		Shading factor (solar control summer mode)	–	0.50 − 0.75	0.50 − 0.75
Lumped parameters	Envelope and infiltration/ ventilation	Heat transfer coefficient H_{sim}	W/(m^{3}K)	0.44 − 0.74	0.19 − 0.38
Performance indicators	Thermal demand	Heating demand	kWh/m^3	19.5.0 − 29.5 (± 20 % from baseline Level 1, Table 13)	7.0 − 10.5 (± 20 % from design Level 1, Table 13)

in its steps with Formulas 5–7.

$$RMSE = \sqrt{\frac{\sum_i (M_i - P_i)^2}{n}} \tag{5}$$

$$A = \frac{\sum_i M_i}{n} \tag{6}$$

$$Cv(RMSE) = \frac{RMSE}{A} \cdot 100 \tag{7}$$

The threshold metrics considered in different protocols at the state-of-the-art for M&V and calibration (ASHRAE, 2014; EVO, 2003; FEMP, 2008), are summarized in literature (Fabrizio & Monetti, 2015) are reported in Table 7 for calibration with monthly data. For an in-depth analysis of indicators for model calibration it is possible to refer to (Ruiz & Bandera, 2017).

4. Results and discussion

As anticipated, the case study chosen is an apartment block residential building located in Bagnolo al Piano, in the Province of Reggio Emilia, in the Emilia Romagna Region in Northern Italy. First, we illustrate the workflow in its main steps. The whole process linking model calibration to parametric performance simulation is subdivided into two main phases, following the methodology illustrated in Section 3 and the reasons expressed in Section 2, together with the experience acquired in previous research (Tronchin et al., 2016, 2019). The first phase, described in Section 4.1, consists in the use of energy signature and regression of medium/long-term energy performance monitoring data to set the basis for the calibration of energy models. The second one, described in Section 4.2, extends the conventional energy signature use (and the underlying regression modelling approach) to enable the comparison of measured and simulated performance data in different weather and operating conditions, for parametric building configurations with multiple levels of detail. This is a necessary part of the research, connected to the creation of the cloud platform for HEART project. In brief, the scope of this research is evaluating the robustness and flexibility of regression-based approaches for multiple scopes within the HEART data platform. In this sense, the ability to calibrate models with different levels of detail is crucial, because of the necessity of evaluating energy performance in multiple ways during building life cycle phases. The use of statistical indicators and visualization techniques (such as scatterplots and parallel coordinate plots) can help in the direction of a (regression-based) complete multi-level calibration approach (Manfren et al., 2013; Yang & Becerik-Gerber, 2015), that will be the focus of future research efforts, described in the conclusion section.

4.1. *Long-term performance monitoring and model calibration using energy signature and multivariate regression*

The workflow aimed at model calibration starts from long-term performance monitoring data. The data used in this research consists in metered natural gas energy consumption for heating and average monthly external air temperatures, collected in the energy audit. In Fig. 2, on the left, we plot natural gas consumption in standard cubic meter with respect to temperature, and, on the right, the corresponding values in energy (determined by the lower heating value of fuel).

After that, in Fig. 3 we transform the data to obtain an average power (energy signature (ASHRAE, 2014; ISO, 2013)) using Formula 1 and we fit different regression models (type 1 and 2, described in Section 3.2), both for natural gas heating consumption (on the left), and thermal heating demand (on the right), considering the estimated losses of technical systems (i.e. emission, distribution, control, generation), calculated using data from energy audit.

The performance of energy signature regressions is reported in

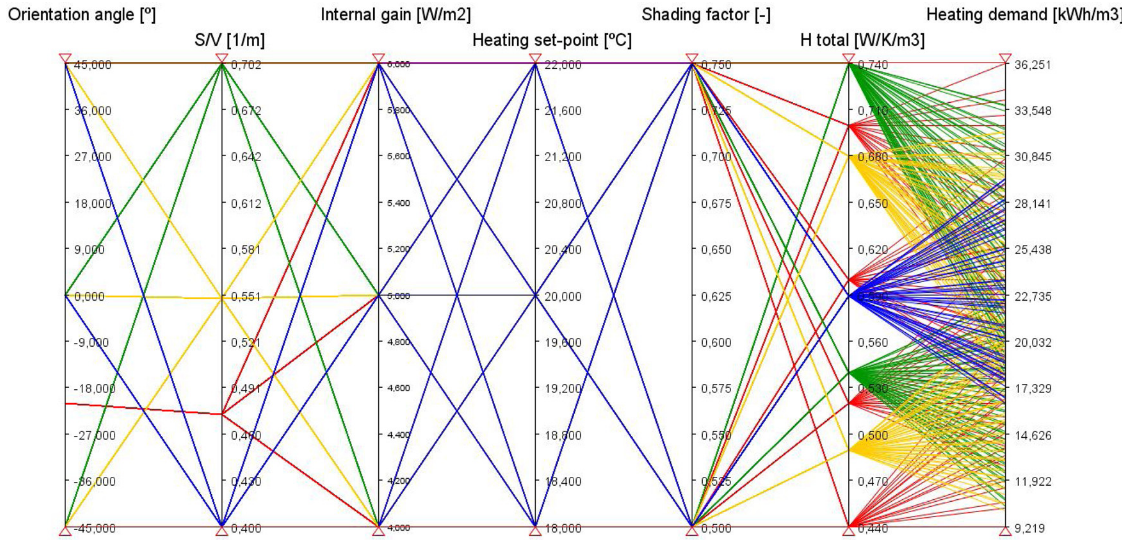

Fig. 6. Parallel coordinate plot analysis – data extracted from parametric simulation dataset based on H_{sim} range 0.44-0.74 W/(m^3K) for existing building performance comparison.

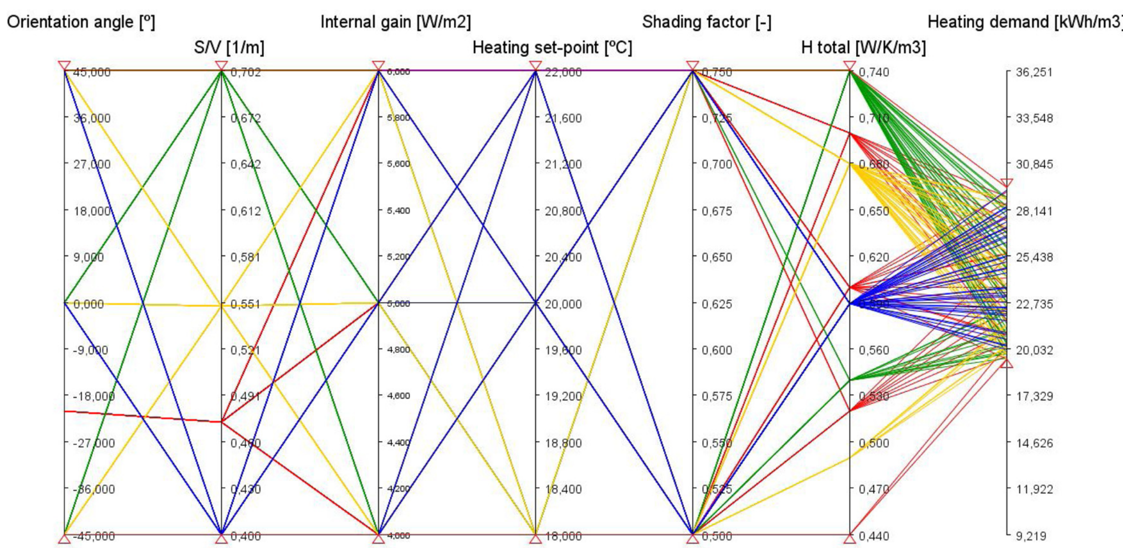

Fig. 7. Parallel coordinate plot analysis – selection of parametric configurations in H_{sim} range 0.44-0.74 W/(m^3K) that match a heating demand in the range 19.5-29.5 kW h/m^3.

Table 8, using the indicators defined in Section 3.3. The data reported show how it is possible to reach calibration threshold (Table 7) with long-term data (2010 − 19) but also how the last 2 years of data alone (2017 − 19) are not sufficient to reach calibration (i.e. in some cases medium-term data may not be sufficient to guarantee a stable baseline.

4.2. Linking model calibration and parametric performance analysis

The necessity of comparing measured and simulated performance with different levels of detail (as explained in Section 3.1) and different conditions (weather, operational settings, etc.) requires an extension of the conventional energy signature approach (ASHRAE, 2014; ISO, 2013), obtained by scaling the energy data by gross volume, for the reasons described in recent research (Pistore, Pernigotto, Cappelletti, Gasparella, & Romagnoni, 2019; Tronchin et al., 2016, 2019). In particular, this passage enables the comparison across different building sizes, characteristics and levels of details as well. In our project we considered three levels of detail in modelling, called Level 1, 2 and 3, as explained before. Therefore, the workflow proceeds through the following steps:

1 comparison between measured and simulated data for intermittent operation (real operational settings) – Level 1 simulation configurations (input in Table 2);
2 comparison between simulated data for intermittent and continuous operation (real and steady-state operation) – Level 1 simulation configurations (input in Table 2);
3 exploratory analysis of simulation data obtained with continuous operation conditions for multiple model inputs (multiple building models/archetypes in different configurations) – Level 2 and 3 simulation configurations (input in Tables 3 and 4).

We start by considering the data reported in Fig. 3. We divide them by gross volume and we compare them in Fig. 4 with the ones obtained with three simulation configurations for Level 1 model (Table 2), varying the three input parameters (internal gains, temperature set-point, air-change rates) reported in Table 9, to account for the impact of their variability on thermal demand for heating. The simulation results

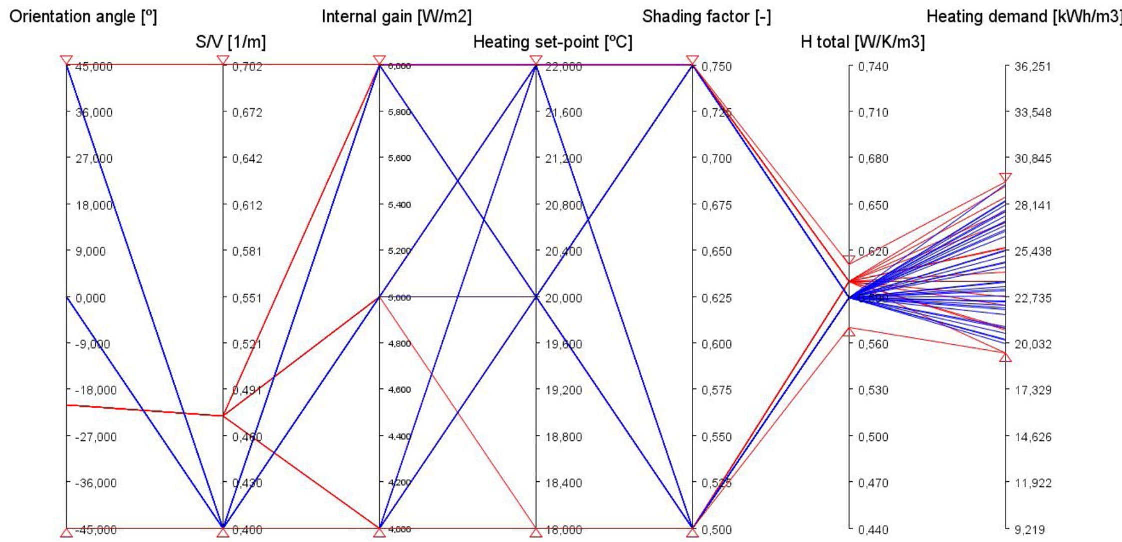

Fig. 8. Parallel coordinate plot analysis – selection of parametric configurations in H_{sim} range 0.44-0.74 W/(m^3K) that match a heating demand in the range 19.5-29.5 kW h/m^3 and H_{sim} in the range 0.57-0.61 W/(m^3K).

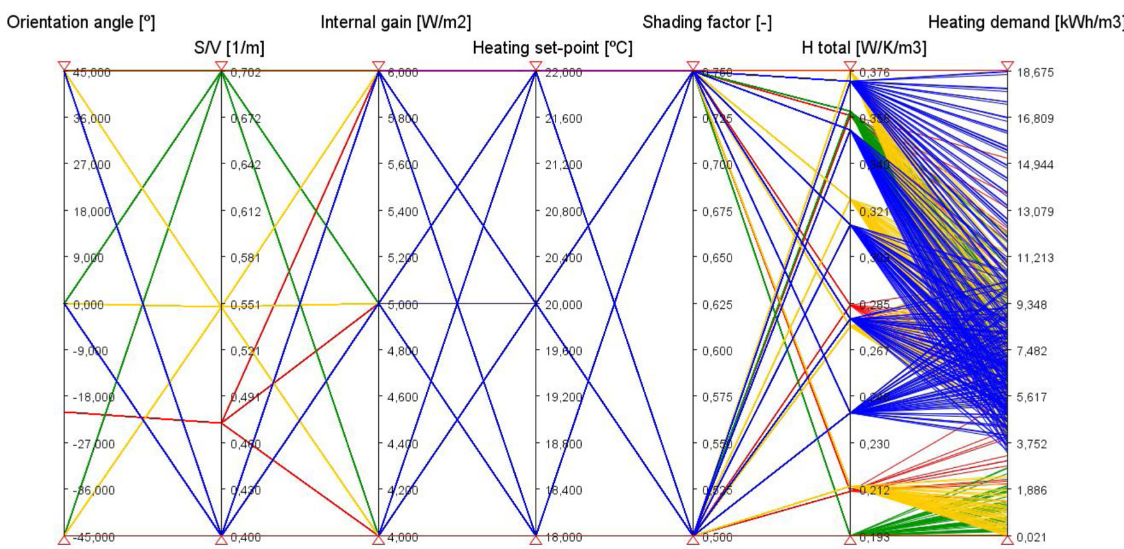

Fig. 9. Parallel coordinate plot analysis – data extracted from parametric simulation dataset based on H_{sim} range 0.19-0.38 W/(m^3K) for design building performance comparison.

are very near to the measured ones and the configuration that fits the data best is simulation 2, considering the statistical indicators reported in Table 10 and the predicted yearly energy demand (calculated using design weather file UNI 10349:2016) (UNI, 2016) in Table 11. In Table 10 we compare also regression coefficients $-a_1$ and $-b_1$ with H_{sim}, considering the approximated physical interpretation introduced in Section 3.2.

As can be noticed, simulated data are in general much less scattered then real data and, as already reported, regression models created with the last two years of data are above the calibration threshold reported in Table 7.

After that, we compare in Fig. 5 energy signature of thermal demand for existing building (baseline) and design configurations both in intermittent (real measured) and continuous operation conditions.

Also in this case, regression models are able to fit data reasonably well in both operation modes, as shown by the statistical indicators reported in Table 12 and by the predicted energy demand (using again design weather data UNI 10349:2016 (UNI, 2016)) in Table 13. In this passage of the workflow we considered continuous operation to enable the comparison with parametric simulation models results for Level 2 (input in Table 3) and Level 3 (input in Table 4) that, at this stage, are run with constant operational profiles. Including different operational profiles, as well as othe weather datasets for different locations, will be part of future research within the HEART project.

The comparison of the simulation results obtained with different configurations is then performed graphically by means of parallel coordinate plots (i.e. exploratory data analysis), considering variations for the ranges of data reported in Table 14. The parameters considered for plotting are a subset of the original parametric data defined in Tables 3 and 4, in Section 3.1.

The building envelope and infiltration/ventilation performance characteristics have been lumped in the heat transfer coefficient (Allard et al., 2018; ISO, 2008; Tronchin et al., 2016, 2019) divided by gross volume H_{sim}, for the reasons expressed in recent research (Pistore et al., 2019; Tronchin et al., 2016, 2019) and synthesized in Section 3.2, i.e. to enable the comparison of different building types, exploiting the approximated physical interpretation of regression coefficients. In order to visualize multivariate data, results have been clustered by building type using surface to volume ratio (S/V) from 0.70 to 0.40, as reported in Table 14. The clusters represented in Figs. 6–11 follow the same

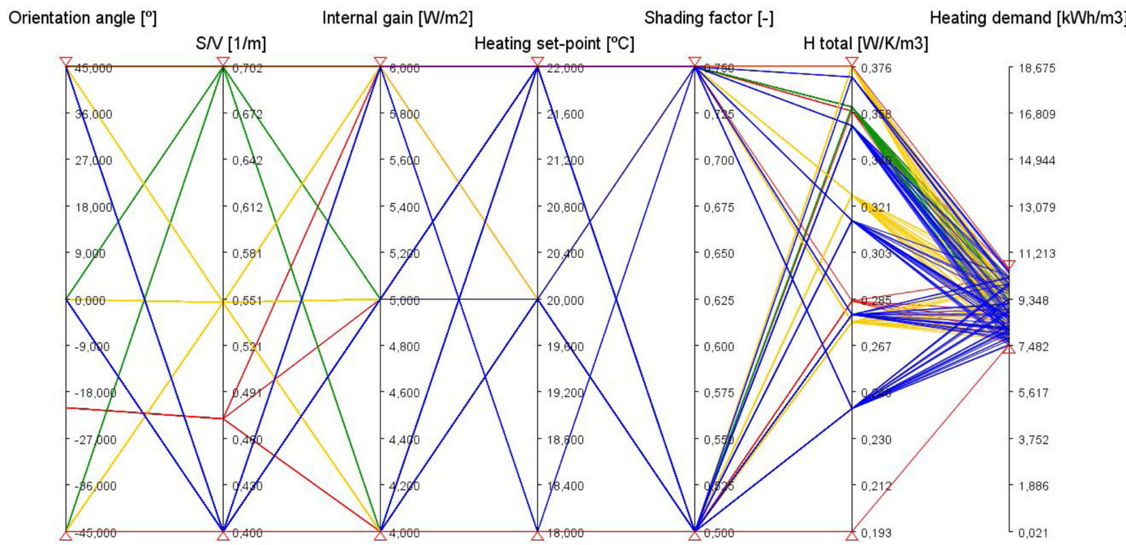

Fig. 10. Parallel coordinate plot analysis – selection of parametric configurations H_{sim} range 0.19-0.38 W/(m^{3}K) that match a thermal demand in the range 7.0-10.5 kW h/m^3.

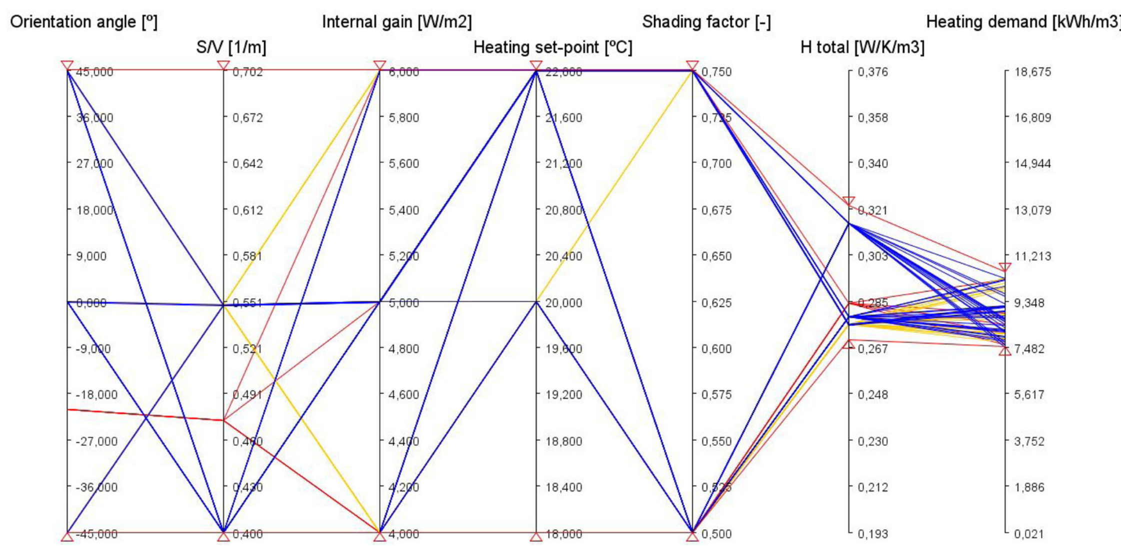

Fig. 11. Parallel coordinate plot analysis – selection of parametric configurations H_{sim} range 0.19-0.38 W/(m^{3}K) that match a thermal demand in the range 7.0-10.5 kW h/m^3 and H_{sim} in the range 0.27-0.33 W/(m^{3}K).

convention:

1 Green, S/V = 0.7, Level 3 archetype 1, described in Table 4;
2 Yellow, S/V = 0.55, Level 3 archetype 2, described in Table 4;
3 Red, S/V = 0.47, Level 2, described in Table 3;
4 Blue S/V = 0.40, Level 3 archetype 3, described in Table 4.

In Fig. 6, we represent parametric simulation results for Level 2 and 3 data with H_{sim} in the range $0.44-0.74$ W/(m^{3}K) and then, for the sake of comparison with existing building performance, we limit thermal demand for heating in the range 19.5–29.5 kW h/m^3 (± 20 % from baseline Level 1 results in Table 13) in Fig. 7, checking the configurations that have similar results and evaluating the impact of variations.

Even after restricting the range of thermal demand to 19.5–29.5 kW h/m^3, there are still many possible configurations and so, in Fig. 8, we use H_{sim} in the range $0.57-0.61$ W/(m^{3}K) to reduce further the number of options. Building archetypes with similar S/V ratio and similar H_{sim} have similar heating demand as expected. In this way, we aimed to verify how H_{sim} could be used to narrow down the number of parametric configurations with similar energy performance, in order to link more transparently the calibration process with parametric simulation. In fact, H_{sim} can be considered as an approximation of $-a_1$ and $-b_1$ coefficient of regression models in Table 6, as explained before in this section and this, in turn, guarantees the possibility to use it both in forward (design) and inverse (calibration) analysis.

After that, in Figs. 9–11 we perform similar steps for the comparison of design configurations, selecting data with H_{sim} in the range $0.19-0.38$ W/(m^{3}K) and then limiting the thermal demand for heating in the range $7.0-10.5$ kW h/m^3 (± 20 % from baseline Level 1 results in Table 13).

Again in Fig. 10 multiple configurations have similar thermal demand and in Fig. 11 we use H_{sim} in the range $0.57-0.61$ W/(m^{3}K) to reduce the number of simulation options further. Again, building archetypes with similar S/V ratio and similar H_{sim} have similar heating demand as expected.

In synthesis, the goal of exploratory data analysis with parallel coordinate plots, both for existing and design configurations, was verifying the possibility of combining multivariate data visualization with the regression-based approach proposed, maintaining a physical interpretation of regression coefficients, as indicated in Section 3.2. In all the simulation cases considered, the use of multivariate visualization helped detecting similarities or differences among simulation cases created with different characteristics and levels of detail.

5. Conclusion

In this paper we presented a research essentially focused on testing the flexibility and scalability of a meta-model based approach to link design and operational performance analysis. This approach is part of the ongoing work for the creation of the cloud data platform of the EU H2020 project HEART (Holistic Energy and Architectural Retrofit Toolkit). The meta-modelling technique used in this project is linear multivariate regression, which have been chosen based on the evidence collected in literature analysis and the experience gained in previous research on model calibration and performance gap analysis. More in general, while the research in this case has been based on an energy audit and detailed data acquisition, the modelling approach proposed can be applicable even when limited information is available (e.g. basic building information and monthly utility bills), but data are sufficient to create a reliable baseline, considering the model calibration thresholds used in state-of-the-art M&V procedures, reported in Section 3.3. Given the underlying uncertainties of the assumption introduced in the energy modelling process and the possibility of having multiple models matching measured data, we used both energy performance indicators and statistical indicators to track the process of model calibration and a multi-level structure of the input for building models (i.e. a harmonized reference/prototype building dataset). This structure is then exploited also for visualization purpose, using parallel coordinate plot for multivariate data. Beside detailed (multi-level) model input, we introduced a lumped parameter H_{sim} (heat transfer coefficient, accounting for transmission and infiltration/ventilation in a simplified way) that can be of help when filtering the data for exploratory analysis, as show in Section 4.2. Other lumped coefficients may be introduced by exploiting the approximate physical interpretation of regression model coefficients, studied in previous research. Further, the approach is scalable and can be applied at multiple levels in the building, from individual thermal zones up to the whole building balance. Additionally, the regression approach enables an effective application of Bayesian techniques that can be introduced to test probabilistically the reliability of the estimates of regression coefficients (e.g. by analyzing statistical distributions of model inputs/outputs). Finally, the multivariate data analysis can be enhanced by including variables (either continuous of discrete/categorical) to represent weather data variability, behavioural variability (e.g. different occupancy patterns) and different operation settings (e.g. different operation schedules). These will be part of future research in the HEART project, which will be focused on the multi-level analysis and visualization of building energy balance components and on the definition of representative weather data files for the project application area, together with an appropriate grid and ranges of simulation inputs to limit the amount of parametric simulations, while enabling an accurate exploration of the space of possible building design options and performance outcomes.

Declaration of Competing Interest

The authors declare no conflict of interest

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