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Linking design and operation performance analysis through model calibration: Parametric assessment on a Passive House building

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

*Published Version:*

Lamberto Tronchin, M.M. (2018). Linking design and operation performance analysis through model calibration: Parametric assessment on a Passive House building. ENERGY, 165(A), 26-40 [10.1016/j.energy.2018.09.037].

*Availability:*

This version is available at: <https://hdl.handle.net/11585/643314> since: 2018-09-20

*Published:*

DOI: <http://doi.org/10.1016/j.energy.2018.09.037>

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This is the final peer-reviewed accepted manuscript of:

Lamberto Tronchin, Massimiliano Manfren, Patrick AB. James, *Linking design and operation performance analysis through model calibration: Parametric assessment on a Passive House building*, Energy, Volume 165, Part A, 2018, Pages 26-40.

The final published version is available online at:  
<https://doi.org/10.1016/j.energy.2018.09.037>

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# Linking design and operation performance analysis through model calibration: Parametric assessment on a Passive House building

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## Abstract

Efficient buildings are an essential component of sustainability and energy transitions, which represent today a techno-economic and socio-economic problem. New paradigms are emerging both for new and existing buildings (e.g. NZEBs) and passive design strategies are becoming increasingly common. However, the adoption of these strategies in mild climates has to be carefully evaluated to prevent overheating in intermediate seasons and increasing cooling loads in summer, considering also climate change scenarios. Additionally, optimistic assumptions about building technology performance are often considered and the variability of occupant comfort preferences and behaviour is generally neglected in the design phase. The research presented aims at verifying the suitability of a simple, robust and scalable calibration approach (based on multivariate linear regression) to link design and operational performance analysis transparently, using a Passive House case study building. First, the original baseline design configuration is compared with a larger spectrum of data generated by means of parametric simulation, following a Design of Experiment (DOE) approach. After that, regression models are trained first on simulation data and then progressively calibrated on measured data during a three year monitoring period. The two fundamental objectives are evaluating the robustness of design phase performance analysis through parametric simulation (i.e. detecting potentially critical assumptions) and maintaining a continuity with operation phase performance analysis (i.e. exploiting the feed-back from measured data).

**Keywords:** Parametric modelling; behavioural modelling; building performance simulation; Passive House; performance monitoring; multivariate regression.

## Highlights:

- Buildings are a relevant element in sustainability transition policies.
  - Rigorous schemes for energy efficiency are important tools for designers.
  - Robustness of performance estimates has to be considered in design phase.
  - Design and operational performance analysis have to be linked transparently.
  - Automated model calibration is necessary to ensure long-term performance monitoring.
-

44    **Table of contents**

45	Abstract.....	1
46	1    Introduction .....	3
47	2    Research methodology .....	4
48	2.1    Motivations for regression modelling approach .....	5
49	2.2    Methodology for case study analysis.....	6
50	3    Case study analysis.....	7
51	3.1    Parametric simulation using Design of Experiment approach.....	7
52	3.2    Analysis of baseline design configuration .....	10
53	3.3    Linking design and operational performance analysis.....	12
54	3.4    Monitoring and incremental model calibration.....	17
55	4    Conclusion .....	22
56	Acknowledgments .....	23
57	References .....	23
58		
59		

## 1 Introduction

Efficient buildings are an essential component of sustainability and energy transition policies today and represent a techno-economic and socio-economic problem. The decarbonisation of building stock is one of the most important goals of policies, considering the impact of buildings at the global scale [1] and, in particular, in highly developed countries [2]. Building stock decarbonisation process embodies the necessity of increasing energy efficiency in end-uses, reducing demand and providing a relevant quota of energy supply by renewable sources. Energy efficiency paradigms are emerging both for new and existing buildings (i.e. Nearly Zero Energy Buildings, or NZEBs) [3] and passive design strategies, exploiting solar and internal gains to balance heat losses due to transmission and ventilation (in heating mode), are becoming increasingly common. These strategies can be particularly effective where heating constitutes, in most of the cases, the predominant part of energy consumption. However, the adoption of these strategies in mild climates has to be carefully evaluated to prevent overheating [4, 5] in intermediate seasons and increasing cooling loads in summer, considering also climate change problem [6], as buildings are long-term assets.

More in general, despite the great research effort put in design tools and technical standards in the last decades, both “re-bound” and “pre-bound” effect have been found empirically and, therefore, the gap between simulated and measured performance has been widely investigated in recent years [7, 8]. The “re-bound” effect [9] in efficient buildings is determined by inappropriate operation strategies, while the “pre-bound” effect [10] in inefficient buildings is determined by a more conscious consideration of the costs of energy services by occupants. Consequently, we have to acknowledge the fact that design phase assumptions and calculation methodologies can highly impact the reliability of our estimates of building performance, considering the essential problem of matching simulated and measured performance [11, 12] through calibration techniques. Additionally, in most of the cases the variability of the impact of occupants’ comfort preferences and behaviour on performance is generally neglected in the design phase [13-15]. Finally, we can identify also an increasing commitment towards resource efficiency [16] in the built environment and the need for a holistic view on the topic of building sustainability [17], considering the whole life cycle impact of technologies for the building sector in a more realistic and reliable way [18-20]. All these elements constitute the motivation for the research presented.

As anticipated, model calibration is essential to link design and operational performance analysis under uncertainty [8] and the research 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 a simple, robust and scalable technique (i.e. multivariate linear regression).

A Passive House building is employed as case study to illustrate our approach. First, the original baseline design configuration is compared with a larger spectrum of data generated by means of parametric simulation, following a Design of Experiment (DOE) approach. After that, regression models are trained first on simulation data and then progressively calibrated during a three year monitoring period. In synthesis, the two fundamental research objectives are increasing the robustness of performance estimates in design phase, through parametric simulation, and maintaining, at the same time, a continuity with operational phase performance analysis, through model calibration. In this way, it is possible to detect first critical assumptions already in the design phase and then to derive critical insights as a feed-back from measured data, during operation

110 phase. The techniques used are chosen because of their simplicity, robustness and  
 111 scalability. The latter is particularly important as shown in recent research on  
 112 knowledge discovery in large scale building stock datasets [21, 22] and on Model  
 113 Predictive Control for the integration of renewables in the built environment [23]. For  
 114 these reasons, the chosen approach is potentially suitable for both individual buildings,  
 115 which can have a minimal cost automated performance monitoring (to keep  
 116 performance under control at a reasonable effort, in long-term monitoring), but also for  
 117 large scale studies [24-26] aimed at energy planning and policy, using inexpensive data  
 118 acquisition and processing procedures.  
 119

<b>Nomenclature</b>	
<b>Variables and parameters</b>	
$A$	average value
$a, b, c, d, e, f$	regression coefficients
$Cv(RMSE)$	coefficient of variation of RMSE
$D$	deviation, difference between measured and simulated data
$I$	solar radiation
$M$	measured/simulated data
$MAPE$	mean absolute percentage error
$NMBE$	normalized mean bias error
$q$	specific energy transfer rate (energy signature)
$P$	predicted data
$R^2$	determination coefficient
$RD$	relative deviation
$RMSE$	root mean square error
$S$	simulated
$SS$	sum of the squares
$y$	numeric value
$\theta$	temperature
$\varepsilon$	error term
<b>Subscripts and superscripts</b>	
$-$	average
$\wedge$	predicted value
$b$	baseline
$c$	cooling
$h$	heating
$i$	index
$n$	number of points
$res$	residual

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 121  
 122 **2 Research methodology**  
 123 The importance of parametric and probabilistic analysis of building performance is  
 124 becoming evident [27-30], both in new construction and retrofit interventions [31, 32].  
 125 Cost-optimal [33] levels of investment have to be considered for the effective  
 126 deployment of energy efficiency practices and, consequently, for the credibility and  
 127 success of policies in this direction. However, occupants' comfort preferences and  
 128 behaviour [14, 15, 34] can lead to a relevant gap between simulated and measured  
 129 performance [7], undermining the effectiveness of policies that have to confront with  
 130 real behaviour [8, 9, 35].

In order to overcome this fundamental issue, a methodological continuity should be established between performance analysis practices across life cycle phases (i.e. model based analysis), using parametric simulation in design phase (generally only a limited amount of parameter configurations is considered for design phase simulations) and progressively calibrating building models to measured data (to learn from feed-back). A great effort has been put in recent years on optimization [36] and simulation-based optimization [37] of building energy performance. Further, Design of Experiments (DOE) and parametric design have received also an increasing attention [27-30], together with Monte Carlo simulation to test the robustness of performance modelling [15, 28, 38].

Meta-models [39] (i.e. surrogate models, reduced-order models) are considered among the most promising techniques to overcome the limitations determined by the dimension of the optimization problems or parametric simulations. The choice of a specific technique can depend on several factors [40]. Indeed, meta-models can be successfully used for different purposes, e.g. in design optimization, [37] calibration [39] and control [41]. In fact, they are very flexible and they can be employed to link design and operation phase performance analysis [42], considering, however, the trade-offs between complexity, predictive ability and transparency (i.e. black-box Vs grey-box models) [40]. In this research we propose piecewise linear multivariate regression models for calibration. This choice is motivated in detail in Section 2.1, considering both design and operational phase issues.

## **2.1 Motivations for regression modelling approach**

Building performance can be studied by means of Key Performance Indicators (KPIs) [43-45], generally aimed at aggregating a larger set of data in a single representative quantity. Clearly, KPIs can be used to characterize both design and operational performance. This section presents the motivations for using a regression-based approach in this sense.

As anticipated, meta-models are flexible techniques which can be used for multiple purposes during building life cycle phases. With respect to design phase issues, we can find in recent literature several examples of multi-variate regression models to support design optimization [46-50], considering also topics such as robustness of energy performance contracting and cost-optimal analysis [38, 51]. Further, with respect to operation phase issues, models are acceptable for calibration if they are able to satisfy the thresholds of measurement and verification (M&V) protocols [52-54], which constitute the minimal requirements. The motivations for the choice of a regression modelling approach in this research are connected to previous research conducted in the field and future prospects, considering relevant topics such as:

1. conceptual simplicity and ease of implementation compared to other meta-model based techniques for calibration [39];
2. automated or partially automated model selection capabilities [55, 56];
3. possibility to account for the impact of different operational strategies and conditions [13-15], considering different levels of thermal inertia [57];
4. scalability and applicability with respect to different types of end-uses [58] and multiple temporal [59, 60] and spatial scales [24, 26];
5. visualization of the impact of users' behaviour [14];
6. model robustness testing, under different behavioural conditions, using Monte Carlo simulation [15];
7. use of Bayesian analysis [61, 62] as an extension of conventional regression;

Finally, the use of simplified but robust and scalable models could potentially open up new perspectives for the application of large scale optimization of distributed energy resource in the built environment [23, 63-68], considering the problem of updating model parameters through periodic recalibration in evolving conditions [6, 69]. In order to render these applications more transparent and automated, further research should be oriented towards the definition of multi-scale and multi-level performance metrics [58, 70] and corresponding visualization techniques.

## **2.2 Methodology for case study analysis**

The research presented is based on a case study analysis. In Section 3.1, the data from the original building design are used as baseline (initial design simulation) and then compared to parametric simulation runs obtained using Design of Experiment (DOE) approach. Therefore, parameters in DOE simulations have been varied with respect to the baseline configuration. Initial design involved the use of PHPP semi-stationary calculation methodology [71], specifically developed for Passive House buildings. In this research simulations are conducted using a validated grey-box dynamic model, suitable to perform multiple runs in a reduced time frame [72, 73], maintaining, at the same time, an acceptable level of reliability. Further, this choice corresponds to the necessity of enabling a future development of the research oriented to the non-intrusive identification of relevant physical parameters of the building [74]. In this research the grey-box lumped model parameters have been initially calibrated to the original baseline configuration in PHPP, to ensure comparability of results, and then varied following two-level full factorial design experiment plans [75], to compute every possible combination of factors and levels. Generally, a full factorial DOE cannot be used because of the computational effort: due to the exponential growth of experiments' number, this is only feasible for a limited number of factors and levels (as in this case study). The alternative choice would be running different fractional designs, where a selection of factor combinations is identified to reduce the number of experiments while maintaining an appropriate exploration of the design space and supporting a faster design workflow. However, by reducing the number of experiments we could possibly neglect some configurations which could be important for the analysis. In principle, we could have looked for a fractional design for this case study, but it would have been specific for the case study itself [29]. In order to derive more general rules for DOE, it would be necessary to apply the regression based approach presented in this paper to groups or typologies of reference buildings [22, 33], but this goes beyond the scope of this research. However, this can constitute the basis for future research, considering previous multi-scale simulation experience [58, 76].

In this case study, multiple DOE runs are used to account for the performance variability determined by envelope components and by occupant's comfort preferences and behaviour. Ideally, the parametric approach aims at understanding the impact of factors and to detect potentially critical assumptions already at the preliminary design level and to ensure the robustness of energy performance evaluation [28, 38]. In real building operation these variations can determine a very relevant gap between simulated and measured performance and, consequently, can compromise the cost-effectiveness of investments in energy efficiency, undermining the credibility of energy efficiency practices [33]. In other words, the objective of DOE simulation is that of addressing critically (i.e. with less optimistic assumptions) the effects of performance variability.

After that, in Section 3.2 the result for baseline design configuration is described more in detail, highlighting visually the relevant components characterizing building energy balance. Further, Section 3.3 describes the necessary steps and tools (in the workflow)



to link design and operational phase performance analysis through model calibration, and to test the applicability of regression models for performance prediction, using energy signatures [77].

Parametric simulation data are used to train multiple piecewise linear multivariate regression models. Finally, models are used for progressive calibration on measured data over a three year time monitoring, described in Section 3.4. In model training and testing phases visualization techniques are used in combination with numeric ones to enable an intuitive interpretation of results and to ease human interaction in an automated (or partially automated) calibration process.

### **3 Case study analysis**

The case study chosen is a Passive House standard residential building constructed at south border of the Province of Forlì-Cesena, near Rimini, in the Emilia Romagna Region in Northern Italy. The case study building is characterized by highly insulated envelope components, a mechanical ventilation system with heat recovery (all-air system), a ground-source reversible heat pump system (GSHP) serving the mechanical ventilation system for heating and cooling demands and the domestic hot water demand. Further, a photovoltaic system for on-site electricity production and a solar thermal system for domestic hot water production integration are present. In the parametric simulations heat recovery has been considered in winter mode operation, taking into account also the relevant impact of auxiliaries [78].

#### ***3.1 Parametric simulation using Design of Experiment approach***

As anticipated, the baseline configuration chosen for simulation is the one used originally for building design. The envelope parameters used in the grey-box model (lumped parameters) have been calibrated to reproduce the same heating demand of the original model in PHPP. Grey-box models are highly flexible, scalable and represent a good compromise between detail and accuracy when modelling building energy dynamics [79, 80]. These models have been used for yearly simulations, including all the energy demands from the building:

1. heating;
2. cooling;
3. domestic hot water (DHW);
4. lighting;
5. appliances.

Internal gains assumed in simulation and reported in Table 1 are averaged on a daily base and are very modest, considering the fact that the building, despite being very large, is actually used only by 4/5 people. It has to be underlined the fact that baseline configuration and DOE run 1 use constant operating schedules, as reported in Table 1, to maintain a comparability with the original PHPP model, but more realistic schedules are considered in the parametric simulation runs 2 (behaviour 1) and 3 (behaviour 2). In two-level DOE vary between two values, indicated with -1 and +1. The number of simulations depends on the amount of parameters chosen and on the combinatorial logic chosen. In this research we consider a full factorial DOE, for the reasons outlined in Section 2.1. The overall simulation data are summarized in Table 1.

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*Table 1: Baseline and Two-level Design Of Experiment simulation data*

Group	Type	Unit	Baseline	Design of experiment	
				Levels	
				-1	+1
Climate	UNI 10349:2016	-			
Geometry	Gross volume	m <sup>3</sup>	1557		
	Net volume	m <sup>3</sup>	1231		
	Heat loss surface area	m <sup>2</sup>	847		
	Net floor area	m <sup>2</sup>	444		
	Surface/volume ratio	1/m	0,54		
Envelope	U value external walls	W/(m <sup>2</sup> K)	0,18	0,23	0,27
	U value roof	W/(m <sup>2</sup> K)	0,17	0,21	0,26
	U value transparent components	W/(m <sup>2</sup> K)	0,83	1,04	1,25
Activities	Internal gains (lighting, appliances and occupancy, daily average)	W/m <sup>2</sup>	1	1	1.5
Control and operation	Heating set-point temperature	°C	20	20	22
	Cooling set-point temperature	°C	26	26	28
	Air-change rate (infiltration and mechanical ventilation with heat recovery in heating mode)	vol/h	0,2	0,2	0,4
	Shading factor (solar control summer mode)	-	0.5	0.5	0.7
	Domestic hot water demand	l/person/day	50	50	70
	Schedules – DOE constant operation	-	0.00-23.00	0.00-23.00	0.00-23.00
	Schedules – DOE behaviour 1	-	7.00-22.00	7.00-22.00	7.00-22.00
	Schedules – DOE behaviour 2	-	7.00-9.00, 17.00-22.00	7.00-9.00, 17.00-22.00	7.00-9.00, 17.00-22.00

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In terms of temperature set-points, it has been considered an increase of two degrees in heating mode and an increase of two degrees also in cooling mode, to account respectively for an increased heating demand and for a reduced cooling demand. In terms of ventilation rate, infiltration and mechanical ventilation with heat recovery in heating mode have been considered.

Technical systems consist of a GSHP system, providing heating, cooling and domestic hot water (DHW), a rooftop photovoltaic plant (BIPV) and a solar thermal system with storage to integrate DHW production. Relevant sizing data of technical systems are reported in Table 2.

*Table 2: Technical system sizing data*

Group	Technology	Type	Unit	Value
Heating/Cooling system	GSHP (Ground-source heat pump)	Brine/Water Heat Pump	kW	8.4
		Borehole heat exchanger (2 double U boreholes)	m	100
On-site energy production	Building Integrated Photo-Voltaic (BIPV)	Polycrystalline silicon	kW <sub>p</sub>	9.2
		Glazed flat plate collector	m <sup>2</sup>	4.32
		Domestic hot water storage	m <sup>3</sup>	0.74

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In order to simulate realistic operation conditions, coherent operating schedules have been created for heating, cooling, air-change rate (ventilation/infiltration) and internal gains (lighting, appliances, people). Schedules have been created using the methodology described in detail in previous research [14, 15] and the corresponding normative references [81]. As anticipated, the DOE simulation runs conducted are 3, one for each

299 set of operation schedules, simulating different behavioural patterns of people living in  
300 the building:

- 301 1. operation is continuous as in baseline design configuration (constant operation  
302 profile);
- 303 2. operation is concentrated between 7.00 and 22.00 (variable operation profile,  
304 behaviour 1);
- 305 3. operation is concentrated between 7.00 and 9.00 and between 17.00 and 22.00  
306 (variable operation profile, behaviour 2).

307

308 The indicators chosen for simulation output analysis are the following ones:

- 309 1. thermal demand for heating and cooling;
- 310 2. electricity demand for end-use (heating, cooling, DHW, appliances and  
311 lighting);
- 312 3. self-consumption of on-site RES electricity production;
- 313 4. renewable energy ratio (RER) [82];
- 314 5. load matching and grid interaction index [83, 84];
- 315 6. non-renewable primary energy demand;
- 316 7. CO<sub>2</sub> emission.

317

318 Most of the performance indicators have been calculated according to the methodology  
319 proposed in the standard ISO 52000-1 [85], which will be adopted in the future energy  
320 efficiency legislation at the EU level (overarching framework for the Energy  
321 Performance of Buildings, or EPB). Further, it has to been underlined the fact the KPIs  
322 chosen are substantially scalable, up to neighbourhood/district [65] scale, city scale [86]  
323 and regional/national scale [87].

324 As introduced before, the whole building energy demand has been taken into account,  
325 weighting delivered and imported electricity asymmetrically. The primary energy and  
326 emission factors assumed for calculation are the ones contained in Italian legislation  
327 regarding energy efficiency in buildings. However, while the delivered energy weight  
328 assumed is 1, the exported energy weight assumed here is 0.4, differently from the  
329 current building performance rating scheme adopted at the national level, which gives a  
330 0 weight for exported energy.

331 The results obtained from DOE simulations have been used to report KPIs on a yearly  
332 base, considering respectively lower bound (LB) and upper bound (UB) of values  
333 obtained. The data are reported in Table 3, showing values for:

- 334 1. baseline design configuration;
- 335 2. lower and upper bound of overall data (DOE run 1, 2, 3);
- 336 3. constant operation data (DOE run 1);
- 337 4. behaviour 1 data (DOE run 2);
- 338 5. behaviour 2 data (DOE run 3).

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*Table 3: Baseline and Two-Level Design Of Experiment simulation data comparison – lower bound and upper bound of KPI yearly values*

Balance level	KPI	Unit	Baseline	Design of Experiments							
				Overall		Constant		Behaviour 1		Behaviour 2	
				LB	UB	LB	UB	LB	UB	LB	UB
Zonal	Heating demand	kWh/m <sup>2</sup>	19.3	17.2	39.6	19.2	39.6	18.0	36.2	17.2	33.8
	Cooling demand	kWh/m <sup>2</sup>	10.8	0.8	12.6	0.8	12.3	1.2	12.6	1.1	11.2
Meter	Self-consumption	%	26.9	16.7	42.6	24.2	30.7	26.4	42.6	16.7	22.2
	Renewable Energy Ratio	%	91.7	75.8	97.3	81.3	94.6	79.4	97.3	75.8	93.2
	Load matching index	%	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Primary Energy	kWh/m <sup>2</sup>	5.0	1.5	24.3	3.2	18.5	1.5	20.1	3.9	24.3
	CO <sub>2</sub> Emission	kg/m <sup>2</sup>	1.1	0.3	5.4	0.7	4.1	0.3	4.4	0.9	5.4

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### 3.2 Analysis of baseline design configuration

Parametric simulation runs described in the previous Section are performed to create a possible spectrum of performance data, under uncertainty. On the other hand, baseline configuration represents simply the initial design hypothesis. In this Section baseline configuration is analysed to verify graphically, first of all, the suitability of a regression-based approach. For this reason, we report monthly data of indicators, plotted against average monthly external air temperature [39, 55, 56, 58], to identify correlations. For energy quantities in particular, we transform monthly data to derive the average power calculated over a monthly operation period; this method is called energy signature [77]. The objective of energy signatures is deriving weather normalized visualizations, suitable for monitoring and calibration in different climate conditions. Monthly monitoring of energy performance is not data intensive and can be done both manually and automatically, by means of data acquisition systems from meters. Further, it can easily scale from single buildings to building stock [58] and cities [24].

Monthly electricity demand composition and related energy signatures are reported in Figure 1 for the baseline configuration, showing the proportion of the different components of electricity demand in the building. The shape of data in energy signatures indicates the possibility of fitting total electric energy demand with a piecewise-linear regression model, while heating and cooling demand can be fitted with two separate linear regression models, as reported in literature [58, 88], allowing a physical interpretation of regression coefficients. The electricity meter balance with respect to demand and on-site production is reported in Figure 2, while delivered and exported energy data are reported in Figure 3, together with the related signatures. In this case also the data patterns can be approximated by linear and piece-wise linear models.

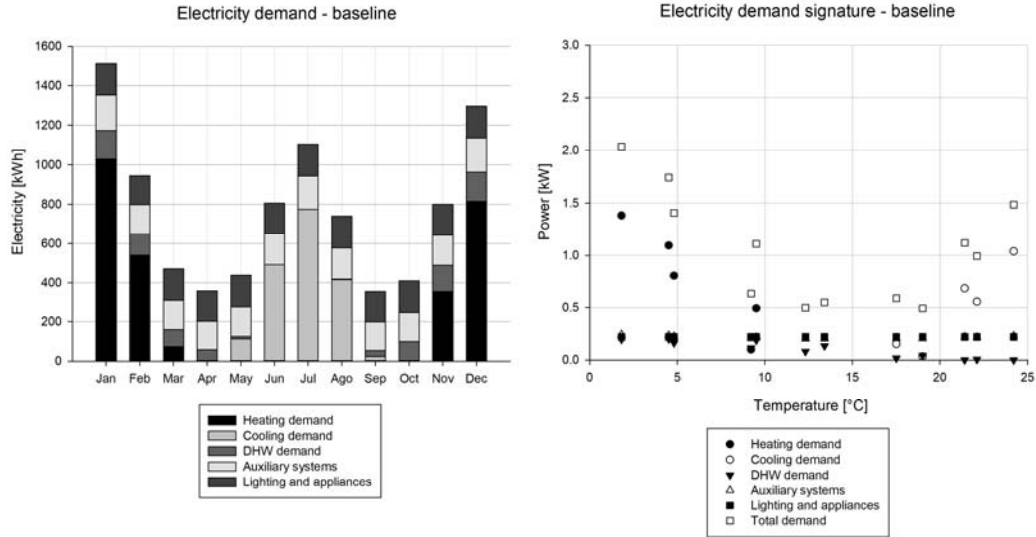


Figure 1: Electricity demand composition – monthly data and signatures

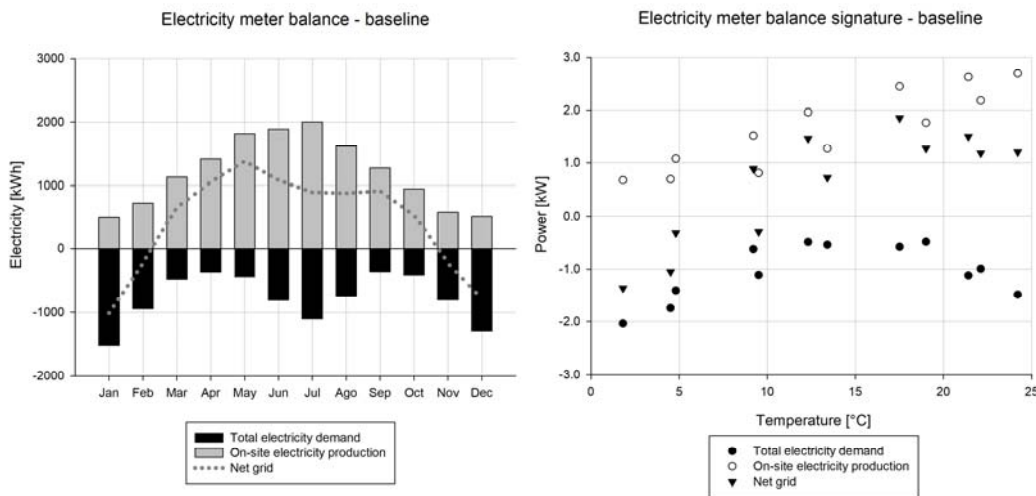


Figure 2: Electricity meter balance - on-site production and demand - monthly data and signatures

The values represented in Figure 2 highlight the fact that the photovoltaic system is able to satisfy the total electricity demand of the building on a yearly base. Further, the values reported in Figure 3 show the interaction of the building with the grid, by means of the patterns of delivered and exported energy. The analysis of these patterns shows indirectly when (on a daily base) the activity at the building level is concentrated, because we can discriminate the quantity of energy self-consumed depending on the climatic variables (temperature and solar radiation). In this way, it is possible to test if the schedules assumed for dynamic simulation are approximately correct even with low resolution data (monthly in this case). Therefore, further research development in this direction is possible by introducing more information about user behaviour (e.g. integrating long-term monthly measurements with periodic short-term measurements at hourly/sub-hourly intervals [59, 60, 89]).

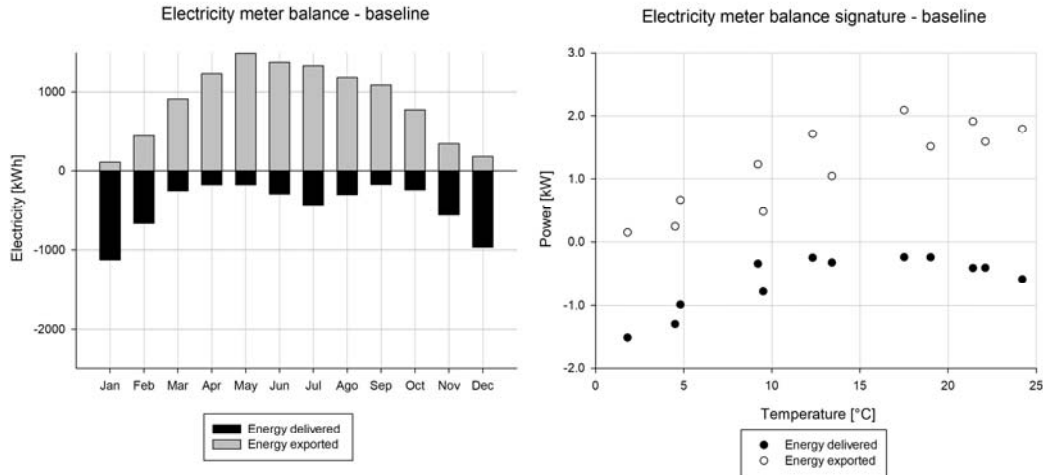


Figure 3: Electricity meter balance - delivered and exported energy - monthly data and signatures

Another way of accounting for the variability of the building interaction with the grid are load matching and grid interaction indexes, which are reported in Figure 4. Load matching index assumes the maximum value of 100% by definition [83, 84].

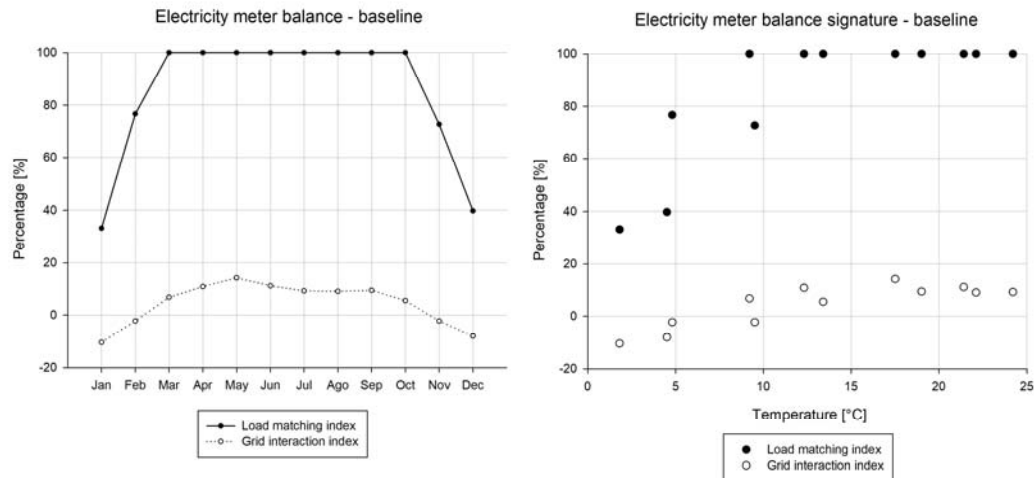


Figure 4: Electricity meter balance – load matching and grid interaction indexes – monthly data and signatures

### 3.3 Linking design and operational performance analysis

The aim of this research was establishing a link between DOE simulation data and operational data, in order to calibrate progressively simple predictive models, maintaining at the same time a comparability with initial parametric estimates. Regression models are essential for two fundamental reasons:

1. providing a simple but effective approach for performance monitoring, for the reasons outlined in Section 2;
2. performing weather normalization of simulation results, generated with a standard climate data file, reported in Table 1.

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410 The choice was adopting a piecewise linear multivariate regression approach,  
 411 considering the general motivations reported in Section 2.1. Actually multiple types of  
 412 meta-models can be considered for calibration purpose as described in Section 2, but we  
 413 decided to use the simplest possible approach to ease model calibration and,  
 414 consequently, performance monitoring, creating a procedure that could possibly scale  
 415 with respect to temporal [59] and spatial resolution of data [24, 39], using multi-level  
 416 analysis [70]. Further, among all the data presented in Sections 3.1 and 3.2, we decided  
 417 to focus on the total aggregated electricity demand, plotted in Figure 2 for baseline  
 418 design configuration, even though the model can be further decomposed with respect to  
 419 zonal energy balance components [58], represented in Figure 1.

420 The piecewise linear multivariate regression models proposed are reported in Table 4.  
 421 The overall predictive model is the combination of three linear submodels, respectively  
 422 for heating, cooling and baseline demand. Two types of models are considered:

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

426

427

*Table 4: Regression models for heating, cooling and baseline demand analysis*

Demand	Model type 1	Model type 2
Heating	$q_{h,1} = a_0 + a_1\theta_e + \varepsilon$	$q_{h,2} = b_0 + b_1\theta_e + b_2I_{sol} + \varepsilon$
Cooling	$q_{c,1} = c_0 + c_1\theta_e + \varepsilon$	$q_{c,2} = d_0 + d_1\theta_e + d_2I_{sol} + \varepsilon$
Baseline	$q_{b,1} = e_0 + e_1\theta_e + \varepsilon$	$q_{b,2} = f_0 + f_1\theta_e + f_2I_{sol} + \varepsilon$

428

429 External temperature is the most important regressor for weather normalization [90].  
 430 However, we decided to include also solar radiation as a regressor, considering the fact  
 431 that we are analysing a Passive House standard building, in which the impact of solar  
 432 gains is relevant and a solar thermal system for the integration of DHW production is  
 433 present as well. Nonetheless, similar approaches can be used for solar photo-voltaic [91]  
 434 and solar thermal plants [92, 93].

435 In order to evaluate and compare properly simulation data in design phase and measured  
 436 data in operation phase, we used a set of statistical indicators. We decided to train first  
 437 the two different types of multivariate piecewise linear regression models on simulated  
 438 data, in order to test them in the first year of operation with respect to measured data.  
 439 Then, from the second year onward, models are directly trained on measured data. This  
 440 part of the research is described in detail in Section 3.4.

441 Going back to statistical indicators, the goodness of fit of a regression model can be  
 442 expressed by the determination coefficient  $R^2$  that can assume values ranging from 0 to  
 443 1 (or 0 to 100%, if expressed in percentual terms), where 1 means that the data fitting is  
 444 perfect. The formula for  $R^2$  is the following one:

445

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

446

447  $R^2$  is an important indicator of the goodness of fit, but it is not the only one to be  
 448 considered. We decided to consider also *MAPE* (Mean Absolute Percentage Error), to  
 449 account for the average absolute value of the difference among measured and predicted

450 data, normalized with respect to measured data themselves. *MAPE* is calculated as  
 451 follows.  
 452

$$MAPE = \frac{1}{n} \sum_i \left| \frac{M_i - P_i}{M_i} \right| \cdot 100 \quad (2)$$

453  
 454 Further, in the state-of-the-art of model calibration procedures [11, 12, 52-54] other two  
 455 metrics are employed, *NMBE* and *Cv(RMSE)*. *NMBE* (Normalized Mean Bias Error) is  
 456 the total sum of the differences between measured (or simulated, before operation) and  
 457 predicted energy consumption at the calculation time intervals (e.g. monthly, hourly) of  
 458 the considered period. The difference is then divided by the sum of the measured (or  
 459 simulated) energy consumption.  
 460

$$NMBE = \frac{\sum_i (M_i - P_i)}{\sum_i M_i} \cdot 100 \quad (3)$$

461 A positive value of *NMBE* implies a model overestimation of energy consumption,  
 462 viceversa a negative value implies an underestimation.  
 463 The *RMSE* (Root Mean Squared Error) is a measure of the sample deviation of the  
 464 differences between measured values and values predicted by the model. *Cv(RMSE)* is  
 465 the Coefficient of Variation of *RMSE* and is calculated as the *RMSE* normalized to the  
 466 mean of the measured values. *Cv(RMSE)* represents a normalized measure of the  
 467 variability among measured (or simulated, before operation) and predicted data. It  
 468 specifies the overall uncertainty in the prediction of the building energy consumption,  
 469 reflecting the errors size and the amount of scatter. Lower *Cv(RMSE)* values indicate a  
 470 better calibrated model.  
 471

$$Cv(RMSE) = \frac{RMSE}{A} \cdot 100 \quad (4)$$

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

$$A = \frac{\sum_i M_i}{n} \quad (6)$$

472  
 473 The threshold limits considered at the state-of-the-art are reported in Table 5,  
 474 considering the most relevant protocols for measurement and verification (M&V)  
 475 existing today.  
 476

477 *Table 5: Threshold limits of metrics for model calibration with monthly data*

Metric		ASHRAE	IPMVP	FEMP
		Guidelines 14		
<i>MBE</i>	%	± 5	± 20	± 5
<i>Cv(RMSE)</i>	%	15	-	15

478  
 479 Simulated parametric data (DOE) are used as reference to link design (when no  
 480 measured data are available) and operational performance analysis. As specified before,



we concentrated on the analysis on simulated total aggregated electric energy demand, training regression models respectively on:

1. lower bound (LB) and upper bound (UB) data for the overall DOE runs dataset (runs 1, 2, 3);
2. three subsets of data, corresponding to constant operation (DOE run 1), behaviour 1 (DOE run 2) and behaviour 2 (DOE run 3).

The results obtained are reported in Table 6, showing the goodness of fit of piecewise linear regression models to simulated data in all the conditions.

*Table 6: Training of regression models on DOE simulation data*

Regression model	Dataset		Training - simulation data DOE			
			$R^2$	$MAPE$	$NMBE$	$Cv(RMSE)$
			%	%	%	%
Type 1	Overall	LB	93.65	9.34	0.06	13.58
		UB	96.64	7.33	0.02	9.01
	Constant	LB	93.97	9.66	0.07	14.22
		UB	96.16	8.81	0.01	10.63
	Behaviour 1	LB	93.44	9.38	0.07	13.19
		UB	96.56	7.31	0.01	9.07
	Behaviour 2	LB	93.43	9.33	0.06	12.79
		UB	96.52	7.23	0.01	8.96
Type 2	Overall	LB	99.90	1.42	-0.02	1.65
		UB	99.77	1.93	-0.01	2.36
	Constant	LB	99.86	3.77	4.82	8.33
		UB	99.65	8.55	-3.57	5.89
	Behaviour 1	LB	99.91	1.02	0.03	1.47
		UB	99.77	1.88	0.00	2.32
	Behaviour 2	LB	99.92	1.11	0.03	1.42
		UB	99.69	2.17	0.00	2.67

We can also represent easily the results of model training process graphically. In this research we decided to plot the distribution of simulated monthly data on a yearly base, together with the corresponding energy signatures (lower and upper bound of simulation data envelopment), compared with model type 1 and model type 2 regression results. The results are represented in Figure 5 for the overall dataset, and in Figures 6, 7 and 8, respectively for constant operation, behaviour 1 and behaviour 2. The use of interval data for parametric simulation is substantially comparable to an epistemic uncertainty assumption [94].

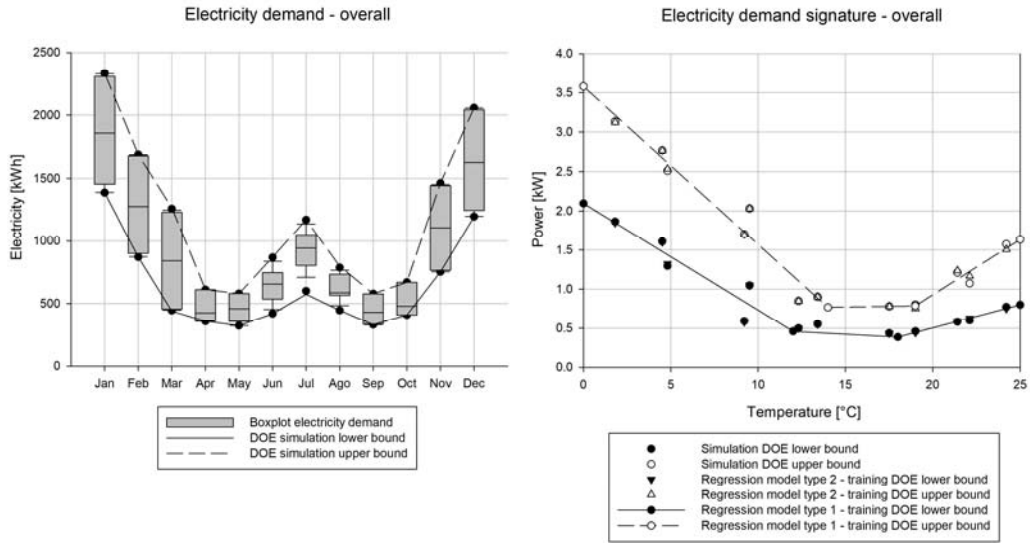


Figure 5: Total simulated monthly electricity demand distribution (boxplot) and comparison between simulated and piecewise linear multivariate regression (energy signatures) – overall data

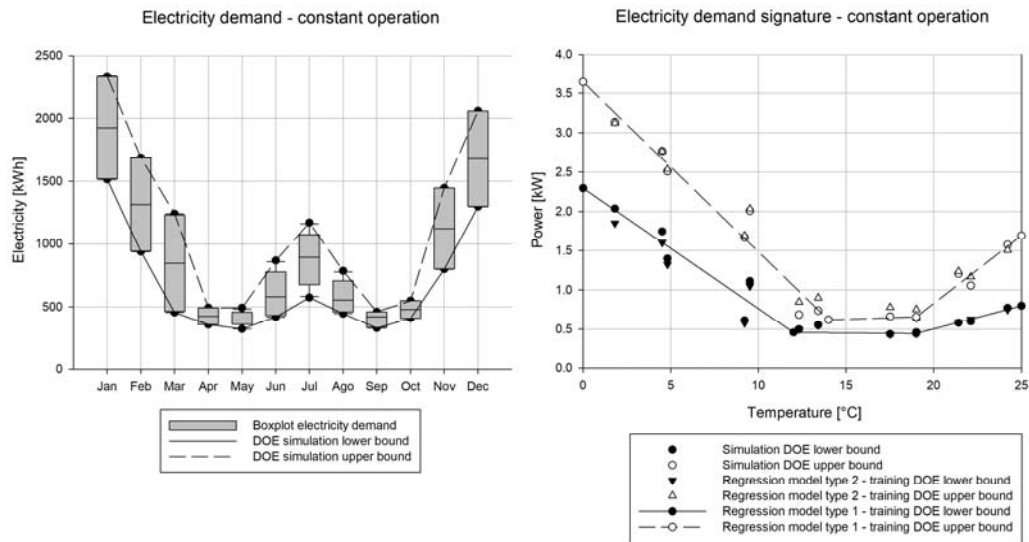


Figure 6: Total simulated monthly electricity demand distribution (boxplot) and comparison between simulated and piecewise linear multivariate regression (energy signatures) – constant operation data

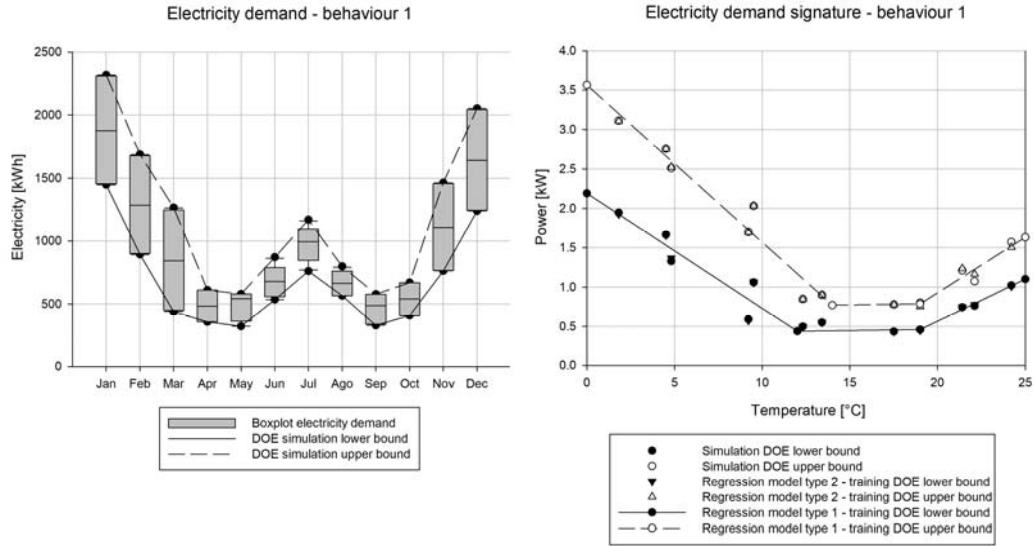


Figure 7: Total simulated monthly electricity demand distribution (boxplot) and comparison between simulated and piecewise linear multivariate regression (energy signatures) – behavior 1 data

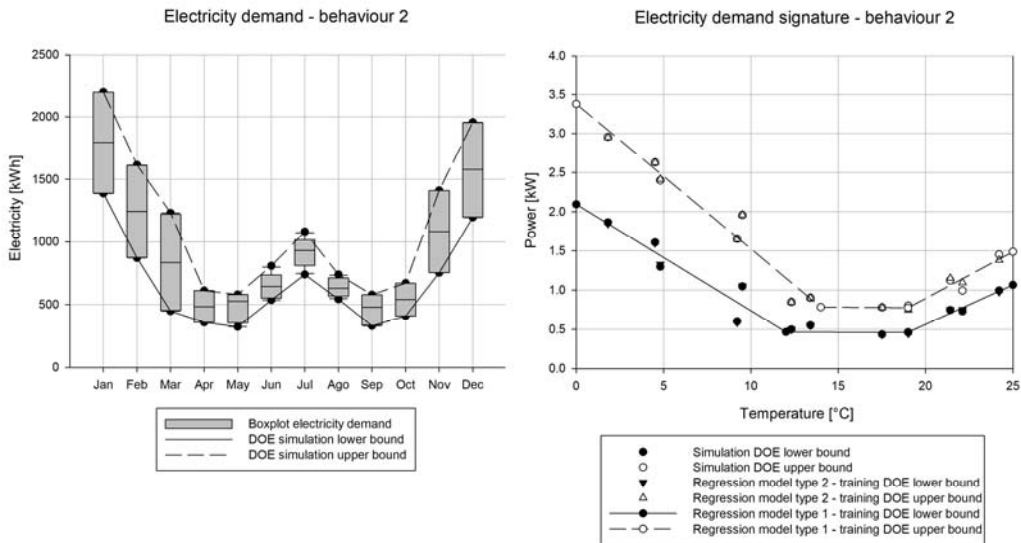


Figure 8: Total simulated monthly electricity demand distribution (boxplot) and comparison between simulated and piecewise linear multivariate regression (energy signatures) – behavior 2 data

### 3.4 Monitoring and incremental model calibration

We decided to use both model type 1 and type 2 for monitoring and incremental model calibration process. The analysis is concentrated on total aggregated electricity demand, as specified before. Models are initially trained respectively on the lower and upper bounds of overall DOE runs data, when measured data are not available (design phase). In this way, we consider the largest possible spectrum of data variability, given by the underlying assumptions for the generation of DOE cases, reported in Section 3.1. After the first year of operation, models are trained on measured data.

The results of model training and testing for the three years of monitoring period are plotted in Tables 7 and 8, respectively for model type 1 and type 2. The phases and subphases of the process are reported in Tables, considering:

1. design phase, model training on DOE simulation data;
2. operation phase, initial operation, uncalibrated model;
3. operation phase, partial calibration, models don't reach calibration thresholds reported in Table 5;
4. operation phase, calibration, model reaches calibration thresholds reported in Table 5.

In general, the results highlighted the necessity of considering multiple statistical indicators in the calibration process. In fact,  $R^2$  is highly dependent on the scatter of data and therefore cannot be considered as the only parameter for predictive model validation, because this could lead to misleading conclusions. In fact, model  $R^2$  can be high even if the model is uncalibrated, uncovering a systematic error. Therefore, the predictive model is acceptable only if its calibration indicators  $NMBE$  and  $Cv(RMSE)$  are within the limits reported in Table 5, according to calibration protocols in M&V.

*Table 7: Incremental calibration during three years of operation – Model type 1*

Phase	Sub-phase	Training dataset	Testing dataset	$R^2$ %	$MAPE$ %	$NMBE$ %	$Cv(RMSE)$ %
Design	Model training	Simulated data DOE - Overall LB		93.65	9.34	0.06	13.58
Design	Model training	Simulated data DOE - Overall UB		96.64	7.33	0.02	9.01
Operation	Initial operation		Measured data – Year 1	76.88	35.51	-50.23	37.60
Operation	Initial operation		Measured data - Year 1	73.08	33.35	20.59	44.39
Operation	Partial calibration	Measured data – Year 1		81.33	12.03	0.02	14.60
			Measured data – Year 2	91.97	13.08	-13.82	16.12
Operation	Partial calibration	Measured data – Year 1 and 2		82.64	11.44	0.04	13.44
			Measured data – Year 3	69.74	18.40	-6.95	19.75

*Table 8: Incremental calibration during three years of operation – Model type 2*

Phase	Sub-phase	Training dataset	Testing dataset	$R^2$ %	$MAPE$ %	$NMBE$ %	$Cv(RMSE)$ %
Design	Model training	Simulated data DOE - Overall LB		99.90	1.42	-0.02	1.65
Design	Model training	Simulated data DOE - Overall UB		99.78	1.93	-0.01	2.36
Operation	Initial operation		Measured data – Year 1	69.91	38.80	-36.46	41.86
Operation	Initial operation		Measured data - Year 1	75.99	28.16	21.33	40.64
Operation	Partial calibration	Measured data – Year 1		85.93	8.05	0.04	12.76
			Measured data – Year 2	88.45	13.72	-13.75	17.07
Operation	Calibration	Measured data – Year 1 and 2		86.07	9.97	0.05	12.02
			Measured data – Year 3	87.54	11.97	-2.21	12.50

As we can see from the data in Tables 7 and 8, model type 1 remains partially calibrated even in the third year of operation, while model type 2 reaches calibration. With low temporal resolution data (i.e. monthly data) we need at least two years of measured data to be able to calibrate a model. It is worth noting that two years of data are also generally considered as a minimal requirement in energy audits. The research highlights the fact that we can monitor easily and inexpensively long-term performance with a spatial scalability up to the utility level [21, 24, 25]. Additionally, models can scale in time up to daily and hourly data resolution [59, 60] to reach calibration within a more limited time-frame of operation, when more data are available. In any case, we consider periodic recalibration fundamental to monitor long-term performance evolution, as indicated also in other studies [89]. Beside statistical indicators used in the calibration process, it is important to provide simple visual analytical tools to render the process of calibration and long-term performance monitoring more intuitive and transparent. In this research we decided to use three visualization tools:

1. time series of measured and predicted energy consumption data (electricity demand in this case), Figure 9;
2. time series of model deviations among measurements and predictions, Figure 10;
3. time series of cumulative sum of deviations (CUSUM) chart, Figure 11.

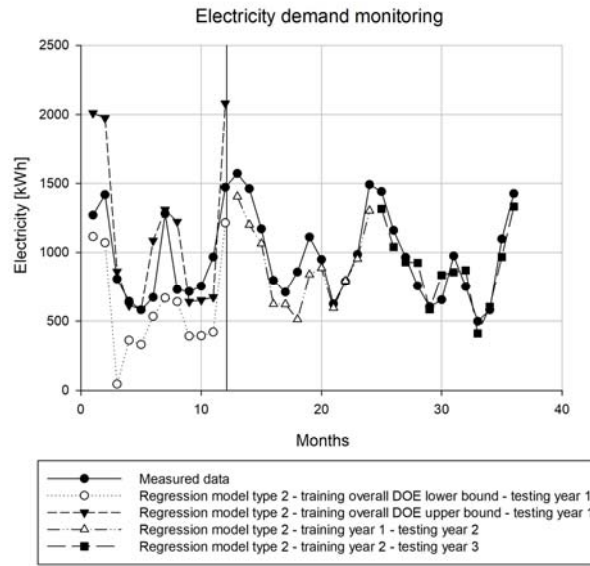
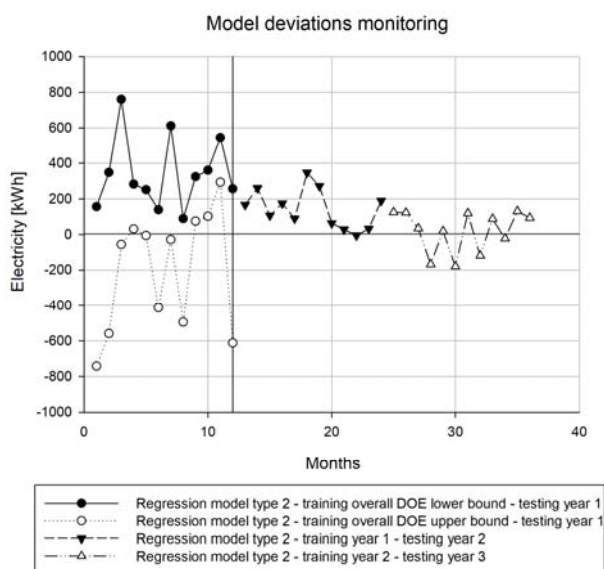


Figure 9: Electricity demand monitoring – time series of monthly data measured and predicted by different models, three years monitoring period

The time series in Figure 9 highlight the progressive calibration process, reached in the third year of operation as explained before, with the substantial alignment among measured and predicted data. The underlying model (a monthly model for the prediction of aggregated electricity consumption) is a “static” model (energy signature), as there is no explicit dependence on time but only on weather conditions and operating hours considered [77]. Subsequently, the deviations among measurements and predictions are calculated according to the following formula.

$$D_i = M_i - P_i \quad (7)$$

583 A positive deviation implies that the model is underestimating energy consumption at  
 584 that point in time (i.e. the measured consumption is higher than predicted), while a  
 585 negative deviation implies an overestimation of energy consumption (i.e. the measured  
 586 consumption is lower than predicted). In this case study we can see how deviations in  
 587 Figure 10 are progressively decreasing and how calibrated model deviations tend to  
 588 oscillate around zero.



589  
 590 *Figure 10: Electricity demand monitoring – deviations among measured and predicted*  
 591 *data, three years monitoring period*  
 592

593 Further, the cumulative sum of deviations is reported to ease the detection of model drift  
 594 with respect to measured data. By using the incremental sum of deviation we can  
 595 identify the cumulative difference between measured and predicted data at a point in  
 596 time. A positive sum of deviations indicates that the actual energy demand is higher  
 597 than predicted (i.e. model is underestimating consumption), while a negative sum of  
 598 deviations indicates that actual energy demand is lower than predicted (i.e. model is  
 599 overestimating consumption). In this research, the cumulative sum of deviations in the  
 600 third year of operation for model type 2 is practically equal to zero, with a minimal  
 601 difference between measurement and prediction (around 2%), confirming the reliability  
 602 of the calibrated model.

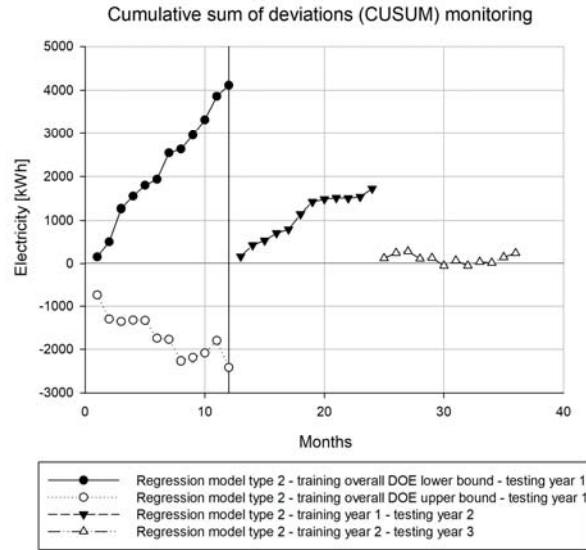


Figure 11: Electricity demand monitoring – cumulative sum of deviations among measured and predicted data, three years monitoring period

Finally, Figure 12 summarizes the whole procedure representing, on the left side, a priori parametric DOE estimates, reported previously in Figure 5, comparing them with measured data. On the right side of Figure 12, calibrated models (a posteriori) are reported.

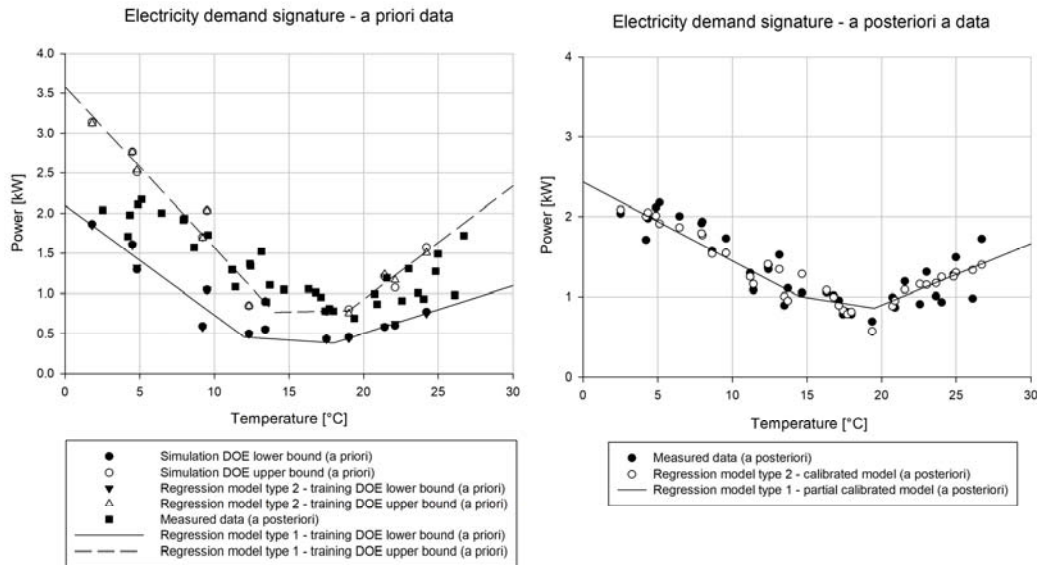


Figure 12: Electricity demand monitoring – overall analysis of a priori and a posteriori data, three years monitoring period

It is worth noting that, even if model type 1 remains partially calibrated, it is still useful to get a simple visual representation of the relevant differences with respect to heating, cooling and baseline demand, by comparing positions and slopes of regression lines. A further analysis of the components of the energy balance can help detecting root causes

of anomalies in energy demand (i.e. considering a grey-box interpretation of regression coefficients) [88], and will be part of future research on this case study.

#### 4 Conclusion

Design optimization in buildings has often been oriented towards specific paradigms without considering properly variability and uncertainty in design assumptions and without questioning relevant factors that could undermine the fundamental goals of paradigms themselves. Passive House standard is a rigorous voluntary scheme for high efficiency buildings, but the use of this standard in the Mediterranean area, characterized by a mild climate, can be debatable, considering climate change scenarios, and relevant uncertainties in performance simulation. For this reason, we selected a Passive House building in Italy as case study. The ability to monitor long-term performance inexpensively and to use easily accessible data is important for multiple stakeholders in the building sector. In fact, the analysis of building performance data using simple, robust and scalable techniques can provide relevant analytical insights improve design and operational practices, as well as to orient policies. In other words, our decisions can be based on feedbacks from the actual performance of building stock, rather than on (simulation-based) estimates that can be very far from reality in many cases, leading to a consistent performance gap. In this research we illustrated how parametric simulation (to test robustness of design configurations) can be combined with regression-based calibration approaches (state of the art of performance monitoring), establishing a continuity between design and operational phase analysis. In this way, we can assume a more critical perspective on building performance, necessary to ensure the credibility of energy efficiency practices, especially with respect to innovative business models where the analysis of cost-optimal levels of investment is a pre-requisite. In fact, risk analysis for efficiency investments is a particularly relevant problem today, embodying the necessity of evaluating performance variability in depth. Additionally, variability in performance outcomes determined by occupants' preferences and behaviour have been often neglected in design but they are essential for the success of innovative practices and policies in buildings. While in the case study presented we concentrated on the analysis of aggregated electricity demand, there are other relevant quantities, such as delivered and exported energy or the percentage of self-consumption of RES production, which can change radically when realistic operation profiles are used instead of standardized assumptions. Even an analysis of low temporal resolution data (e.g. monthly automatically metered data) conducted in an appropriate way (i.e. when sufficient metadata are available) can help uncovering the impact of user behaviour. This impact can determine a large variation of performance both in economic terms, depending on the specific business model adopted, and in environmental terms, because of temporal variation of interaction with energy infrastructures (i.e. delivered and exported energy patterns). Finally, the approach can be developed further when thermal metering data are available, and this will be part of future research.

As a conclusion, instead of simply evaluating the formal correctness of modelling approaches, it is necessary to introduce progressively parametric design in practice and in policy, considering, on the one hand, more realistic operation profiles for buildings and, on the other hand, more detailed and realistic data for grid interaction (energy conversion factors, tariffs, CO<sub>2</sub> emission, etc.). In this way, design practices in the built environment could evolve coherently with energy infrastructures, exploiting synergies in terms of technology and business models. However, in order to progressively overcome limitations, it is necessary to work coherently on modelling and on the availability of



relevant design and operational data, integrating efficiently long-term (low resolution) with short-term (high resolution) monitoring.

## Acknowledgments

The authors would like to acknowledge Eng. Giuseppe Salvà Gagliolo for the initial data collection and analysis on the case study building.

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This work was carried out within the research project n.201594LT3F which is funded by PRIN (Programmi di Ricerca Scientifica di Rilevante Interesse Nazionale) of the Italian Ministry of Education, University and Research.