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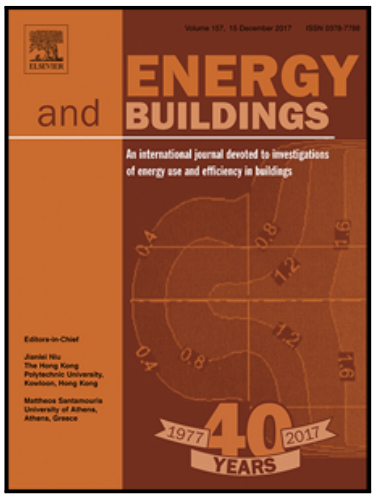

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Reduced-order Modeling for Energy Performance Contracting

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Abstract

Buildings subject to Energy Performance Contracts (EPCs) are usually quite complex public buildings, sometimes relatively old and usually barely documented from the technical standpoint. Gathering comprehensive and reliable technical information is a time consuming and expensive process that has to be carried out within the submission deadline. In these conditions, the standard approach to energy performance forecasting which uses detailed simulation is practically unfeasible.

This paper proposes a reduced-order modeling approach that is tailored to the EPC tendering phase. The proposed methodology extends a third order building model, introducing explicit, albeit still abstract, representations of the heating/cooling system, of the weather influence and of the end-user gains. The extended parameter set reflects to a large degree the information that is readily available in practical on-site surveying, or that can be easily calculated from that information. As a consequence of the simplified physics, a knowledge driven, practical calibration procedure, which provides an effective way of reducing uncertainty, is proposed. The calibration procedure analyses the uncertainty present in the available knowledge and uses the constraints imposed by the implemented physics on the parameters' dynamic to assess their value estimation.

The modeling approach is exemplified through three case studies: the first one provides the comparison of the reduced-order model predictions with the outcomes of a detailed model of a small hospital, the second one is used to compare the reduced-order model predictions with the detailed measurements of energy consumption of a real building, and the third case study exemplifies the use in operational context with scarce information.

Keywords: Reduced-order modeling, Energy performance contracting, Model calibration, Thermal modeling

1. Introduction

Energy Performance Contracts (EPC) are contractual obligations between a beneficiary and an energy service provider (normally an Energy Service Company - ESCO), where budgets are

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established in relation to a contractually acknowledged level of energy performance [21, 36]. The key features of EPCs can be summarized in a few points: (1) The EPC provider supplies all services required to design and implement a comprehensive energy saving project at the customer's facility; (2) The energy efficiency investments are repaid directly from the energy savings and related financial savings; (3) The EPC provider assumes the contractually agreed performance risks of the project; and (4) The EPC provider guarantees the achievement of the contractually agreed level of savings and is obliged to compensate shortfalls in savings. According to the U.S. Department of Energy [20], the adoption of the EPC format offers several benefits, such as guaranteed improvements, cost savings and enhanced performance [35, 32, 22]. However, a number of barriers still hinder the full application of EPC. The Transparense EPC project, an EU-wide survey [11], reports that both ESCOs and beneficiaries suffer from the complexities introduced by the EPC framework. Energy policies from individual European governments are mostly seen as ineffective given the complexity of the EPC concept, the lack of trust in the EPC industry, low customer demand and split incentives between landlord and tenants [34]. The financial crisis has had further negative consequences on the implementation of EPC as it has become more difficult to borrow money due to the increasingly stringent requirements of the financial companies.

In this scenario, obtaining finance to fund an EPC project is, rather unsurprisingly, a major stumbling block for EPC providers and/ or EPC customers across the European Union. In fact, a fundamental financial management issue characterizes the EPC concept. The overall balance of EPCs strongly depends on the achievement of the planned energy performance in real operating conditions, as the energy efficiency investments are repaid directly from the energy savings. Thus, achieving the energy efficiency levels established at the design stage is fundamental. Consequently, in EPCs more than in any other contractual form, the robustness of the financial set-up is critically based on the reliability of the energy efficiency forecast [5, 17]. From the technical point of view this aspect opens an unprecedented challenge for the energy audit and performance simulation [10, 23, 15, 16].

Currently, ESCO technical departments implement building energy audits according to well established procedures [4] [19]. The American Society of Heating, Refrigerating & Air-Conditioning Engineers (ASHRAE) recommends Level II and Level III audits for capital-intensive modifications, and is common in the EPC case. Both level II and III are information intensive. Level II audits include an in-depth analysis of energy costs, energy usage and building characteristics and a refined survey of how energy is used in the building, while Level III audits further include monitoring, data collection and engineering analysis. Consequently, their implementation in the EPC call for tenders phase, requires detailed technical knowledge of the building under contract, which usually is not available.

In the majority of cases, uncertainty characterizes the technical information available in the EPC call for tenders phase [7]. Buildings subject to EPCs are usually quite complex public buildings (hospitals, schools, etc.) and sometimes relatively old. Very often there are significant gaps in the technical information because of the many service, repair, modification events and the natural aging of the building over time.

Comprehensive and reliable technical information gathering in such conditions is therefore a time consuming and expensive process. Furthermore, the time that is usually available from the call for tenders to the submission deadline is relatively short, hence, on-site surveys are necessarily limited. In summary, most of the technical information necessary to the ESCO for accurate tendering design is affected by uncertainty, if not completely missing. In many practical cases, the

only energy consumption data available for establishing the baseline for the building is the energy bill and, in many cases, it is not only related to the building under contract but also to other buildings. In this scenario the standard approach to energy performance simulation, based on the availability of a large amount of information, is practically unfeasible. A modeling procedure specifically tailored to manage the uncertainty affecting the EPC framework is required.

Different modeling approaches have been developed to suit contexts with varying objectives and data availability [33]. Three general categories of building energy forecasting models have been reported in the literature which include white-box (physics-based), black-box (data-driven), and grey-box (combination of physics-based and data-driven) modeling approaches [3]. Black-box models use monitored data to introduce the model parameters. Since a relatively large set of data is required to achieve the necessary reliability in prediction, the back-box approach is not suited for the information scarce EPC context. White-box models predict the energy behavior of buildings by implementing a set of well-defined physical laws. Manual or computer aided parameter calibration procedures are used to match the predictions with measured data [24]. The monitored data set can be as limited as monthly energy consumption data. However, in many practical cases, the building model is made of hundreds or thousands of parameters, making simulation computationally intensive and calibration very complex. Flexible and efficient low-order white-box modeling approaches have been developed mainly for efficient simulation at district and city scale, and for one-step prediction in model predictive energy control systems [14]. Grey-box modeling is a mixed law-data driven approach, which implements low-order building physics and uses statistical methods for model identification [1]. Despite their reduced-order structure, grey-box models provide relatively accurate energy performance predictions [27] once trained with monitored data. However, in spite of the fact that grey-box models are not applicable in the EPC context because of the required monitored data sets, reduced-order models remain expressive enough to capture the basic energy behaviors of real buildings and to forecast energy consumption.

In summary, reduced-order, law-driven models, represent a good basis for implementing a modeling framework for EPC. They have a high degree of generality, the same model structure can be applied to a large number of building typologies. They require a limited set of information and may, in principle, provide quite accurate predictions of energy consumption. Nevertheless, two fundamental issues are still open. First, the structure of the reduced-order models developed so far do not explicitly represent the information available in typical surveying phases. Some adaptations to the model structure must be implemented to explicate the dynamics of the thermal gains, i.e. the control of the heating/cooling systems and a number of schedules involving users and operations. Second, and most important, the calibration phase should be arranged so that uncertainty can be explicitly managed, and the achievement of sufficient reliable evidence to support the decision maker.

Uncertainty analysis has been largely studied in the modeling field [30], usually in conjunction with sensitivity analysis [28]. Uncertainty analysis is concerned with the lack of knowledge about the environment and the system. Uncertainty derives from errors and approximations in data measurement, parameter values and model structure. Uncertainty about the model structure can be reduced through model identification. Uncertainty about model parameters can be reduced by model calibration. The calibration of detailed building energy performance models, involving thousands of input parameters is a highly under-determined problem, which yields multiple non-unique solutions [2, 13, 3]. A methodology for calibrating detailed building simulation models against the utility billing data is proposed by Reddy et al. [25, 26]. Their analysis points out a

severe over-fitting issue in the calibration of detailed models based only on the monthly energy consumption data, since, as they state, a satisfactory overall calibration to the utility billing data will not guarantee accurate identification of the individual parameters in the simulation model. Consequently, they propose a methodology for reducing the modeling parameters to a manageable set, based on technical domain knowledge, and to use numerical calibration to adjust the reduced set. An iterative methodology for identifying reduced-order model structures able to capture the heat dynamics of buildings is proposed by Bacher and Madsen [1], by fitting a monitored dataset using numerical-statistical methods applied to models of different order. As pointed out by Miletic et al. [18], reducing parameter uncertainty through a blind algorithmic approach may result in values that are far from the real set. In under-determined problems the positive and negative effects of some parameters may cancel each other out, resulting in a significant deviation from the real set, despite the final convergence of the calibration algorithm. Anchoring parameter values to domain knowledge is generally acknowledged as a good strategy for overcoming the cancellation issue.

In this paper, a third order building model [1] is adopted for representing the building thermal behavior, including the heating/cooling system, the weather influence and the occupant gains. Although the model is still abstract, the parameter set has been extended to reflect the information that can be easily collected during the EPC tendering phase through data collection and on-site surveying. The reduced-order model, taking into account the main physical dependencies among the variables, helps to reduce the degrees of freedom for the calibration phase. A knowledge driven practical calibration procedure, which provides an effective way of reducing uncertainty, is developed in this paper. The procedure faces the uncertainty affecting the available knowledge by exploiting the physical constraints for assessing the estimation of the unknown parameters.

The developed modeling approach is applied to three case studies, all concerned with rather large buildings. The first case study will be used to compare the reduced-order model predictions with the outcomes of a detailed model of a small hospital, which has been previously calibrated on the real building. This will allow a detailed comparison among parameters that are not usually available in monitored data sets. A second case study will be used to compare the reduced-order model predictions with detailed measurements of energy consumption of a real building controlled by a Building Energy Management System (BEMS), thus providing evidence about the application of the proposed modeling approach to real cases, where uncertainty about the physical and operational parameters is present. A third case study will be used to test the modeling approach in an operational context with scarce information available.

The paper has the following arrangement. Section 2 details the model structure, its parameter set and the calibration procedure. Sections 3, 4 and 5 introduce the first, the second and the third case study respectively, detailing the calibration procedure and the prediction results. Section 6 concludes the essays discussing the limits of the current implementation and future works.

2. The reduced-order model

In this section the reduced-order model structure is discussed. Initially, the conceptual structure of the model is introduced, then the implementation details in the Modelica language [9] are discussed, finally the rationale of the calibration process is introduced.

2.1. The conceptual structure

The conceptual structure of the reduced-order model is an extension of the third order model proposed by Bacher and Madsen [1]. It is shown in Figure 1 using the same electrical symbol set. A third order model has been selected as recommended by Reynders et al. [27], with the only addition of the heat flow versus the ground, implemented as the series of a constant temperature T_{ground} plus the resistance R_g. Hence, R_{ie} is the average resistance of the opaque envelope, R_{ea} is the outdoor air–envelope coupling resistance, R_{ia} is the air infiltration and forced ventilation resistance, R_m and C_m are the medium thermal resistance and capacity, C_e and C_i are the envelope thermal capacity and the indoor air thermal capacity respectively. The system is modeled as a variable heat gain Φ_h coupled with the environment by thermal resistance R_{ih} and capacity C_{ih}. The internal gains Φ_u, the solar radiance through windows Φ_{ws} and on the opaque surfaces Φ_{os} are modeled as additional variable gains. Two schedules concerning system operation and occupancy have been added, as well as the weather data set, to provide the time line of the external and internal gains. Finally, two feedback control signals have been introduced to implement the thermostatic control of the heating/cooling system on the indoor temperature T_{in} and on the heating system medium temperature T_f. Furthermore, depending on the specific control configuration, the thermostatic control of the indoor temperature can be changed with a climatic control based on the outdoor temperature T_{out}.

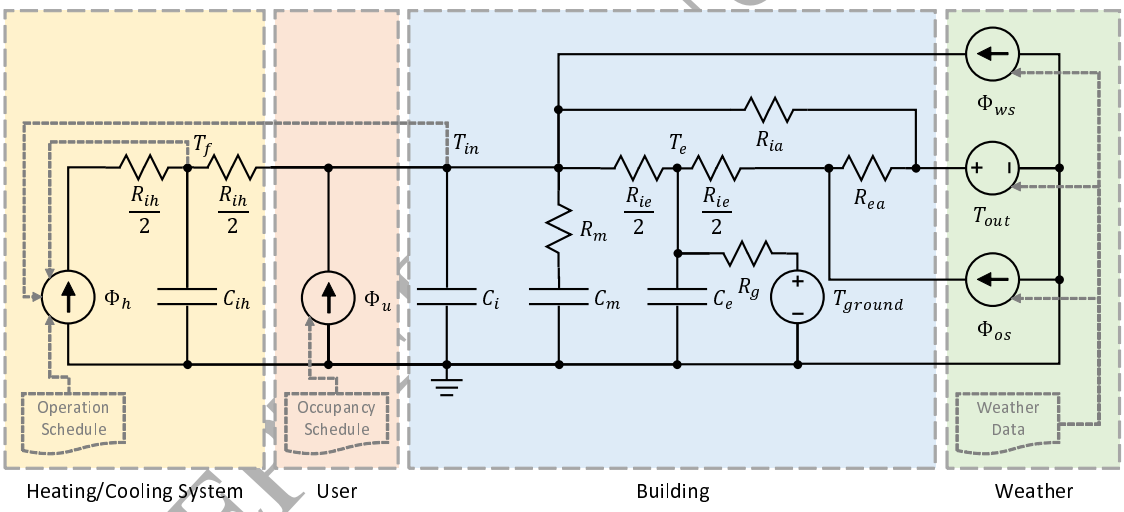


Figure 1: The conceptual schema of the grey-box model

2.2. The Modelica implementation

The conceptual structure of the reduced-order model has been implemented in the Modelica language [8] using the Buildings library [31]. As in the conceptual schema, the Modelica model is arranged in four main components: the Building, the Heating/Cooling System, the Occupancy and the Weather (see Figure 2).

2.2.1. The building component

The building component (Figure 3) implements the Building Model block of the conceptual schema (Figure 1). Its parameters are reported in Table 1. The envelope and interior wall resistances and capacitances (R_{ie}, C_e, R_m, C_m) are implemented as lumped thermal components from

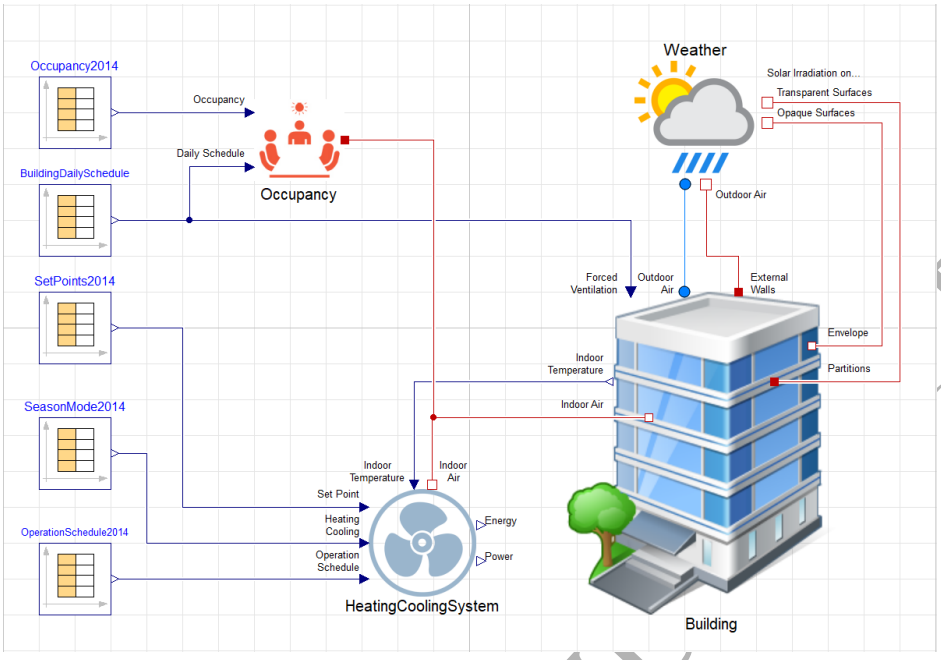


Figure 2: The Modelica implementation of the whole grey-box model

the Heat Transfer Modelica Standard Library. As in the conceptual model, a resistance-capacity-resistance schema ($R_{ie} - C_e - R_{ie}$) is used to represent the building opaque envelope. A resistance-capacity series ($R_m - C_m$) is used to represent the building's internal partitions and slabs. The building volume V_{ol} and the indoor air volume V_{air} have been explicitly implemented, and, in order to mirror more closely the data available in real situations, the R_{ia} resistance of the conceptual model, which regulates the heat flows provided by air infiltration and forced ventilation, has been implemented using mass transfer physics through the air flow rate L_{ea} and forced air ventilation rate V_{rt}. The forced ventilation component is a standard Modelica mass flow source, which provides the target mass flow rate at the outdoor temperature. Three heat ports are provided to input thermal gains from the external sources: occupants (Φ_u in Figure 1), solar radiance to internal walls through windows (Φ_{ws} in Figure 1) multiplied by A_{win}, G_v, and solar radiance to the external opaque envelope (Φ_{os} in Figure 1) multiplied by A_{pq}, G_v.

2.2.2. The heating/cooling system component

The heating/cooling systems component has been implemented as a thermostatically regulated heat gain with internal control loops on the fluid temperature that can operate either in heating/cooling mode providing positive/negative gains. The thermal source (Φ_h in Figure 1) is modeled by the installed heating/cooling power P_{ow} and efficiency E_{ff} (see Table 1), as in the conceptual model. It is coupled with the indoor environment through the resistance R_{ih} and the capacity C_{ih} that approximate heat diffuser coupling resistances and the heating/cooling fluid capacitance. Two proportional/integrative (PI) feedback loops have been used to mirror the usual heater/cooler control. Real heating/cooling systems operate between two fluid temperature thresholds: usually the heater is switched off when the fluid temperature reaches the upper threshold to avoid overheating and the cooler is switched off when the the fluid reaches the lowermost temperature. The hysteresis range (parameter H_{ys}) is referred to the set-point S_{etp}. The implementation

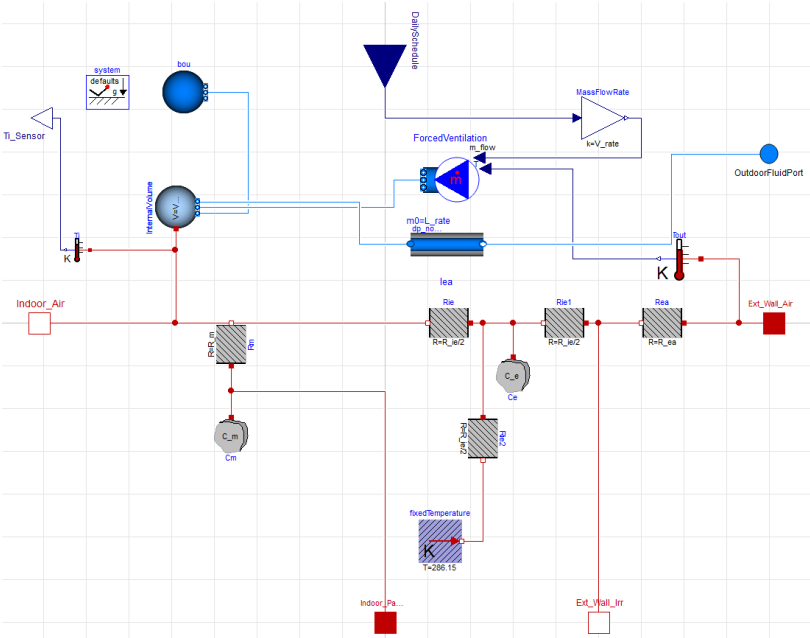


Figure 3: The Building component in modelica

of this nonlinear behavior, which limits the power transfer from the heater to the environment, provides a more realistic dynamic of the fluid temperature and, consequently, of the indoor air temperature. Finally, the system operation schedule O_{per} regulates the system on/off switch.

2.2.3. The weather and the occupancy components

The weather component calculates the solar gains through the windows, to the opaque envelope and the external temperature from standard weather data files. The weather data file W_{ea} is imported by means of the `ReaderTMY3` component of the Buildings library. Outdoor pressure and temperature are made available through related Modelica heat and fluid ports. Both the direct solar irradiation on a tilted surface and the hemispherical diffuse irradiation are computed using an anisotropic sky model (Perez, 1990). Two components have been built on the basis of the `MixedAir` class of the Buildings Library for the windows gains and opaque envelope calculations. The eventual reduction of the total solar energy transmittance caused by the external shading is then taken into account with the parameter G-value G_v that is calculated according to [6].

The occupancy component simply calculates the internal thermal gains by summing the contributions due to the occupancy and equipment (G_{eq}). A fixed thermal source G_p (default 130W for each person) is multiplied by the estimated average amount of people visiting the building monthly O_{cc}.

2.3. The calibration process

The calibration process is indeed the most critical phase of the modeling procedure in the EPC context. A sustainable calibration process makes modeling affordable and compliant with time and cost limits of EPC. However, a monitored data set is often unavailable for most situations where EPCs are actually proposed, and the minimization of the discrepancies, often significant, possibly occurring between uncalibrated model predictions and the actual metered building energy use [3],

Table 1: The reduced-order model parameter set

Name	Description	Source	Reliability
Building			
V_{ol}	Building Volume	Project data or survey	High
A_{pq}	Opaque envelope area divided as per orientation (e,w,n,s)	Project data or survey	High
A_{win}	Window area divided as per orientation (e,w,n,s)	Project data or survey	High
G_v	Solar shading coefficient	Project data, survey	Medium
R_{ea}	Outdoor air - envelope coupling resistance	Regulation	High
R_{ie}	Averaged resistance of the opaque envelope	Project data, survey	High
C_e	Heat capacity of the opaque envelope	Project data, survey	High
R_m	Thermal resistance between the walls and furniture and the interior air	Regulation	High
C_m	Heat capacity of the interior walls and furniture	Project data, survey	High
R_g	Resistance between the interior and the ground	Project data, survey	Medium
T_g	Surrounding ground temperature	Literature, survey	Medium
V_{air}	Internal air volume	Project data, survey	High
L_{ea}	Air infiltration resistance	Regulation[29]	Low
V_{rt}	Mass flow rate through forced ventilation	Project data	High
System			
R_{ih}	Thermal resistance between the HVAC system and the interior	Technical data-sheets	Low
C_{ih}	Heat capacity for the HVAC system	Technical data-sheets	Medium
E_{ff}	Efficiency of the HVAC system	Technical data-sheet	Medium
P_{ow}	Installed heating/ cooling power	Technical data-sheet	High
H_{ys}	Hysteresis range of the thermostat	Technical data-sheet	High
Operation			
O_{cc}	Average monthly occupancy level	Monitored or interviews	Low
O_{per}	System operation schedule	Monitored or interviews	Medium
S_{etp}	Indoor temperature set-points	Monitored or interviews	Medium
Environment			
W_{ea}	Weather data file	Web	High
G_p	Heat gain per person	Regulation	High
G_{eq}	Heat gain due to fixed equipment and systems	Survey	Medium

raises the issue of defining a model calibration procedure for the EPC operational context. Reducing the model parameters to the limited set typically available in the EPC operating conditions, and providing a knowledge driven calibration procedure, is the strategy proposed in this research to make modeling sustainable in the EPC context.

The reduced-order model, detailed in section 2.2, is described by 25 parameters (Table 1), arranged in four classes. Among them, 14 parameters can be usually estimated quite reliably, 8 are usually affected by some degree of uncertainty, and 3 are not so easily available or knowledgeable. The calibration process is tailored to the structure of the reduced-order model and is aimed at reducing the uncertainty affecting the parameters. The use of reduced-order models, which maintain the same structure for a large number of building typologies and the relative simplicity of the implemented physics, allows the definition of a general calibration procedure. The calibration baseline is established using the monthly energy consumption data of one year. Energy consumption data of a second year are required for testing the prediction accuracy. Initial estimations of parameter values are formulated on the basis of the available knowledge, either general technical knowledge or specific information gathered through monitored data, surveys or interviews. Then the parameters are adjusted iteratively until the simulated monthly energy consumption fits the baseline. The calibration process is arranged in four phases, according to the four classes of parameters as shown in Table 1. Since the physics implemented in the reduced-order model are relatively simple, it is possible to lay-out a number of practical calibration guidelines that give insights about the consistency of the calibration results, thus substantially reducing the risk of over-fitting.

The calibration process is, therefore, arranged in four phases (see Figure 4).

1. *Data Analysis* - The first phase concerns data acquisition and analysis. The available technical information is collected through surveys and interviews, parameters are identified, calculated and ranked by assigning each one a certainty factor based on the quality of the available information. The parameters that can be determined on the basis of reliable information are fixed. The remaining parameters are ranked according to their uncertainty degree. In addition, the baseline is defined in this phase. It is worthwhile pointing out that in some cases, especially in large building blocks, the energy supplied to the building and, consequently, the baseline itself may be affected by high uncertainty.
2. *System Calibration* - The second phase is articulated in two steps and is aimed at achieving the correct operating conditions of the heating/cooling system. Two calibration guidelines can be defined for this phase.

   The objective of the first step is to reach an effective system coupling with the indoor environment. The simple heating/cooling system model is essentially described by four parameters: *installed power* P_{ow}, *efficiency* E_{ff} , *thermal resistance* R_{ih} and *capacitance* C_{ih}. Installed power and efficiency are rather reliable parameters. They can be derived by the analysis of technical data-sheets in the first phase. The heat capacity of the medium can also be calculated quite reliably from available technical manuals. On the contrary, the value of the coupling resistance may be rather uncertain because it is significantly affected by system aging. Hence, the thermal resistance R_{ih} must be regulated so that the transferred power is enough to control the environment temperature. This condition can be effectively assessed by plotting the heating/cooling medium temperature against the indoor air temperature. The coupling resistance R_{ih} should be reduced until indoor air temperature reaches a consistent trend.

   The second step of the system calibration phase concerns the control of the system oper-

ation. In addition to the obvious daily on/off schedule, the power supplied by the system to the indoor environment is regulated by a thermostatic loop. The system is switched on/off when the indoor air temperature passes the set-point threshold, with a certain hysteresis. In the reduced-box model, a single indoor air temperature approximates the average indoor air temperature of the whole building. Since, especially in large buildings with high temperature gradients among different rooms, a perfect air mix cannot be assumed. In fact, the temperature that regulates the thermostatic loop is the one occurring around the real thermostats, which may be quite different from the simulated average indoor air temperature. Consequently, an operational control mismatch may occur between the real and the simulated cases. In order to minimize its effect, the thermostatic control loop constraint of the reduced-order model must be relaxed by widening the hysteresis of the thermostat until the simulated supplied power reflects the measured one. A general heuristic can be outlined to drive the control mismatch mitigation. A shift in the thermostat control temperature affects energy consumption when the indoor air temperature naturally tends to be around the control set-point. This usually occurs during mid seasons, like late spring or early autumn. Hot summers or cold winters are usually unaffected by this condition. Hence, as a general rule, energy consumption mismatch occurring only in April, May, September or October can be a symptom of this condition.

3. *Building Parameters* - The third phase concerns the adjustments of the remaining building parameters which have a high degree of uncertainty. For example, one of the parameters that usually is estimated with some difficulty is the external air flow rate due to air infiltration and natural ventilation. External air flow due to the difference of pressure between indoors and outdoors can be adjusted by means of the air infiltration parameter *Lea*. An overestimation of this parameter will have an effect on energy consumption, as it increases the energy consumption in winter and summer seasons, with either no effect or even a reduction in energy consumption in the spring and autumn, depending on the outside temperature. The effects of the variation of the parameter value can be easily observed, and the value adjusted accordingly. This process can be carried out for all the physical parameters describing the passive building components.
4. *Operation Schedules* - The fourth, and perhaps most critical, phase involves the adjustment of the schedules of the internal gains. Different from the previous phase, this is essentially a pure knowledge based operation. If perfect knowledge about occupancy has been collected during the first phase, this step can be skipped, otherwise a monthly average occupancy and equipment usage should be estimated based on observation and interviews. In fact, the monthly adjustment operated during the schedule calibration can, at this time, in any case produce a perfectly calibrated prediction of energy consumption. Hence, great care should be posed to avoid trespassing reasonable values of the scheduled quantities.

The process can be iterated until calibration is reached. The final assessment phase is based on the ASHRAE recommendations [4] using the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error (CV-RMSE) indexes. In this phase, the analysis of the distribution of the monthly error is particularly important. In some cases, anomalies can be observed in one or two months that cannot be explained even after a many iterations. Anomalies mean that the energy consumption forecast generally fits the baseline apart from in one or two months. In perfectly informed contexts, anomalies imply a calibration failure. But in a partially informed context, like in the EPC case, anomalies may be due to the lack of information

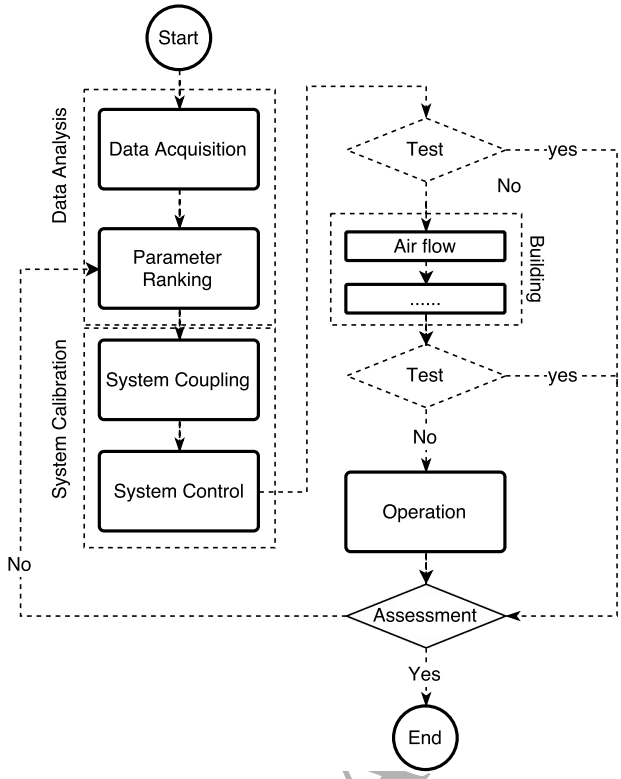


Figure 4: The calibration process flow

or to untraced and localized events (such as occasional system malfunctioning or faults). Hence in these cases, it is still possible to provide support to the decision maker by isolating anomalies and excluding them from the calibration process. In the end, the decision maker will be provided with a decision support scenario, made of the calibrated model, the related predictions and information about the anomalies encountered during the model's development, which represents the best possible approximation of the operational context, given the available information.

In the following three sections we will discuss the accuracy that can be reached by the reduced-order model in the prediction of energy consumption of three complex buildings, and we will exemplify the application of the calibration process in real operational contexts. The first case study demonstrates to what extent the reduced-order model is able to establish the energy consumption prediction of a detailed model of a real building, that was previously calibrated on measured data. By comparing the outcomes of a reduced and a detailed model, enables us to pinpoint details characterizing the nature of the approximation. The second case study describes the calibration process and the prediction results of the reduced-order model on a real building, whose BEMS records detailed energy consumption. This case study has a twofold purpose. First, it explains the effectiveness of the calibration process conducted, with an information set that represents a typical EPC operational context. Second, the comparison of the energy prediction with the detailed dataset of the real energy consumption points out the effect of the thermostat hysteresis parameter. Finally, the last case study discusses a situation where anomalies are encountered and analyzed within the modeling framework.

3. The Hospital of Sant'Elpidio a Mare (Italy)

The community clinic is a seven-storey building located in Sant'Elpidio a Mare (Fermo, Italy). The clinic has undergone several organizational rearrangements over recent years, that have determined variations in terms of occupancy levels, number and typology of heated and non-heated thermal zones. The building's net heat surface area measured 2460 m^2, and the gross heated volume was equal to 8127 m^3. The building is made up of two blocks. The first was built in the 1970s and hosts all the wards and clinics of the hospital. The second block was built in the 1980s and serves the rest of the building through a large staircase, a lift and some waiting rooms. A reinforced concrete frame superstructure bears both blocks of the building. The blocks are built using the traditional technologies of external masonry walls and hollow masonry unit partitions. The insulation level of the envelope is quite low, due to the age of the external walls, windows and roof. The whole building is old-fashioned and built using the technology that was typical of the 1970s and 1980s in Italy. The energy performance is definitely worse than the standards and regulations currently in force. At present, there is no mechanical air supply, hence the indoor air quality is provided by infiltration and incidental air leakage through the building envelope. During the on-site surveys, the personnel of the clinic stated that they usually open the windows when they feel that the indoor air quality is no longer adequate. The medical ward was open on the second floor, and the clinics were mainly accommodated on the first floor.

Figure 5: The Hospital of Sant'Elpidio a Mare (Italy): north-west facade.

An energy efficiency project was initiated for this building in 2015, and a detailed model was produced and calibrated on the 2013 energy consumption. In order to build a sound framework for comparing the models outcomes, the same environmental data set is used both in the detailed model and in the reduced model simulations, the reduced model parameters are calculated from the parameters of the detailed model, and the climatic control logic of the heating system of the detailed model has been copied in the reduced model. Hence, all the divergences between the two models are due to the approximations introduced by the reduced-order modeling. Three simulation outcomes are analyzed: the indoor temperature, the water supply temperature, the absorbed power and the cumulative energy consumption for the calibration year (2013). As stated in [12], Figure 6 shows that the reduced model fits the reality well, here approximated by the detailed model for the year 2013. Even if the internal air temperature of the reduced model is not representative of any

Table 2: The Hospital of Sant'Elpidio a Mare (Italy): main features.

Feature	Description
Location	- Latitude: 43.234252 N - Longitude: 13.688765 E
Dimensions	- Floor area: $2471m^2$ (heated part) - Volume: $9120m^3$ (heated part)
Envelope	- Exterior walls: plaster (0.01m), hollow brick (0.12m), air gap (0.27m), brick (0.09m) - Floor: plaster (0.01m), hollow slab (0.20m), reinforced concrete (0.04m), screed (0.08m), flooring (0.02) - Windows: single and double glazing
Heating/Cooling system	- Boiler and radiators
Lighting	- Lighting load: $11240W$
Occupation	- Monday to Sunday: 0:00 – 24:00
Operation	- Absence of environmental control (open loop)
Consumptions	- Annual fuel consumption for heating: $35836Sm^3$ (year 2013)

space inside the building, it falls inside the temperature range of the different zones of the detailed model. The same holds for the water supply temperature. Absorbed power and cumulative energy consumption almost overlap the detailed ones.

Comparison with the measured monthly energy consumption used for calibration (see Figure 7), shows that the energy residuals do not overpass 10% during the heating months. In order to exclude over-fitting, the calibrated model has been validated with data measured during the year 2015, thus providing the very good results shown in Figure 8: $NMBE = 0.15\%$ and $CV - RMSE = 5.23\%$.

4. The Library of the Universitat Politècnica de Catalunya in Terrassa (Spain)

The library of the Universitat Politècnica de Catalunya (UPC) (Figure 9) is located in Terrassa (Spain), near Barcelona. The library is a three storey building. The ground floor contains some shops and the building entrance. Reading rooms are located on the second and third floors, which also hosts some offices and small meeting rooms. The library has a capacity of about 350 people, and it is used from 9 am to 9 pm Monday to Friday. Sometimes it remains open during the weekend. In August it is usually closed. The external walls are made of bricks separated by two layers of insulation and an air gap. All the external facades have windows. South oriented windows have aluminum louvre solar shadings. The current heating and cooling system is the result of a renovation work carried out in 2012: it consists of five heat pumps that serve fan coil units. The internal temperature is not extensively monitored, the thermostat set-up is the only available data related to indoor temperature. Weather data was taken from a local weather station database. In summary, the Terrassa UPC Library is a rather well known building. The basic characteristics of the building are summarized in Table 3.

4.1. Model Calibration

1. *Data Analysis* - All the building data of Table 1 have been collected from the building's drawings and brief surveys. The available data can be considered highly reliable, except the

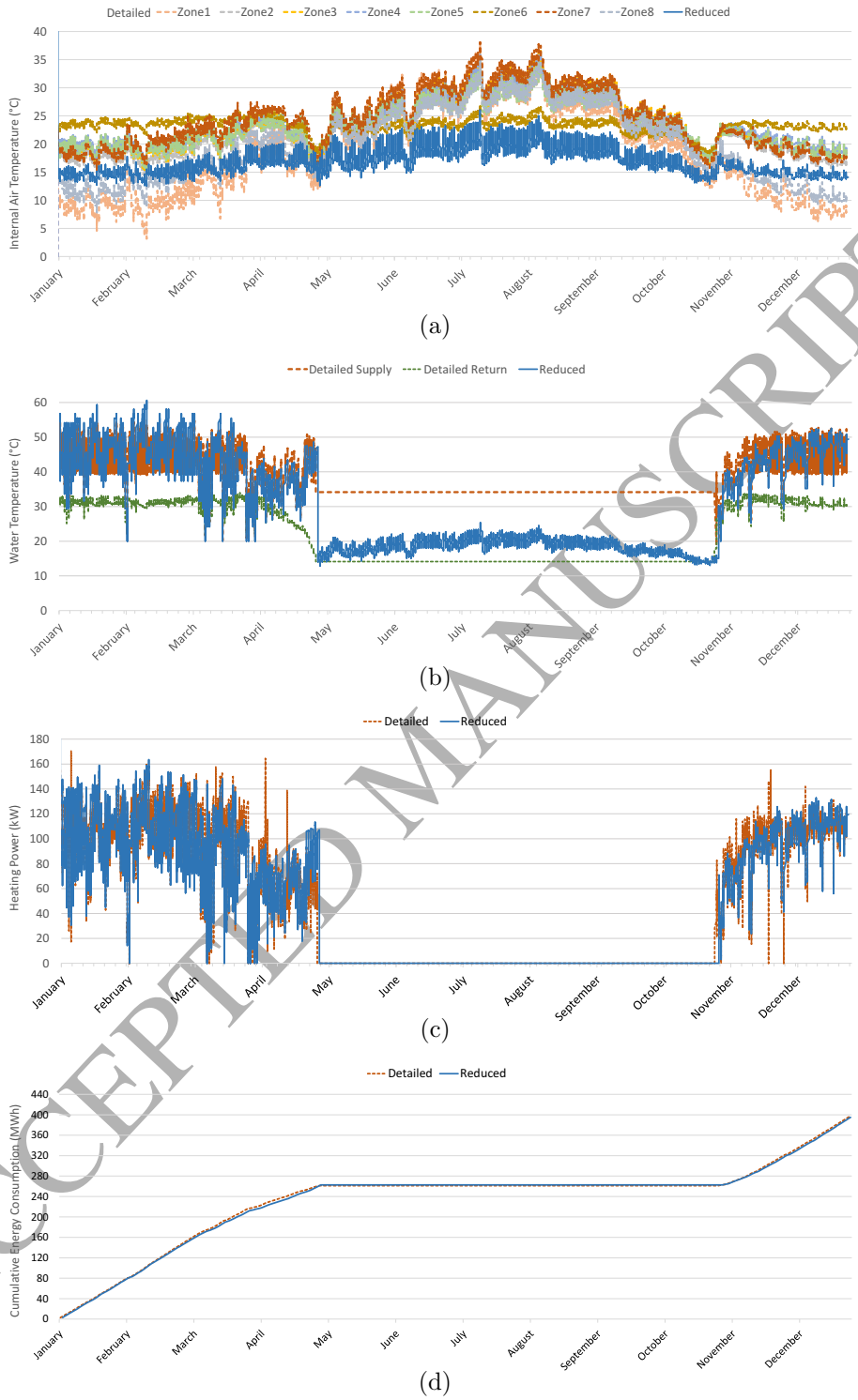


Figure 6: Hospital of Sant'Elpidio a Mare (Italy): point-wise comparison between the detailed model (dashed line) and the reduced model (solid line) for internal air temperature (a), water temperature (b), heating power (c) and cumulative energy consumption (d).

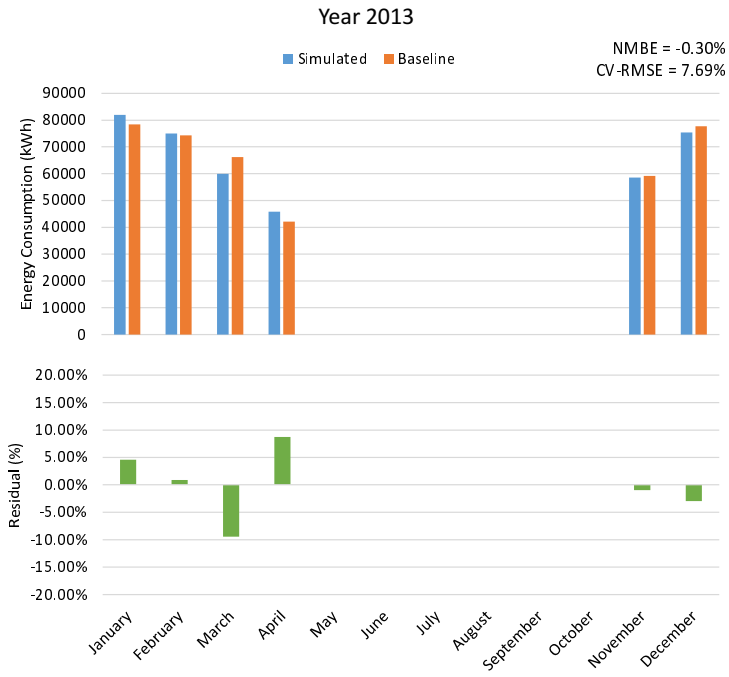


Figure 7: Hospital of Sant'Elpidio a Mare (Italy): measured energy consumption and residuals for the calibration year (2013)

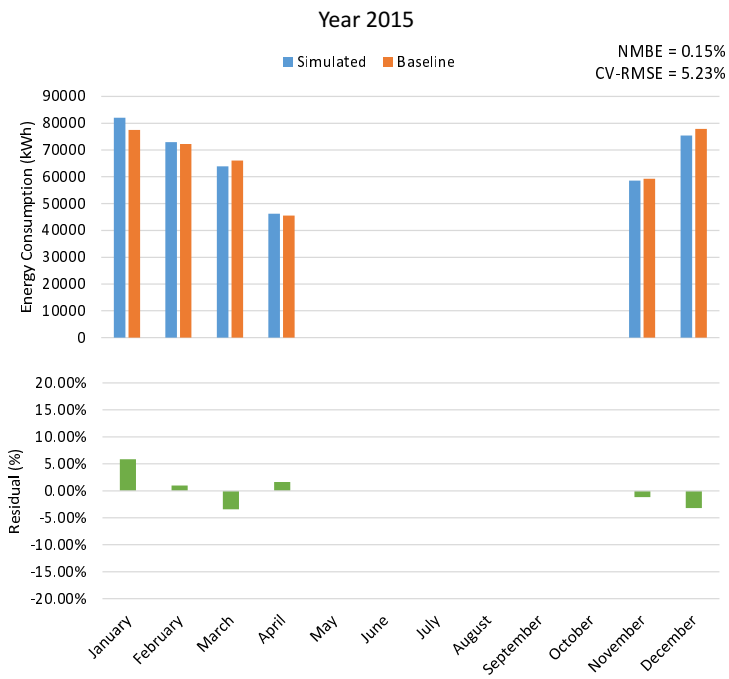


Figure 8: Hospital of Sant'Elpidio a Mare (Italy): measured energy consumption and residuals for the validation year (2015)

Figure 9: Library of the Universitat Politècnica de Catalunya (Spain): south and est facades.

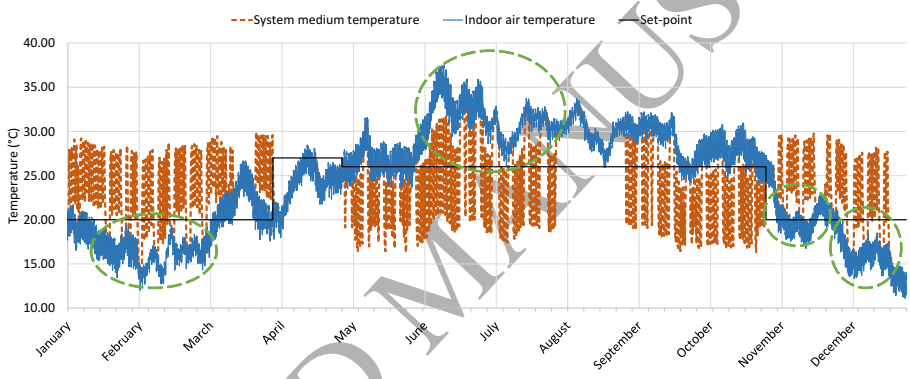
Table 3: Library of the Universitat Politècnica de Catalunya (Spain): main features.

Feature	Description
Location	- Latitude: 41.563770 N - Longitude: 2.021395 E
Dimensions	- Floor area: $797m^2$ - Volume: $9325m^3$
Envelope	- Exterior walls: brick (0.14m), expanded polystyrene (0.04m), air gap, expanded polystyrene (0.04m), plasterboard (0.025m) - Floor: reinforced concrete, hollow slab (0.4m) - Windows: single and double glazing (U-value $5.6W/m^2K - 2.5W/m^2K$) with solar shadings
Heating/Cooling system	- Heat pumps with fan-coil units
Lighting	- Lighting load: $17868W$
Occupation	- Monday to Friday: 9:00am – 9:00pm
Operation	- Set-point temperature: winter $21°C$ – summer $25°C$
Consumptions	- Annual electrical energy: $159674kWh$ (year 2014)

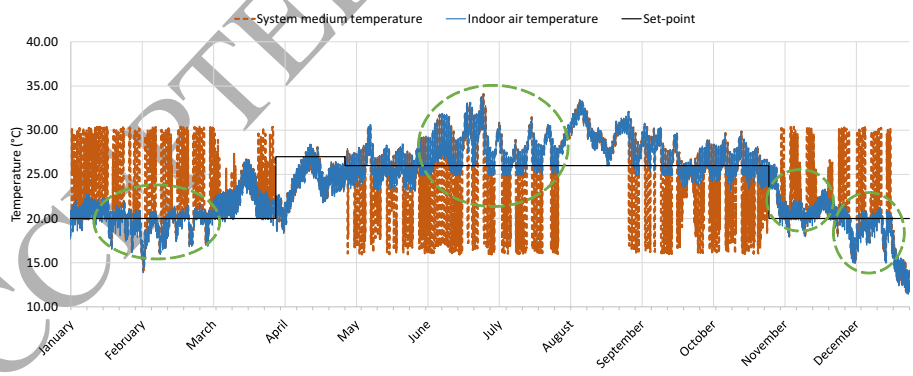
air infiltration rate, which may also depend on the building users window opening. The heat exchange with the ground has been considered negligible, because of the absence of underground spaces. The building's heating/cooling system is controlled by a BEMS. Hence, a detailed record of energy consumption is available and the energy consumption baseline can be calculated exactly. The temperature control uses thermostats that are set to prescribed temperature set-points. The building operators can increase or decrease the thermostat set-points by one degree in order to adjust the internal comfort. This introduces some uncertainty about the set-point value during the day. On the second floor, the mechanical ventilation is supplied by an air-conditioning system. The forced air ventilation rate is therefore controlled and can be assumed reliable. The building occupation is monitored by an entrance tracking system and by sampling the occupancy level daily. Hence the occupancy data can be considered reliable.

2. *System Calibration* - The system *installed power* P_{ow}, *efficiency* E_{ff} and *capacitance of the medium* C_{ih} have been determined from technical data sheets. The *thermal resistance* R_{ih} has

been adjusted by calibration. Figure 10 shows the plots of the heating/cooling medium temperature against the indoor air temperature and the set-points. The coupling resistance R_{ih} has been reduced until indoor air temperature reaches a consistent trend. The left side shows a cooling regime trace where the resistance is too high and the indoor air temperature (solid line) cannot reach the horizontal line of the set-point, while the system medium temperature (dashed line) is constantly below. On the right side, the resistance has been reduced until the indoor temperature is reasonably around the set-point. When the system is switched off, during the night, the system medium temperature reaches the indoor air temperature. After this first calibration step ASHRAE figures are NMBE= -33.37% and CV-RMSE = 22.94% using the 2014 calibration data-set. The high mismatch is due to a severe negative bias in the mid-seasons. From March to May and in September and October, the outdoor temperature is relatively close to the set-point. In that operating condition, the difference between the temperatures used for the system control, i.e. the real thermostat temperature measured in a particular point of the buildings and the approximated indoor temperature of the reduced-order model, may cause severe divergence from the baseline.



(a)



(b)

Figure 10: Library of the Universitat Politècnica de Catalunya (Spain): system medium temperature (dashed line), indoor air temperature (solid line) and set-point plotted with overestimated Rih (a) and calibrated Rih (b).

It is possible to mitigate the mid-season forecasting mismatch by loosening the control constraints of the reduced-order model, by extending the hysteresis gap of the thermostat. This lets the indoor temperature fluctuate around the set-point during the mid seasons, but does

not affect the cold and hot seasons because of the higher temperature difference between outdoors and indoors. Hence, the thermostat hysteresis H_{ys} has been adjusted to compensate for the gradients of the internal temperature eventual. Figure 11 shows the energy transfer rates monitored by the BEMS during the April and May months (solid dark line), the simulated one during the same period before the hysteresis adjustment (solid gray) and the calibrated simulation (dashed). It can be seen that opening the hysteresis parameter adjusts the simulated energy transfer during the April-May months. The same can be seen for September-October. The other months remain unaffected. This behavior is due to the fact that during mid season months, the control is more dynamic, as the outdoor temperature is close to the indoor comfort threshold. The system calibration phase achieves a very good NMBE= 0.54% and CV-RMSE = 9.03%.

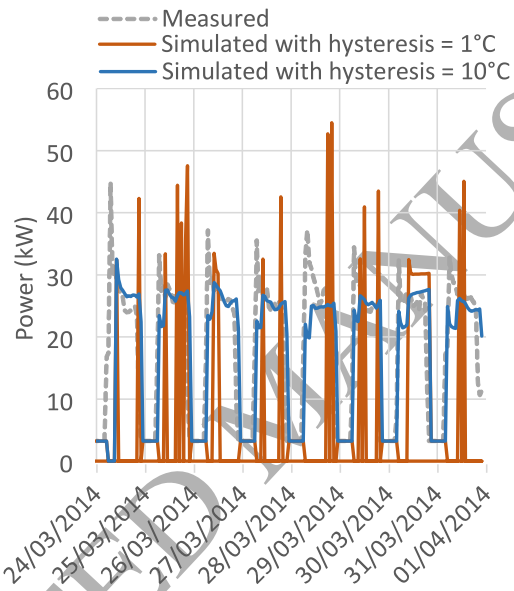


Figure 11: Library of the Universitat Politècnica de Catalunya (Spain): measured and simulated heating power with different thermostat hysteresis values.

3. *Building Parameters* - Almost all the building parameters were fixed in the Data Analysis phase except from the air infiltration flow rate L_{ea}. Its calibration does not significantly improve the final result, achieving NMBE = -0.47% and CV-RMSE = 8.11%.
4. *Operation Schedules* - The occupancy schedule was fixed in the data analysis, and the system operation was derived from the monitored energy supply data. Heat gains due to equipment was adjusted during the data analysis phase based on the fact that, as the building is a library, it is likely that students will use a laptop during their visit.

The final assessment, shows that the reduced-order model was able to match the energy consumption of the library building (see Figure 12), and to extrapolate reliably the energy consumption for subsequent years (see Figure 13). Just two calibration steps have been necessary to achieve NMBE= -0.47% and CV-RMSE = 8.11% using the 2014 calibration data-set. Forecasted energy consumption for the year 2015 is calculated using the parameter set calibrated with the 2014 data-

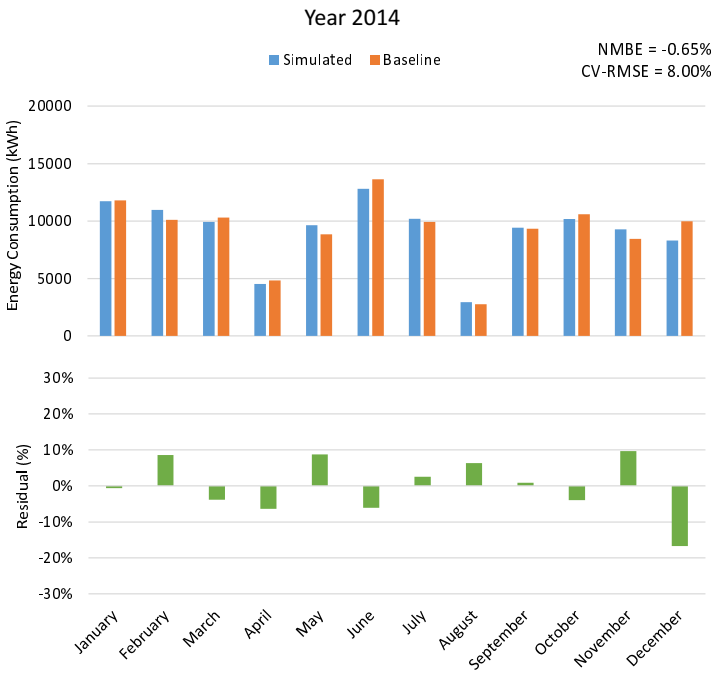


Figure 12: Library of the Universitat Politècnica de Catalunya (Spain): calibration result for year 2014 of the reduced-order model.

set. The 2015 forecasts shows 1.63% NMBE and 11.04% CV-RMSE. No further iterations are necessary.

5. The Smeaton Building in Plymouth (UK)

The third case study is the *Smeaton Building* on the Plymouth University Campus located in Plymouth, UK (Figure 14). The technical knowledge about the *Smeaton Building* was affected by severe uncertainty, principally about the system parameters, the energy consumption and the occupancy schedules. Formulating a detailed model of the building's operating conditions was practically impossible within the time and cost boundary of a typical EPC tendering phase. As a forecast of the energy consumption is still required, this case study demonstrates how the modeling process can still be used for formulating the best possible explanationation of the observed building behaviour.

The *Smeaton Building* is a four-story building. The net floor area is about 2484 m^2 and the floor to ceiling height is about 2.90m. The exterior surface of the boundary walls is made of sandwich panels, while the interior surface is made of concrete blocks with an air gap and bricks, then finished with plaster. On the ground floor, there are no sandwich panels on the external facade. The building has single glazing on the south side, and double glazing on the north side. Every window has internal shades. The occupation profile is not monitored and it is different for each room because a lot of teaching rooms are present.

1. *Data Analysis* - Information about the *Smeaton Building* systems were collected by visual inspection, measurement and interviews carried out during approximately a one day survey.

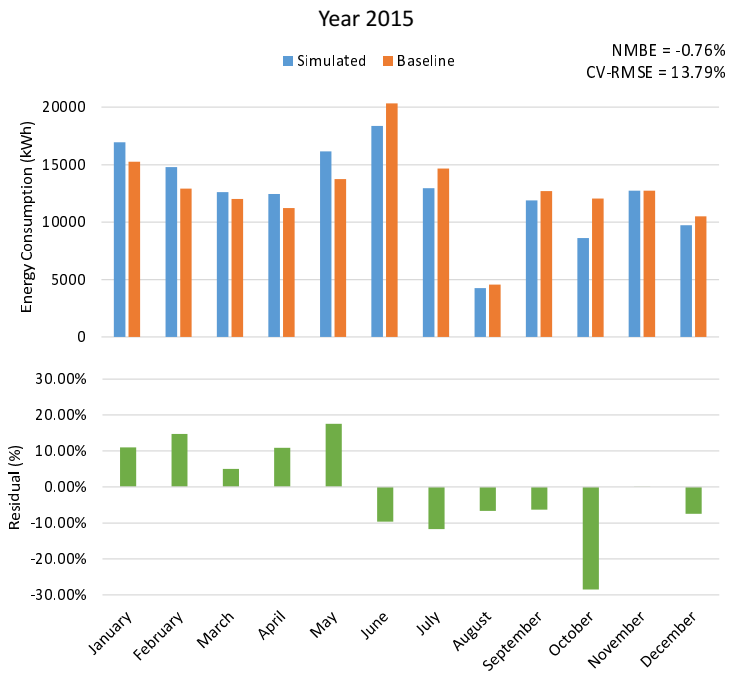


Figure 13: Library of the Universitat Politècnica de Catalunya (Spain): energy consumption forecast for year 2015 of the reduced-order model.

Figure 14: The Smeaton Building (UK): south facade.

Table 4: The Smeaton Building (UK): main features.

Feature	Description
Location	- Latitude: 50.374800 N - Longitude: -4.139861 E
Dimensions	- Floor area: $6621m^2$ - Volume: $19469m^3$
Envelope	- Exterior walls: sandwich panels (0.093m), concrete blocks (0.300m), air gap (0.180m), bricks (0.105m), plaster (0.013m) - Floor: cast concrete (0.200m), insulation (0.130m), screed (0.100m), linoleum (0.005m) - Windows: single 6mm glass in south facade, double 3mm/13mm air glass in north, east and west facades.
Heating/Cooling system	- boiler and radiators (with forced ventilation).
Lighting	- N.A.
Occupation	- Monday to Sunday 07:00 - 22:00
Operation	- Set-point temperature: winter 20°C
Consumptions	- Annual electrical energy: $466899kWh$ (August 2014-July 2015)

As the building's heating energy is supplied by a boiler shared with other buildings, and no direct metering was available, the supplied heating power and the energy consumption baseline had to be extrapolated, assuming a proportion between supplied energy and floor surfaces. Under these severe uncertain conditions, the calibration process was principally aimed at finding out a credible parameter arrangement based on the evidence provided by the simulated internal energy dynamic.

2. *System Calibration* - The supplied power parameter was increased until the system was able to drive the indoor temperature to the set-point of 20°C. Then, in a second step, the system efficiency was adjusted to minimize the energy consumption offset. These two initial steps mostly affected the NMBE factor.
3. *Building Parameters* - The third phase involved the ventilation rate, which was adjusted to compensate for mismatches between cold and mid-season months, improving CV-RMSE.
4. *Operation Schedules* - The occupancy assumption was also affected by a high degree of uncertainty, as no monitoring data was available. Hence, an average daily occupancy rate, based on interviews, was used.

After three steps, a promising NMBE= -1.03% and CV-RMSE = 17.86% were reached. Figure 15 shows the baseline and the simulated energy consumptions for the heating months. Nevertheless, according to [4] the model was not yet calibrated. This is essentially due to the prediction mismatch in May, which amounts to 46% (see Figure 15). In order to decide if this is an anomaly, a threshold on the 99.9% confidence interval ($CI_{99.9}$) is computed for the absolute value of the residuals. By using the consumption estimations reported in Figure 15, the corresponding range is $CI_{99.9} = 22\%$. Since the 46% of prediction mismatch in May largely exceeds the confidence interval range, it can be considered anomalous. In fact, eliminating the May mismatch results in a calibrated model, with NMBE= 3.40% and CV-RMSE = 7.06%. There may be multiple causes for the May mismatch. It could have been caused by unknown operational conditions, system maintenance or other totally

occasional and unknown factors. But it is unlikely that the mismatch could be the result of a simulation fault. In fact, a detailed analysis of the simulation results suggest that the low predicted consumption in May was due to favorable climatic conditions, an event that is known with good certainty. This observation supports the likelihood that the energy consumption mismatch could be due to an external event, and that the simulation results provide a valid explanation of the building's energy behavior. Of course, the validity of the explanation is further supported by the validity of the initially made assumptions.

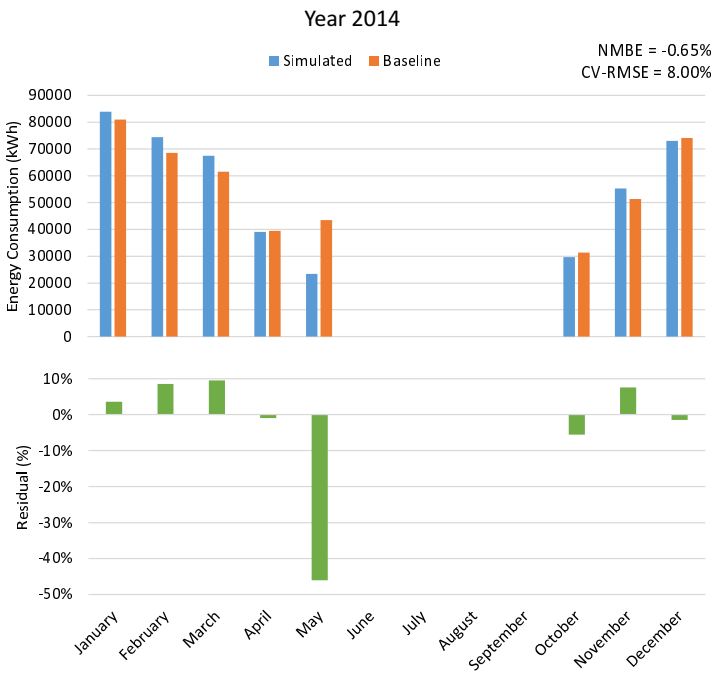


Figure 15: Smeaton Building in Plymouth (UK): calibration result for year 2014 of the reduced-order model.

6. Conclusions

A new modeling approach has been developed in this paper to address the energy audit for EPC tenders, in which the common situation of limited and uncertain information about the building prevails. A general reduced-order model structure was developed in Modelica language and has been discussed in detail. The calibration process is presented and applied to three different case studies relative to three different climatic zones and intended uses. A detailed Modelica model has been developed for the Hospital of Sant'Elpidio a Mare (Italy), and it was calibrated and used as a frame of reference for assessing detailed energy consumptions and temperatures, usually not available in real buildings. The simulation results showed that the energy and temperature trends of the reduced model are sufficiently close to that of the detailed model. The same reduced model was then compared with the energy measures for the calibration year (2013) and a forecast year (2015), ensuring compliance with ASHRAE recommendations in both cases. The developed calibration procedure was then applied and discussed in relation to the Library of the Universitat Politècnica de Catalunya in Terrassa (Spain), for which the reduced-order model was able to match

the measured energy consumption both for the calibration (2014) and the forecast year (2015). In both case studies the model showed a good generalization capacity: the error affecting the forecast energy consumption are largely within in the ASHRAE. The Smeaton Building in Plymouth (UK) was then used as a case study for a building with scarce and highly uncertain information. The developed calibration procedure was applied and discussed, and yielded satisfactory results for all but 1 month for which, an anomaly is detected in the energy data. This papers also shows the diagnostic ability of the reduced model, which could help the technical department tendering for EPC to select the most reliable energy data. Further research would be needed to integrate the thermal model with air quality and comfort models in order to better control occupants' comfort and for managing forced ventilation.

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