Calibration methodology for combined heating and ventilation models

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ABSTRACT

By 2050, Europe aims for energy-neutral buildings, necessitating effective integration of renewable energy sources and smart grid management. To address peak energy demands and prevent grid congestion, building-level energy management is crucial. This paper presents a stepwise calibration methodology for hybrid building models, enhancing flexibility in HVAC systems and thermal buffers.
The methodology involves: (1) utilizing known building and installation data to reduce calibration parameters, (2) independently calibrating subsystems like floor heating and cooling, (3) selecting optimal time periods for parameter estimation based on different physical mechanisms, and (4) validating the model with actual measurements.
The SirinE hybrid model combines physical and data-driven components, leveraging known building data to minimize the need for detailed measurements. Successfully applied in various projects, SirinE improves PV energy self-utilization and electrical energy demand.
Future work will focus on automating calibration, enhancing model robustness against user behaviour and sensor failures, and refining the hybrid model for evaluating residential renovations in an open source version. This methodology supports efficient energy management and integration of renewable sources in the built environment.

KEYWORDS

Heat-network, ventilation-model, calibration, control, congestion

1 INTRODUCTION

By 2050, the entire built environment in Europe must be energy-neutral. A major challenge in this energy transition is integrating energy-producing neighbourhoods into the existing energy infrastructure. The exponential increase in photovoltaic (PV) systems, electric vehicle charging, batteries, electric cooking, and heat pumps will lead to higher peaks in electricity demand and supply (Bunn 2016). The intermittent availability of various renewable energy sources, along with associated trade platforms, will require energy systems to switch between energy sources smoothly and on short notice.
The maximum demand and supply are limited by the capacity of the grid connection, which can be a fixed value or time-limited by the district service operator (DSO). Energy systems must be capable of smartly balancing supply and demand at the district level to avoid network congestion. To ensure stability and security of supply, the energy network will need to incorporate a mix of different commodities (electricity, heat, and possibly hydrogen networks).
Building-level energy management (in houses, offices, hotels, etc.) can play an important role in reducing peak demands by distributing energy demand over time and across different commodities. Control based on building models can assist in load balancing by accurately predicting how much energy can be shifted in time for ventilation, heating, cooling, and domestic hot water at specific moments. Currently, other commodities like batteries, PV, and

EV charging are often used to enable flexibility due to the time required to calibrate these models.

For the market uptake of HVAC flexibility, it is important to have a model that can be initiated very rapidly. The challenge is to develop a building model controller that includes an automated calibration procedure that can be initiated by an installer within a few hours. To balance energy production within the capacity constraints of the local grid, reliable predictions of both decentralized renewable energy production and building energy use are needed. Choosing the right control scenario requires short-term predictions based on different scenarios, ideally providing a one-day-ahead forecast of both energy demand and decentralized renewable energy production.
Occupant behavior significantly influences a building's energy demand, making it essential to predict the impact of behavior on energy use. Involving occupants in the process may lead to behavioral changes, requiring the prediction model to continuously adapt.
Current research in this field follows two main directions. The first focuses on smart district-level control using Artificial Neural Networks, agent technology, or Model Predictive Control (Canizares 2014) (Mynhoff, 2018) (Mocanu 2018). These models often represent individual building energy requirements simplistically and statistically, using fixed demand/supply curves. The second research direction involves single-building scheduling and control studies using physical models simulated in specific tools, such as TRNSYS or Energy-Plus (Ascione 2016) (Schirrer 2016) , or RC networks (Deconinck, 2017).
Recent academic focus has shifted from black-box models to hybrid models, which offer better predictions and higher robustness (Bourdeau 2019). Hybrid models use known physical relations, such as the cooling down of a building, and therefore require less informative data than black-box approaches. Unknown aspects, like user behaviour, are modelled using black-box techniques or profiles. The current generation of hybrid building models primarily focuses on a single type of building and often uses fixed user profiles for heating demand.
Both research directions require calibration time, but this paper focuses on the calibration method of hybrid building models. TNO has developed and successfully tested this hybrid model for model predictive control (Borsboom, 2022) and is currently working on an open-source version for the Dutch government to evaluate building renovation measures. The described stepwise calibration methodology can be applied to both these models and other physical based models

2 METHODOLOGY TO QUANTIFY FLEXIBILITY ON A BUILDING LEVEL

At the district level, there is a need to balance the supply and demand of energy as well as to manage congestion to stay within the grid's maximum capacities. The District Service Operator (DSO), responsible for the proper functioning of the grid, will manage buildings to control congestion and therefore available consumption or delivery capacity. Energy markets provide price incentives at various timescales for the prices of energy for both supply and demand within a given time horizon. These controls will translate into signals for a controller located behind the energy meter, at the building or building campus level. This controller can manage one or more active components in such a way that the demand or supply of energy changes over time. For this, it is important that the controller receives an accurate prediction of the available flexibility. For example, it is important to know how much cooling demand is predicted and how much this can be increased or decreased at a certain point in the time horizon used by the DSO or Energy Market.
The first step is to identify which components can be actively controlled. Key components for managing the electricity grid include the HVAC system, PV panels, EV charging stations, local

heat buffers, and batteries. Additionally, smart appliances, such as household appliances, offer further control possibilities. This paper focuses specifically on shifting heating demand within the building model.

The second step involves predicting the flexibility potential of these active components, described through active demand response (ADR) events (EIA Annex 6, 2019). An ADR event specifies how a component's flexibility can be adjusted, such as changing a temperature setpoint by a fixed amount within a set time frame. Shifting energy use at specific times impacts consumption either upward or downward and can lead to a rebound effect later. The building model calculates these shifts and rebound effects based on control signals and other input parameters, such as outside temperature and occupant behaviour. Currently, various standards have been developed to describe ADR events, including PAS 1878/1879, EEBUS, and S2 of EN 50491-12-2.
The third step is to select the most effective control strategy based on ADR predictions. ADR describes how a component responds to fixed control strategies. In Model Predictive Control, multiple control strategies can be simulated within a single time step using the building model. These ADR scenarios are evaluated using a cost function derived from price signals from the Distribution System Operator (DSO) or the energy market, leading to the selection of the optimal control signal for the active component.
Currently, various standards have been developed to describe ADR events, including PAS 1878/1879, EEBUS, and S2 of EN 50491-12-2.

3 HYBRID BUILDING MODEL SIRINE

An important issue in determining the ADR of a building to changes in the active control inputs is that the ADR is dependent on dynamically varying external conditions, such as ambient temperature, solar radiation, wind, the current thermal energy stored in the building structure, user behaviour and constraints in the operation of the HVAC installation. This makes the ADR a complex multi-variable function that is hard to determine, requiring informative data over the whole operational range.

To avoid the need for large and high-information content datasets of historical data of buildings in a district, a hybrid modelling approach is taken. The basic idea is that limiting the number of unknown parameters, that must be estimated from the data, will reduce parameter identifiability problems.

SirinE is a hybrid predictive digital twin model for buildings (Borsboom, 2022). It comprises a physical building model that solves heat flow balance equations and a data-driven occupant model that simulates occupant interactions with building components (e.g., thermostats, windows, electric appliances), incorporating these actions into the heat flow balance equations.

The main idea behind SirinE is to leverage available building data and known physical relationships to minimize the need for high quality data. There is usually plenty of time-series data available from energy meters, temperature sensors, and smart building systems (e.g., heat pumps, building and control systems (BACS), smart home systems, smart thermostats, electric vehicle systems). However, this data is often not detailed enough to calibrate a model for reliable energy predictions. By using known building and installation data, SirinE reduces the requirement for highly detailed data. An additional advantage is that the relations between measured variables are governed by physical laws and that parameters have physical interpretation and allowable ranges.

The building model of SirinE includes a heat balance and ventilation network (Kornaat 2020) that is automatically derived from the Building Information Model (BIM), which describes the geometric configuration and construction properties of the building (including all spaces, walls, windows, doors, roofs, etc.), and the Building Energy Model (BEM), which describes the building's heating, cooling, and ventilation equipment and controllers. With the automatic generation of the heat network, the simulation model can be easily adapted to different building types, such as apartment buildings, row houses, and office buildings. Furthermore, the data used to calibrate the model utilizes standardized ontologies like Haystack, making the simulation model easily scalable for different building typologies.

This heat network needs calibration for two reasons: firstly, not all necessary information is always available, such as the masses of the floors and walls. Secondly, the provided information may not be accurate, such as thermal bridges or airtightness being less than specified due to construction quality. This paper describes a strategy to calibrate the heat and ventilation networks.
SirinE includes a generic occupant module (framework) that reproduces the interactions of occupants with the building. The occupant module contains distinct submodules, each associated with specific occupant behaviour, such as occupancy, window interactions, or thermostat setpoint adjustments. The implementation is flexible, allowing each submodule to connect to various predictive models, ranging from simplistic approaches (e.g., fixed hourly profiles) to complex AI algorithms. Receiving the building's state at each timestep from the building simulator, along with weather information, the occupant module predicts occupant behaviour for the next timestep and sends it back to the building simulator. The AI-based occupant module, combined with the physics-based building simulator, makes SirinE a hybrid digital twin.

The building heat balance model dynamically interacts with the occupant model, implemented in an agent-based framework. All individual users (or groups of users defined as a user role) are agents that interact with the heat balance model in a dynamic simulation over the prediction horizon. The occupant models that have been implemented (simple hourly schedules, models for thermostat and appliances based on sliding averages, Markov chain models for window-opening behaviour) highlight the hybrid nature of SirinE. However, it is important to note that this is a general framework that can be coupled with any occupant model. We have developed different strategies to calibrate user behaviour, and this paper focuses on the calibration of the ventilation and heat networks.

4 CALIBRATION STRATEGY

4.1 Introduction of the calibration strategy

The calibration strategy developed can be described in a number of steps, ranging from zero up to 4.

Table 1: Calibration steps

Step	Description of the calibration step
0	Collect information from the building BIM and HVAC installation data sheets. Eliminate from estimation all parameters that are known with sufficient confidence
1	Identify subsystems which can be calibrated independently
2	Identify special time periods in which part of the parameters can be discarded, limiting the number of parameters to be identified.
3	Perform overall parameter estimation
4	Perform validation over a time series not used in parameter estimation

The idea behind this methodology is to start in step 0 with as many known properties of the building and installation, and known physical relationships, using the heat and ventilation network. This approach addresses the issue that time series data available for calibration is often insufficiently informative, leading to large parameter uncertainty and inaccurate model predictions.
In step 1, we identify subsystems with parameters that can be calibrated independently, such as a floor heating system. In step 2, We identify special time periods in which part of the parameters can be discarded. Limiting the number of parameters to be identified. We also utilize the fact that different physical transfer mechanisms have different dynamics. For example, ventilation can heat a space faster than solar radiation and heat conduction. By choosing time periods where the effect of a transfer mechanism is large compared to others the parameters involved can be estimated neglecting correlation with other parameters. For instance, ventilation can be calibrated when there is a large difference between indoor and outdoor temperatures, while solar radiation can be calibrated best during the transitional seasons.
The complete set of parameters will be estimated in step 3 using the already determined parameters in steps 0,1 and 2 as initial estimates and uncertainty ranges.
Step 4 involves validating the simulation against actual measurements.

The different steps are detailed in the section below. To illustrate the calibration steps, data and estimation results for a 4-room apartment in an apartment building, with data recorded over a 1-2 year period, will be shown. The well-insulated apartment has a ground source water-to-water heat pump for domestic hot water and floor heating and is equipped with individual PV panels.

4.2 Step 0 BIM/HVAC information collection

To reduce the number of parameters that need calibration, we incorporate as much known building information as possible into the physics-based ventilation and heat network. By utilizing known physical relationships, such as heat conduction and radiative heat transfer, less informative data is required for calibration. This process begins with collecting Building Information Modeling (BIM) data and HVAC installation data sheets.
For the SirenE model, the required building geometry information includes details on the façade, roof, floor, windows, doors, inner construction areas, and orientation, as well as the

material properties of each layer of these elements. The BIM information is then used to automatically configure a 50 nodes RC-network of the building.

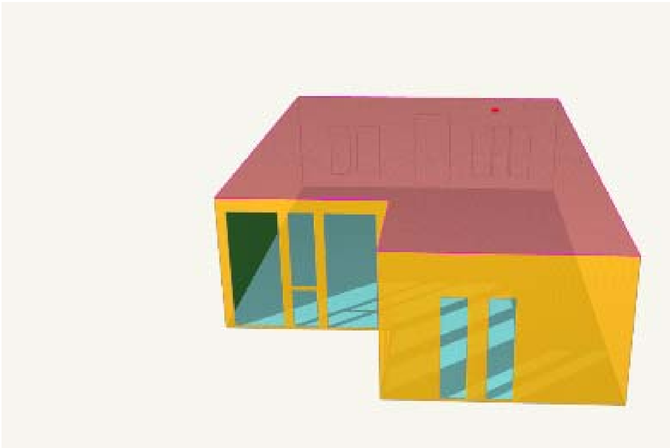

Figure 1: Apartment geometry derived from the BIM

Information on the heat pump, floor heating, floor cooling, boiler dimensions, and PV installation is retrieved from manufacturer data sheets or EPBD calculation inputs. User behaviour must be calibrated, which can be done through questionnaires or derived from real data if available, including room temperature setpoints, CO_2 levels, and electricity consumption. Alternatively, standardized user profiles can be used.

4.3 Step 1 Identify subsystems which can be calibrated independently

Depending on the standard available equipment sensors, subsystems can be calibrated independently.

In the example case, the heat pump (HP) control system is typically equipped with temperature sensors at the inlet and outlet of the evaporator and condenser loops, boiler temperature sensors, switches for floor heating, floor cooling, domestic water heating modes, and power consumption of the HP. A simple physical HP energy balance model is sufficient to describe the HP's dynamic response. A relative efficiency factor (compared to the data sheet) and a COP correction factor are calibrated based on the measured data. The floor heating power calculated from the measured data may suffer from discretization noise due to the low accuracy of the temperature sensors, but this effect averages out. The maximum difference in cumulative floor heating power at any time is less than 1%.

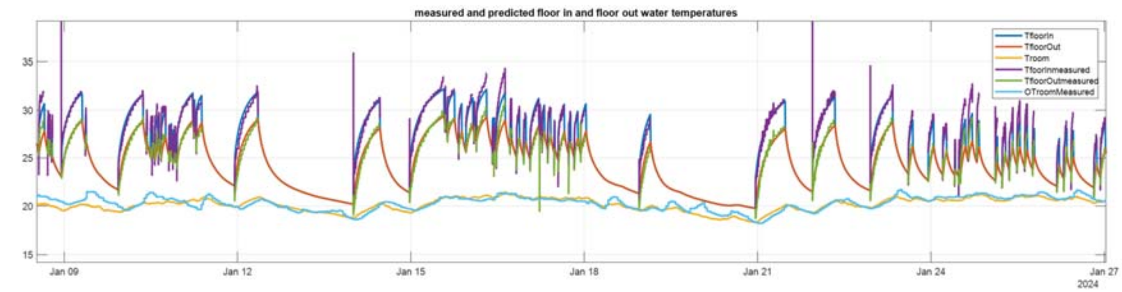

Figure 2: Model predicted floor input/output temperatures and measured temperatures.

The PV-system power output is accurately described as a function of the measured solar influx and needs no further calibration

4.4 step 2 Identify special time series in which a subset of parameters can be discarded

We identify specific time periods during which some parameters can be excluded, thereby reducing the number of parameters to be identified. For instance, in the spring and autumn, there are extended intervals when the heating system is off, so the floor heating system has no impact. We also leverage the fact that different physical transfer mechanisms have distinct dynamics. For example, ventilation and solar radiation have a faster dynamical effect on space temperature than heat conduction. By selecting time periods when the effect of a particular transfer mechanism is greatest, these mechanisms can be calibrated independently. For instance, ventilation can be calibrated when there is a large difference between indoor and outdoor temperatures, preferably when there is no heating or cooling. Meanwhile, solar radiation can be calibrated more effectively during transitional seasons when there is less

difference between indoor and outdoor temperatures. The effect of solar influx through windows on room temperature heavily depends on internal and external shading.
The dynamics of solar influx through windows differ significantly from those of thermal conduction or ventilation, which is correlated with wind speed.

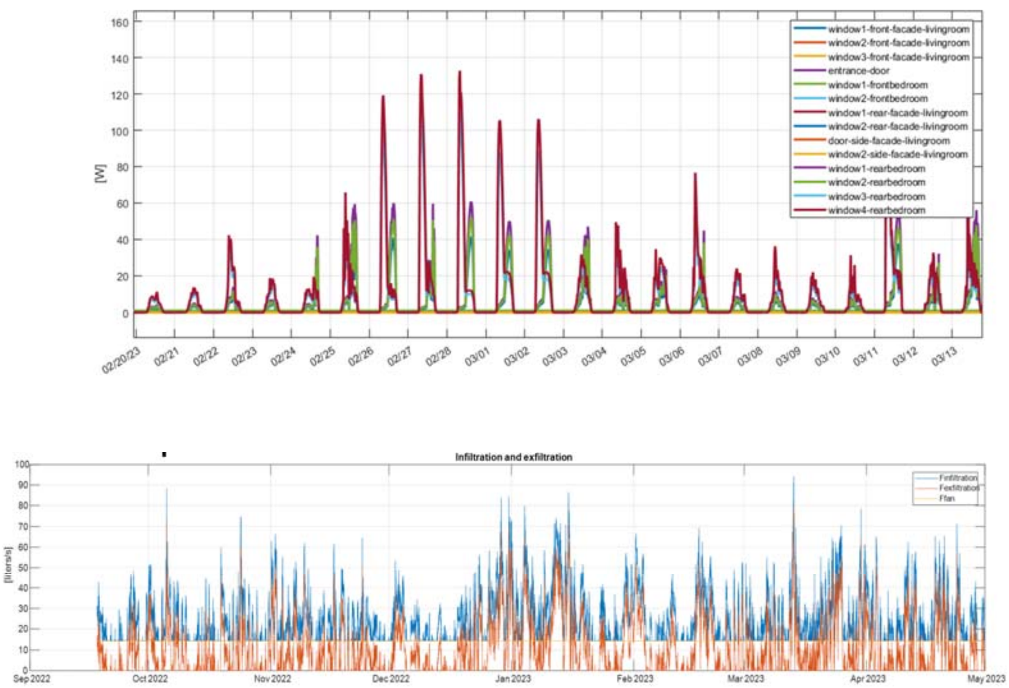

Figure 3: (top) simulated effect of solar radiation through each window and (bottom) simulated effect of infiltration and exfiltration

4.5 step 3 Overall parameter estimation

After fixing parameters independently identified in the previous steps the parameters are not yet fixed are calibrated, using a non-linear output error minimization solver.

For the example case the result is shown below.

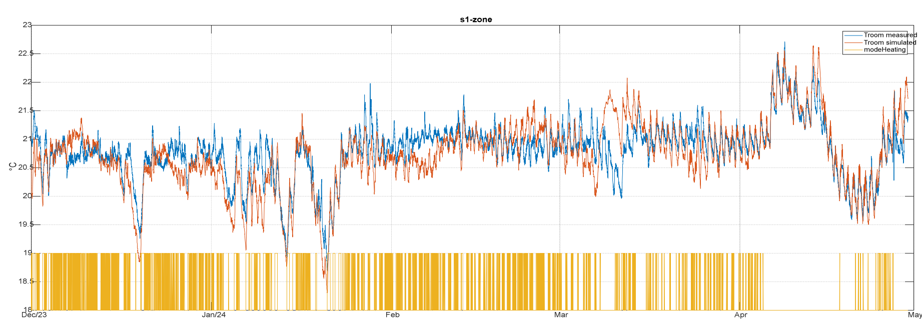

Figure 4: Measured and model predicted living room temperatures and floor heating mode

Although the dynamics is described sufficiently accurate over the total time series, there are periods with high mismatch that need further analysis. For example, in March sensor values of the heat pump mode and of solar influx were frozen for 5 days. In the parameter minimization problem such periods are neglected in calculation of the output error.

4.6 Future directions for the advancement of the methods

This method has been applied in various office buildings for monitoring and calibration in the Mooi Brains for Building project and in several apartments as part of the Horizon2020 Syn.ikia project for a model predictive controller. This controller has been successfully implemented in various apartments, doubling the self-utilization of solar power. Important future directions for development include making the method more robust against deviations in building, installation, and user behavior. This includes dealing with failed sensors, incorrect weather data, and neighboring apartments that are either very warm or hardly heated at all.

Another important direction is the development of automatic procedure for the calibration process to minimize the time required to configure the controller with an adequate prediction model for the MPC. For example, maintenance parties have suggested a configuration time of only several hours for a typical office building.
Main items in achieving fast calibration are automatic configuration of the heat and ventilation network from standard BIM/BEM formats and robust parameter estimation from BMS history datasets with medium or even low informative data quality.

5 CONCLUSIONS

In the future, it will become increasingly important for buildings, including residential and commercial campuses, to align energy demand with the irregular availability of sustainable energy. At the same time, it is crucial to stay within the existing capacity of the energy grid to prevent congestion. Effective control is necessary to respond properly to signals from the Distribution System Operator (DSO) and the energy market. Currently, managing active components like climate installations and thermal buffers is often too time-consuming and costly, leading to the preference for battery solutions or controlling electric vehicle charging stations instead. Automatic methods for calibrating model-based controllers can significantly contribute to reducing the initialization time and costs of these controllers. The calibration methodology described here can provide a solution and has been useful, for example, in applying a controller in Syn.ikia to enhance the self-utilization of PV energy. In the coming period, various projects will focus on developing an automatic calibration method. It is also important that this method is robust against different deviations in user behaviour and failures in sensors and installations. Additionally, further work will be done on the hybrid building model, including an open-source model for evaluating renovation measures of residential properties, with calibration based on the energy usage of the building's initial configuration (Kornaat 2023).

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