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Thermal modeling and calibration of Greener building in Grenoble

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ABSTRACT. In the evaluation of advanced building management and control systems, the accuracy and reliability of the building's thermal simulations are very important. They are key to developing and testing new energy management strategies. The study presents the modeling process for the Greener building in Grenoble, including the numerical thermal model creation, and calibration of the numerical model with measured data. The main objective of this study is to accurately simulate the thermal dynamics of the building, allowing the evaluation of efficient energy management and control strategies. The numerical model creation requires the collection and analysis of various types of data, all of which are essential for achieving a realistic and functional model. These data include local weather conditions, thermal properties of the building materials, measured energy consumption profiles, recorded temperature data, etc... To enhance the model's accuracy, a calibration process is undertaken using a tool developed by the CSTB using data collected from a large set of measurement sensors and energy meters in the living lab zone of the Greener building. The calibration tool allows the adjustment of model parameter values through comparison with measured data, ensuring that the model accurately reflects the actual thermal behavior of the building.

KEYWORDS: Thermal Modeling, Data Collection, Model Calibration.

1. INTRODUCTION

This research highlights the importance of data collection and data precision for calibration in the development of a reliable thermal model, and its importance for testing predictive control algorithms. The coupling of a calibrated model with simulated energy management algorithms provides an effective methodology for evaluating and ranking various control algorithms according to their performance criteria. It also opens new perspectives for improving building energy efficiency and contributes to the development of innovative control techniques.

The study focuses on the Greener building in Grenoble (Delinchant et al. 2016), a benchmark for sustainable architecture, to present a comprehensive thermal modeling process encompassing model creation, calibration, and application of the model to evaluate predictive control algorithms. The primary goal is to simulate the building's thermal dynamics with high accuracy and ensure that simulations align closely with real-world measurements. This research underscores the significance of collecting and analyzing diverse data sets, including local weather conditions, thermal characteristics of building materials, energy consumption patterns, and recorded temperature data.

The calibration process is an essential part of the study. It uses the Caliente tool (**CAL**ibration for **EN**rgy consump**T**ion in **EX**isting buildings) created by CSTB. This tool uses data from many sensors in the Greener building to calibrate the model and make sure it accurately matches the building's real thermal activity. Overall, this research highlights the importance of data collection and their precision for the calibration of a reliable thermal model.

2. CALIBRATED MODELS IN CONTROL ALGORITHMS TESTS

The calibration of models to accurately represent the thermal behavior of buildings has drawn considerable attention in recent academic studies, particularly for the evaluation of control algorithms. For instance, (Ma et al. 2012) explored the efficiency of Model Predictive Controllers (MPC) when applied to HVAC systems to reduce energy and demand costs in simulated commercial buildings. The approach involves a simulated multi-zone commercial building with a variable air volume (VAV) cooling system built in EnergyPlus. A significant part of the research is dedicated to system identification to establish accurate thermal models. This step is critical for the performance and reliability of the MPC algorithm, as it ensures that the model closely reflects the real-world performance of the building's HVAC system.

Similarly, a study by (Široký et al. 2011) concentrates on minimizing energy consumption in building heating systems by integrating advanced control techniques like MPC. The study outlines two approaches to building modeling: statistical and RC (Resistance-Capacitance) modeling. The choice of modeling approach depends on data availability and building physics knowledge. The article suggests that large measurement data sets lend themselves to a statistical approach for building modeling, which is preferred for creating MIMO (multiple-input multiple-output) system models. In a related context, (Wetter et al. 2020) explored building energy simulation through the Spawn project, integrating Modelica and the Functional Mockup Interface for detailed co-simulation. This project enhances model predictive control by linking control models with EnergyPlus for comprehensive building analysis.

Building on these foundational studies, the current research aims to create a use case by applying several innovative control strategies to the Greener building in Grenoble, to quantify their performance and evaluate them in terms of effectiveness. Therefore, the present study, while drawing inspiration from these previous works, aims to establish its specific use case by creating and calibrating a building thermal model.

3. GREENER BUILDING: CASE STUDY BUILDING OVERVIEW

3.1. BUILDING PROFILE

3.1.1. Overview: An architectural synopsis

The building selected for this study is the “Greener” building located in Grenoble (Delinchant et al. 2016). Greener is a five-floor building, built in June 2015, with a floor area of 22717 m², and a capacity of accommodating about 2000 occupants. The building hosts the electrical engineering lab in Grenoble, G2ELab, and INP ENSE3 university. It also includes a library and a university restaurant.

G2ELab is the Electrical Engineering Laboratory of Grenoble-Alpes University, and it is located on the southern side of the fourth floor of Green-er. The total surface of the lab is 357 m², and it consists of six offices, an experimentation area, a student hall, and corridors.

3.1.2. Data availability

The Greener building selected for our thermal modeling study stands out for the extensive availability of detailed plans and technical documentation. These resources are valuable in constructing a comprehensive thermal model. The building's plans provide precise footprints and layouts, essential for accurately modeling the spatial dynamics of thermal behavior. Additionally, the technical reports accompanying the building offer a wealth of information on the construction specifics, including the characteristics of the building envelope, walls, and windows. This data is crucial in understanding the

heat transfer properties and insulation qualities of the structure. After the creation of the model using the footprints of the building, the selection has been refined and concentrated on the lab (G2ELab) thermal zone.

3.2. THERMAL CHARACTERISTICS AND ENERGY SYSTEMS

3.2.1. Building envelope

Regarding the building envelope, the interior walls consist of lightweight interior partitions formed by an air gap surrounded by two layers of plaster. For the exterior walls, the composition includes cladding, an air gap, insulation, and a layer of heavy concrete (from external to internal surface). The ground floor is constructed with insulation and heavy concrete. The exterior roof is composed of polyurethane insulation and heavy concrete. In terms of the windows, double-glazed Argon-filled windows are utilized.

3.2.2. Energy systems

To maintain thermal comfort in the laboratory, a combination of ventilation, heating, and cooling systems is implemented. Ventilation is provided by fresh air delivered through a central Air Handling Unit (AHU), located on the building's rooftop and supplemented with a central water coil for air preconditioning (Figure 1). For temperature control, there are two primary sources:

1. **Air Preconditioning:** At the AHU level, a coil system preconditions the air, serving both heating and cooling purposes. This preconditioned air is then distributed throughout the lab.
2. **Room-Specific Temperature Adjustment:** Each room is fitted with a terminal coil, that allows for the adjustment of the room temperature.

Additionally, a reversible hydronic ceiling system is installed in each room. This system connects to the district heating network for heating in the winter and to local chillers for cooling in the summer, ensuring a comfortable environment year-round.

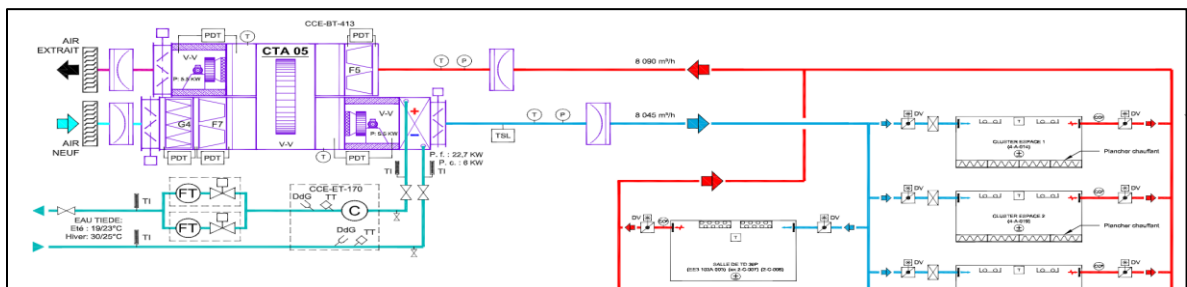


Figure 1: The Air Handling Unit (CTA 05) layout and its connection to the rooms in the living lab zone.

4. METHODOLOGICAL FRAMEWORK FOR THERMAL MODEL CREATION AND CALIBRATION

4.1. DIMOSIM MODEL AND ZONING

The simulations are carried out using DiMoSim (District Modeller and Simulator) (Garreau et al. 2021), which is a bottom-up dynamic simulation platform for energy systems in buildings and districts developed since 2013 by the CSTB (www.cstb.fr). This tool is built on an object-oriented structure. The building and energy component (production, storage, networks) models are based on physical description. The necessary input data for the Dimosim model encompasses several key elements. This includes a weather data file (in .epw format), which provides detailed meteorological information. Additionally, simulation parameters are required. In addition, a Geojson-type file detailing key building

characteristics, such as opaque and transparent envelope properties, along with the building's energy system type and geometry, is essential for model creation.

The building model was divided into four main thermal zones as shown in Figure 2: the principal one, which is the lab (G2elab), three other zones representing the rest of the floor containing the lab, the floor above the study zone, and the last one is the zone presenting the three floors below the lab zone (Greener 0, 1, 2). The focus of the study, the G2ELab zone, comprises a total of eight distinct areas, including six shared offices, a specialized experimental zone for laboratory activities, and a university classroom. To effectively analyze the thermal dynamics of the lab zone, an aggregated modeling approach is adopted: all eight zones into a single, unified thermal zone.

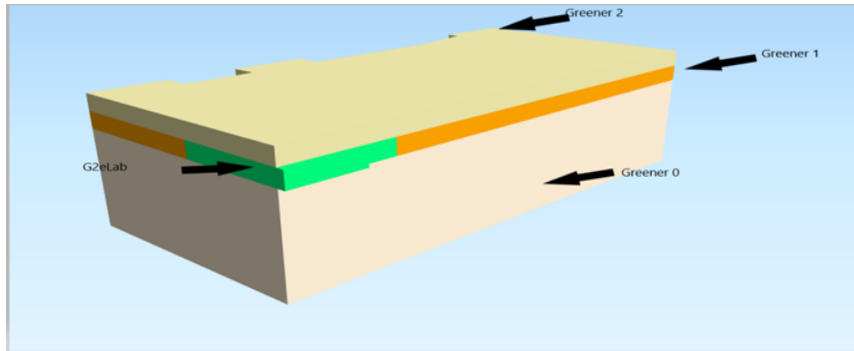


Figure 2: Qgis 3D building model view (<https://www.qgis.org/fr/site/>).

4.2. EMPIRICAL CALIBRATION

4.2.1. Data collection

The essential data for the Geojson file, including the building's footprints and the thermal attributes of its walls and windows, are extracted from the building's technical documentation. Additionally, a new meteorological (Meteo) file is created using data gathered from the meteorological station situated on the roof of the building. This incorporation of actual weather data ensures that the building's environmental conditions are accurately reflected and utilized in the analysis.

Furthermore, to accurately calibrate the model, it's important to quantify both the total heating and cooling consumption of the lab and the individual energy consumption of each office. To facilitate this, an extensive dataset was collected from the lab's database, recording energy and temperature sensor readings from June 2015 to 2022. We note that all of the data used in the study from the lab sensors will be published soon in Open Source.

4.2.2. Calibration scenarios and simulation results

Our initial evaluation of the newly developed thermal model concentrated on a mono-zone model, treating the entire laboratory as a single thermal zone. The procedure adopted is to improve the data input for the thermal model to more accurately reflect the actual building's conditions. To accomplish this, we initiated a series of simulation scenarios, starting with a basic set of hypotheses. As we progressed and observed discrepancies between the simulation results and the actual recorded data, both in terms of dynamic behavior and absolute thermal consumption, we progressively improved the quality of the model's input data, trying to accomplish a manual calibration benefiting from the certain values of parameters provided from the lab database. This process of improvement continued until we used all available data to reduce the gap between simulated and observed results, in this process, one scenario corresponds to a set of input variants. In this section, we will present the best results we get for the

empirical calibration. The scenario providing those results is outlined as follows: Information regarding the building's envelope, such as insulation and thermal properties, is derived from technical reports. For the air change rate, we've adopted the actual hourly values measured during the study period. We collected the actual recorded airflow for each room in the study zone from the local airflow meters and then aggregated these individual measurements. The weather file is created using exterior temperature, with global, diffuse, and direct solar radiations recorded in the local weather station. Actual temperature readings from meters within the zone are used to create dynamic setpoint profiles, rather than using fixed profiles for economy and comfort setpoints. This approach incorporates the maximum amount of data available and refines the model to better reflect the actual conditions in the building. The results of the simulations are shown in Figure 3.

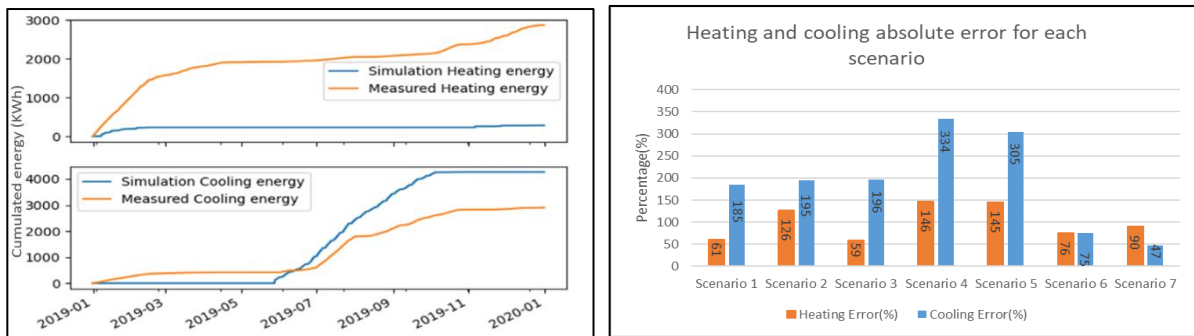


Figure 3: To the left: Monozone simulation calibration results for the year 2019, with the maximum amount of data available for model input (scenario 7).

To the right: Errors calculated between nominal values of heating and cooling energy for each scenario of inputs.

In concluding the simulation of various scenarios as shown to the right in Figure 3, we have drawn two main conclusions from the analysis. First, having access to a large amount of data was generally advantageous, sometimes leading to a reduction in the discrepancy between simulated and actual consumption, as we can see, for scenario 7 with the maximum use of data, the absolute error between simulated and measured energy consumption reached 90% for heating and 47% for cooling. However, introducing all available data as input parameters can increase the complexity of the problem. We observed that in some cases, scenarios with less data input resulted in lower discrepancy errors during the heating season (scenarios 1 and 6), and similar results were noted for the cooling season when compared to scenarios using a full available data set. This suggests that the interplay and individual impact of various data on heating and cooling can add complexity to the simulation. Second, data quality is a significant challenge in our efforts to align simulation outcomes with actual measurements. An example of a potential issue is the performance of cumulative energy meters, which log data upon reaching a specific threshold rather than at consistent time intervals. This characteristic could have influenced the discrepancies between our simulated results and the recorded energy consumption. Furthermore, in our study, as mentioned earlier, the data has been resampled to a one-hour time step, a process that carries the risk of data loss, having the raw data time step different from one hour.

Based on these conclusions, we will present "Caliente", a tool developed by the CSTB to calibrate Dimosim models using baseline consumption data as in our study. The intricacies of this tool and its application to our model calibration will be explained in the following section of the article.

4.3. CALIENTE CALIBRATION TOOL

In the second part of our study, we will use a different method to calibrate our model by using a specific calibration tool named "Caliente", created by CSTB. An article describing in details this tool will be published soon. In this article, we will explain briefly and in general how to use this tool on our Greener thermal model for calibration.

4.3.1. General overview about calibration methodology in Caliente

Caliente is a generic calibration package (Python) for the calibration of building energy simulation tools. In this case study, this package has been adapted and updated for the Dimosim simulation tool. The calibration can be done with measured energy data, at an aggregated level (annual results) or dynamic level (monthly, hourly or sub-hourly time series)

The calibration of buildings parameters can be done using the following mechanism: Initially, it details the building's thermal properties and occupancy. Next, baseline data such as building conditions and energy consumption are supplemented with weather data. A sensitivity analysis then identifies critical parameters and their uncertainties, which are finally used in the calibration phase, where uncertainties and baseline errors are fine-tuned to create a calibrated input file for simulations.

4.3.2. Greener model calibration using Caliente

As stated before, the living lab zone is equipped with a huge number of sensors and meters, for single zones and also for groups of zones. Measured data to be used includes the total heating and cooling load of the centralized air-handling unit (AHU) as well as the heating and cooling loads of reversible hydronic ceiling panels in each zone. The calibration was performed dynamically on the total thermal heating and cooling load of the building. The model has considered the G2ELAB building but also surrounding buildings to properly calculate the solar irradiation exposure due to the shading of surrounding buildings. A sensitivity analysis was performed to identify the modeling parameters with the most significant impact on calibrating the heating and cooling demand.

4.3.3. Model calibration performance

As stated before, the objective of the calibration is to reduce the uncertainty in the input parameters and tune them to have simulation results close to the baseline reference data. For this purpose, different standardized statistical indices can be used for the calibration, depending on the type of results to be evaluated and the objectives of the calibration. In this case study, the index used for the calibration is the Normalized Mean Bias Error (NMBE). This error is applied to the entire time series of one year (2019) where the difference between measured and simulated values is calculated and averaged over the whole time series and then normalized. The simulations with different parameter combinations are analyzed to reduce this error by adjusting the input parameters. For the calibration model performance, the normal mean bias error for the heating demand was calculated to be 2.56% and -13.99% for the cooling demand. The best results obtained from using the calibration tool are shown in Figures 4 and 5.

4.3.4. Results discussion

The graphs in Figures 4 and 5 demonstrate that using the Caliente tool significantly narrows the gap between the actual measured data and the simulated data in the thermal model. Although the simulated model doesn't exactly match the reference in terms of energy used at each time step, its general trend closely follows the actual consumption. This similarity suggests that the calibrated model accurately represents the real building's thermal behavior, making it suitable for testing and assessing control algorithms. It is important to note that in this study, the calibration of another multi-zone model is realized. For this model, each room is considered a thermal zone, which complicates the calibration process when taking into account variables zones conditions, or consumptions. An energy consumption peak around autumn is poorly represented by the model. This could be an effect of a certain part of the building with minimal sun exposure needing to start heating their zones earlier than the rest of the zones in the building. Since only a single zone is modeled, these effects are not calculated by the model.

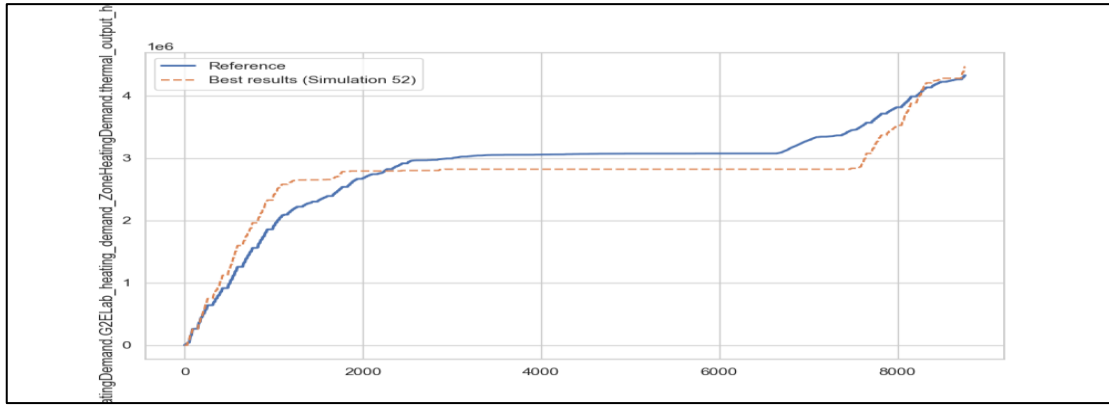


Figure 4: Best result of heating season calibration for one year period with 15 variants of parameter combinations.

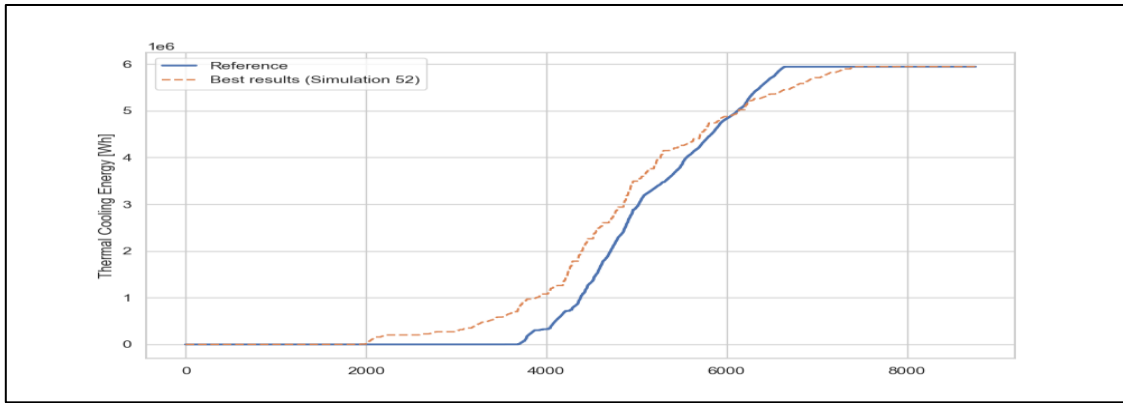


Figure 5: Best result of cooling season calibration for one year period with 15 variants of parameter combinations.

5. COUPLING CONTROL ALGORITHMS WITH CALIBRATED MODEL

In this section, we showcase how a model predictive controller (MPC) algorithm, when integrated with our calibrated model, helps maintain thermal comfort in the G2ELab zone while minimizing energy usage. This algorithm anticipates both external weather and internal conditions, optimizing temperature settings through a genetic algorithm to efficiently manage the zone's energy systems.

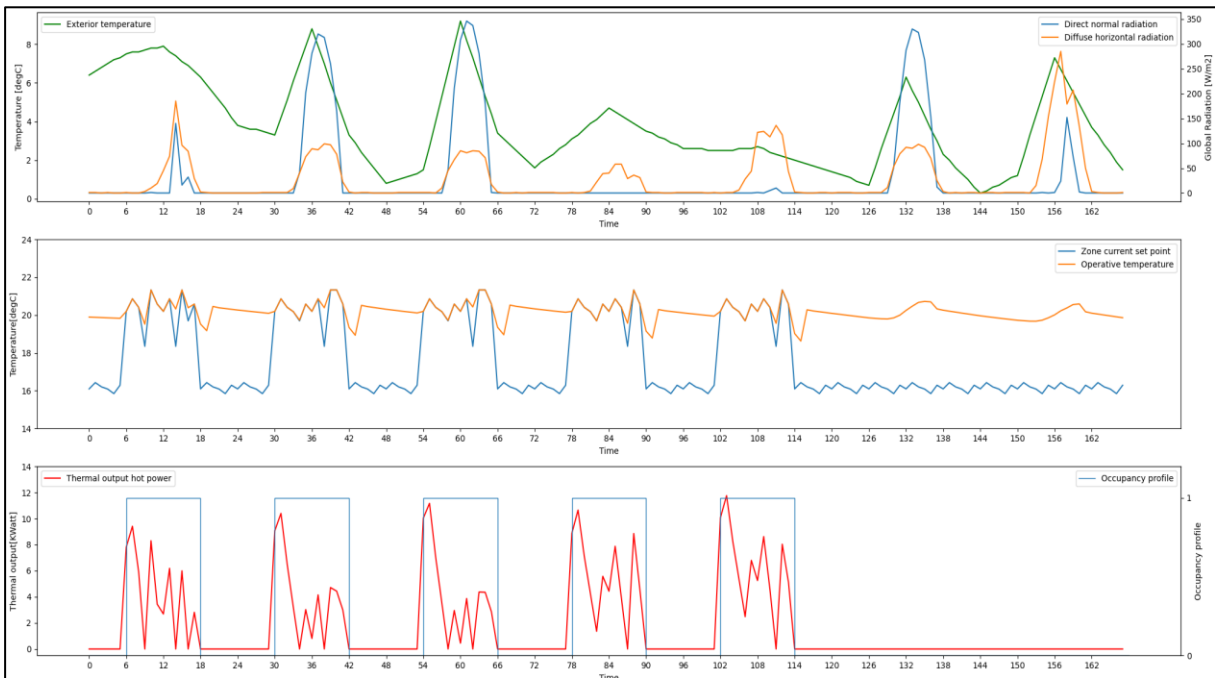


Figure 6: Example of using a Model Predictive Controller algorithm for the calibrated model.

Figure 6 illustrates the algorithm's role in creating comfortable conditions by predicting occupancy and weather changes. The upper chart presents the external environmental factors. The middle chart displays a one-week overview of the management decisions made by the MPC. This includes the desired temperature targets ('Zone current set points') that the MPC communicates to the building's heating system. The term 'operative temperature' refers to the calculated temperature within the building's zone (average between air and mean radiant temperature). The lower graph shows the amount of heat provided by the building's heating systems to meet the MPC's temperature set points. These set points are adjusted according to occupancy patterns; for example, heating is turned off when the building is unoccupied, as indicated by the end of the week period on the graph. The goal of integrating the MPC with the calibrated model is to assess the algorithm's effectiveness. This evaluation, including a detailed discussion of the methodology for testing the control algorithms, will be covered in a separate article at the conference.

6. CONCLUSION

In this article, we present the method we used to create and calibrate a thermal model for the Greener building in Grenoble, with a focus on the living lab zone. The article presents the usefulness of the data available in the lab in the creation of the model. The variety of sensors installed in the lab, providing data on energy consumption and temperature evolution, as well as the reports containing the thermal characteristics and the data from the weather station installed at the top of the building, was very useful in the creation of the model. A basic empirical calibration was applied first, aiming to reduce the difference between the measured energy consumption and the simulated one, by using the available data to improve the input of the models, this calibration has significantly reduced this difference. The high availability of data was very useful in improving the input of the model, but on the other hand, the interaction between the measured parameters and the uncertainties in some data made the problem more complex. In the other part of the study, a calibration tool is used to further reduce the difference and ensure that the calibrated model represents the real behavior of the building. This refined calibration process resulted in a thermal model that reflects better the actual energy consumption patterns, even though the exact energy values at each time step may differ. This result suggests that while the model may not be perfect in every detail, it serves as a valuable tool for testing and evaluating control algorithms. Through this work, we ensure that the model reflects the thermal behavior of the building.

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