Final report

1. Project details

Project title	Human-in-the-Loop Digitalisation & Energy Management of Buildings - HuiL-DEMand
File no.	64021-1021
Name of the funding scheme	EUDP, Energy Efficiency, Demonstration
Project managing company / institution	CLIMIFY ApS.
CVR number (central business register)	42021830
Project partners	DTU, UpSmarting ApS, Center Denamrk, ENFOR A/S, Høje TaastrupKommune, Rudersdal Kommune.
Submission date	04 July 2024
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2. Summary, Results, Conclusions and Perspectives

2.1 Summary

HuiL-DEMand addressed inefficiencies in building energy management & operation. It demonstrated a system integrating BMS, IoT sensors and AI to optimize the heating based on real-time data and occupant feedback in 2 schools. The innovation lay in its user-centric approach, allowing automated adjustments to maximize comfort and minimize energy use.

2.2 Results, conclusions and perspective

HuiL-DEMand demonstrated that efficient operation of buildings can be achieved by digitilizing them and applying appropriate evaluation and control algorithms. The Human-in-the-Loop approach, where occupants do not actively change set-points but instead provide qualitative feedback, proved effective for efficient operations. Classifying and modeling occupants' preferences was feasible: we developed the first version of the Comfort-ID, a mathematical model predicting occupants' feedback based on actual room temperature, building location, and weather conditions. This model also helps minimize unsatisfied occupants and complaints. Furthermore, comfort tolerance ranges were used as input for the developed Model Predictive Control of room temperature, demonstrating that energy savings and enhanced occupant comfort are attainable results.

The results of this project will be utilized differently by various stakeholders. CLIMIFY has brought to market the software developments made through the project and will continue to explore the application of COMFORT-ID in collaboration with DTU and other partners in future projects. The main effects derived from the developed technologies include:

- A clear path for digitalization for building owners.
- Reduced energy bills for the existing building stock.
- Increased occupant satisfaction.
- Potential for buildings to provide flexibility services.

2.3 Projektresumé

HuiL-DEMand adresserede ineffektivitet i bygningsenergistyring og drift. Det demonstrerede et system, der integrerer BMS, IoT-sensorer og AI for at optimere opvarmning baseret på realtidsdata og brugerfeedback i 2 skoler. Innovationen lå i dets brugercentrerede tilgang, der muliggør automatiske justeringer for at maksimere komfort og minimere energiforbrug.

2.4 Resultater, konklusioner og perspektiv

HuiL-DEMand demonstrerede, at effektiv drift af bygninger kan opnås ved at digitalisere dem og anvende passende evaluerings- og kontrolalgoritmer. Tilgangen med mennesket i løkken, hvor beboere ikke aktivt ændrer indstillinger, men i stedet giver kvalitativ feedback, viste sig effektiv til effektiv drift. Klassificering og modellering af beboeres præferencer var muligt: Vi udviklede den første version af Comfort-ID, en matematisk model, der forudsiger beboeres feedback baseret på den faktiske rumtemperatur, bygningens placering og vejrforholdene. Denne model hjælper også med at minimere utilfredse beboere og klager. Derudover blev komforttoleranceintervaller brugt som input til den udviklede prædiktive modelkontrol af rumtemperaturen, hvilket viser, at energibesparelser og forbedret beboerkomfort er opnåelige resultater.

Resultaterne af dette projekt vil blive udnyttet forskelligt af forskellige interessenter. CLIMIFY har bragt de softwareudviklinger, der blev gjort gennem projektet, på markedet og vil fortsætte med at udforske anvendelsen af COMFORT-ID i samarbejde med DTU og andre partnere i fremtidige projekter.

De vigtigste effekter, der følger af de udviklede teknologier, inkluderer:

- En klar vej for digitalisering for bygningsejere.
- Reducerede energiregninger for den eksisterende bygningsmasse.
- Øget tilfredshed blandt beboere.
- Potentiale for at bygninger kan tilbyde fleksibilitetstjenester.

3. Project objectives

3.1 What was the objective of the project?

The HuiL-DEMand project aimed to reduce CO2 emissions associated with building heating and to maximize indoor comfort through a robust, scalable, and easy-to-implement energy management system. Within this project, we demonstrated that cost-effective solutions could achieve higher occupant satisfaction and lower energy usage by accurately incorporating occupant needs into the control system.

3.2 Which energy technology has been developed and demonstrated?

In the HuiL-DEMand project, we focused on developing and demonstrating a monitoring and automation technology. This system integrates third-party IoT devices, data-driven methods, and Model Predictive Control (MPC) developed by DTU, alongside weather forecast models from ENFOR, and data storage technology from Center Denmark, all within the vendor-neutral platform, CLIMIFY. Two schools were selected as demonstration sites to develop and test the proposed energy management system.
Key Features of the Technology that we demonstrated are:

1. Data Acquisition and Integration: IoT sensors were installed to collect data on indoor air quality and system performance. This data was integrated with existing Building Management Systems (BMS) data to identify and minimize energy waste, particularly in water-based heating systems.
2. Occupant-Centric Control: Building on the core principles of HuiL-DEMand, we transitioned from traditional set-point-based control to a perception-based approach. Using the FEEDME app, occupants were able to provide feedback on indoor conditions, enabling dynamic adjustments to heating settings for both immediate and long-term needs, facilitated by the implementation of the Comfort-ID model.
3. Optimization of Energy Use (simulation only): The system optimized building energy consumption and maximized the use of renewable energy sources by considering occupants' presence, their comfort preferences, weather conditions, and variable energy prices to effectively adjust heating and cooling schedules. Although the technology shows great promise, it has been implemented at the simulation level only thus far.

Innovations and Benefits:

- The introduction of smart thermostats and user interfaces that prevent unauthorized adjustments and ensure optimal thermal comfort based on real-time feedback.
- Enhanced occupant comfort and energy efficiency through a perception-based control approach and model predictive control that anticipates heating needs based on occupancy and external weather forecasts.
- The project's approach also included tracking occupants' presence via a Bluetooth network and CO2 levels, allowing for a highly tailored environmental control.

The project is highly relevant, especially when looking at the "Det Energiteknologiske Udviklings- og Demonstrationsprogram – Strategy 2020-2030". This project proposal is mainly related to the area "2, Energieffektivisering" (Energy Efficiency) with a particular focus on buildings; the project addresses the efficiency of buildings components, upgrading them through a smart control (e.g. switching off old pumps/fans etc. in unoccupied periods, by monitoring indoor climate and energy usage and hence recognise issues due to components that are not performing). Moreover, the project address to energy efficiency of the entire building system.

The first peculiarity of this project lies in its scalable and flexible solution: the use of IoTs allow a quick and non-intrusively retrofit (basically "dust-free"), easily applicable at old, historical buildings, but also at simple residential and non residential buildings: deep retrofit solutions save big amount of energy, but alone won't be enough to address the entire building stock quickly (actual retrofit rate of buildings is around 1% per year).
The second peculiarity of this project lies in the digitalisation and model-based automation of the existing building stock: the use of renewable energy sources in buildings is a must to make buildings carbon neutral. Our approach prepares the ground for the adoption of big scale flexibility solutions, hence helping in the strategy 2020-2030 area "1 Mere grøn el – og til flere formal" (more green energy – and for more purposes). Finally, the project is also related to the area "7, Fleksibel el-anvendelse, netudbygning og digitalisering". The solution presented in this project can be used in buildings connected to district heating or any other heat source. If connected to district heating (DH), the flexibility provided to the DH network could be exploited by the use of heat pump in the DH network, and more in general to avoid peak periods. When using heat pumps, the flexibility would be directly offered to the power grid.
Combining the two peculiarities listed above, our digital solution will contribute to accelerate the transition to a carbon free building stock.
More in general, the project fits with the strategy to make public buildings green, and healthy schools. The Høje Taastrup municipality has just finalized its new strategic climate action plan 2030. This plan partly focuses on energy optimization in buildings and on indoor climate in schools, with the use smart technologies, perfectly fitting with the scope of this project.
Finally, a last comment on the Danske Klimalov. One of the objective of the "Danske Klimalov" (the Danish Climate Law) is to reduce CO2 emissions by 70%, compared to the levels of 1990. Until 2020, thus in 30 years, Denmark managed to lower down CO2 emissions by 35%. In the next 10 years Denmark needs a further reduction of 35%. This reduction is not achievable without addressing the actual building stock. Ours solution Is perfect to contribute in achieving this goal, being effective and easy to roll out.

4. Project implementation

4.1 Project evolution

The project progressed well, with most Milestones and Deliverables met on time; only a few milestones experienced delays of up to a few months. The projects GANTT is illustrated in Figure 1. Critical aspects of the project included a shift in focus by one of the partners, UpSmarting. After losing a key employee, UpSmarting shifted from hardware integration to consultancy. Despite this change, they still managed to make data available for the project, although their tasks and budget were reduced accordingly. Part of their intended work was assumed by CLIMIFY. The project was very well received by the final end-users, namely the occupants of the selected three demos, who experienced enhanced indoor climate and easy control of their facilities. Additionally, the two municipalities involved in the project are satisfied with the results. Changes in the employees among municipalities and other partners could have challenged the project execution, but new employees were brilliantly involved by the partners, ensuring smooth transitions.

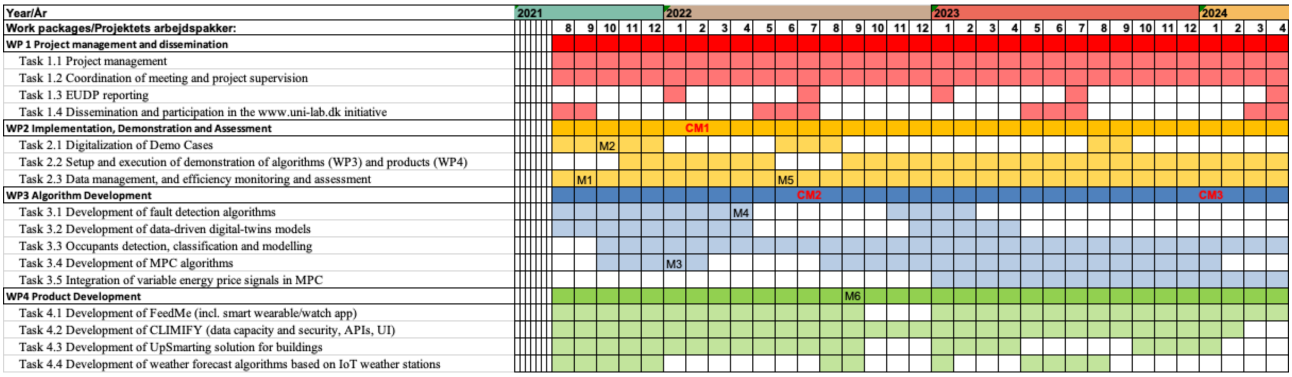

Figure 1 GANTT of the project.

The milestones of the project are listed below:

- M1 Definition of assessment criteria (energy, comfort, CO2 emissions), based on existing standards/guidelines/certification processes
- M2 Demo case are equipped with the minimale valuable combination of IoT components (sensors, actuators, energy meters) based on the criteria defined in M1 and the requirements from WP3 and WP4
- M3 First simple algorithm for controlling room set points according to occupants feedback
- M4 First version of fault detection algorithms
- M5 First assessment of the implemented solutions
- M6 Developed versions (2.0) of FeedMe, CLIMIFY, and MetFor™; First version of UpSmarting hardware and software solution for builsings
- Commercial milestones/Kommerc. milepæle
- CM1 First demonstration of fully monitored and partially automatized demo buildings. Publication of results on Danish newspapers and journals, and international conferences.
- CM2 First integration of the algorithms from WP3 into the products, with conequential first commercialisation of the algorithms.
- CM3 Second integration of the algorithms from WP3 into the products, with conequential commercialisation of the new algorithms.

4.2 Risks associated with conducting the project

We have consistently identified, evaluated, and implemented containment measures for risks throughout the project. The table below (Table 1) details the main risks along with their corresponding containment actions and measures.

Table 1. *Identified risks during the project, their probability, impact, and related preventive measures*

Risk	Risk Type	Probability (1 = least, 5 = greatest)	Impact (1 = least, 5 = greatest)	Preventive measures
Chip shortage on market	Market	5	2	The shortage of Chips has initially delayed the project.
Usage of Danfoss Thermostats Ally	Tech	5	2	The Ally thermostats are robust and generally of good quality. However, they are not designed for non-residential buildings. To adapt their usage for a school, we purchased several gateways and repeaters, creating a network with a total of 8 access

				points. Despite these efforts, some of the eTRVs still go out of reach. In agreement with Rudersdal, we are now fully transitioning to MClimat VICKI, an eTRV that utilizes LoRaWAN technology.
Thermostats getting vandalised	Tech	5	3	Some of the smart thermostats in Demo 1 were vandalized. We constantly replaced those that were damaged. Initially, we installed protective cases to prevent breakage; however, these cases inadvertently facilitated the disabling of the thermostats from the radiators. We also positioned new furniture around the radiators to better conceal the TRVs. Ultimately, we replaced the thermostat adapters with new metal ones and the backplates with reinforced versions. These measures have more reliably secured the thermostats in place.

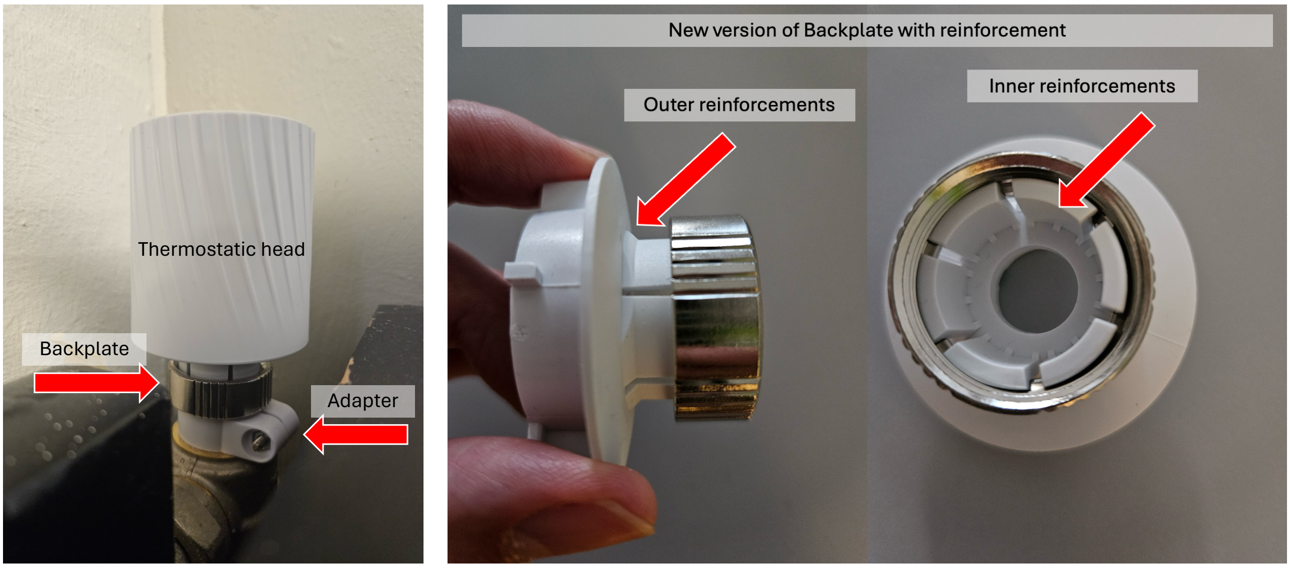

Figure 2 Example of an MClimate Vicki Thermostat installed on a radiator (left) and its backplate after the company upgraded it with reinforced 45° elements to maximize stability against accidental and intentional breaks.

5. Project results

5.1 Results related to WP1, Management & Dissemination

WP1 is related to project management and dissemination. In this WP, we selected and administered the four demos:

- Borgerskolen Vinkelbygning, Høje Taastrup: DEMO 1.
- Birkerød Skole, Rudersdal: DEMO 2.
- Ole Rømer-Skolen, Høje Taastrup: DEMO 3.
- DTU 303B (backup demo): DEMO 4.

The selection of these demos was made to maximize demonstration opportunities, minimize risks, and ensure backup solutions for testing technologies and algorithms.

Figure 3 Borgerskole Nordbygning (Vinkelbygning).

DEMO 1: School building located in HTK (Figure 3). This has been our primary demo for showcasing the technologies. In this demo, a building dating back to 1900, we managed to digitalize all the classrooms and teachers' rooms by installing indoor environmental sensors and smart thermostats. Moreover, a direct connection through MQTT to the building's BMS enabled researchers to modify and adapt more set points than just those of the thermostats, benefiting both the modeling activities and the comfort of the occupants. Four specifically selected rooms were equipped with double indoor climate sensors (to test reading differences due to installation positioning), window sensors, and heat meters (two heat meters for four rooms) to better validate the modeling activities. The control of set points was consistently based on feedback from the work-environment representative, who collected input from colleagues. This method ensured effective communication and high satisfaction among employees and pupils, without distracting teachers from testing technologies under development.

Figure 4 Entrance area of Birkerød Skole.

DEMO 2: This demo (Figure 4) involved a school building in Rudersdal where indoor climate sensors, window sensors, and smart thermostats were installed in approximately half of the school. Additionally, the ventilation system was monitored through clamp-on solutions. The school janitors were responsible for operating the installed system, providing feedback to the project participants, and collecting feedback from the occupants.

DEMO 3: School building located in HTK (Figure 5). Initially, we planned to install heat meters in all demos, but the suspected presence of asbestos in the insulation material of the pipes, located in the cellar of this demo, prevented UpSmarting from finalizing their installation in the school. Cutting old insulation would have posed a risk we could not afford. Additionally, many thermostatic valves were found to be stuck (one out of four on average). For these reasons, and given the large area of the demo, we primarily used this demo to test the extension and communication quality of the established LoRaWAN network over such an extensive surface, yielding positive results.

DEMO 4: DTU office and lecture building 303B, ground floor. This demo was established to implement and test control algorithms. Since the building houses the DynSys group, whose researchers are involved in the HuiL-DEMand project, we had the freedom to test algorithms and could count on higher acceptance from project participants. In this demo, we monitored the indoor environment and window openings, and installed LoRaWAN smart thermostats to control the climate in the offices. Occupants used their mobile phones (iPhones and Android) and Apple Watches to control the climate through qualitative feedback provided via the FeedMe app.

Figure 5 Ole Rømer Skole

The DEMO 1, 2 and 3 have been integrated in uni-lab.dk. Other dissemination activities is related to the generation of scientific manuscripts, listed in the related annex, and the creation of demo-cases in the CLIMIFY homepage.

5.2 Results related to WP2, Implementation, Demonstration and Assessment

Work package related Milestones – all achieved:

- M1 Definition of assessment criteria (energy, comfort, CO2 emissions), based on existing standards/guidelines/certification processes
- M2 Demo case are equipped with the minimale valuable combination of IoT components (sensors, actuators, energy meters) based on the criteria defined in M1 and the requirements from WP3 and WP4
- M5 First assessment of the implemented solutions
- CM1 First demonstration of fully monitored and partially automatized demo buildings. Publication of results on Danish newspapers and journals, and international conferences.

5.2.1 Task 2.1 Digitalization of Demo Cases (M2)

In Task 2.1, we evaluated various monitoring hardware options, selecting the most suitable ones for installation in the demo cases.

Figure 6 Left: Elsys ERS CO2 sensor. Right: MClimate CO2 Sensor & Notifier. While the MClimate sensor operates on standard AA 1.5 V batteries (with up to 10 years of battery life), the Elsys ERS CO2 sensor uses industrial 3.6 V AA batteries, offering a battery life of over 11 years with data reading and sending every 10 minutes. The Elsys CO2 sensor includes an incorporated PIR sensor and is slightly more costly than the MClimate sensor.

Milestone M2 was achieved, equipping the demo cases with the minimal valuable combination of IoT components such as sensors (Figure 6), bluethooth beacons (Figure 7), actuators (Figure 8 and Figure 9), gateways (Figure 10), energy meters (Figure 11) based on the criteria defined in M1 and the requirements from WP3 and WP4. Several hardware modifications were implemented to enhance system robustness, during project duration:

- Danfoss smart thermostats were replaced with new MClimate Vicki LoRaWAN thermostats, which helped reduce the return temperature to the district heating heat exchanger.
- The Vicki thermostats were outfitted with a security case.
- The Vicki thermostats were returned to the manufacturer for a firmware upgrade.
- The original plastic adapters of the Vicki thermostats were replaced with metal adapters to enhance robustness.

Figure 7 Bluetooth beacons are used to locate users of the FeedMe app within buildings, facilitating the feedback collection process. Users do not need to manually select which room they are in; the app automatically recognizes the room based on proximity to the room's beacon.

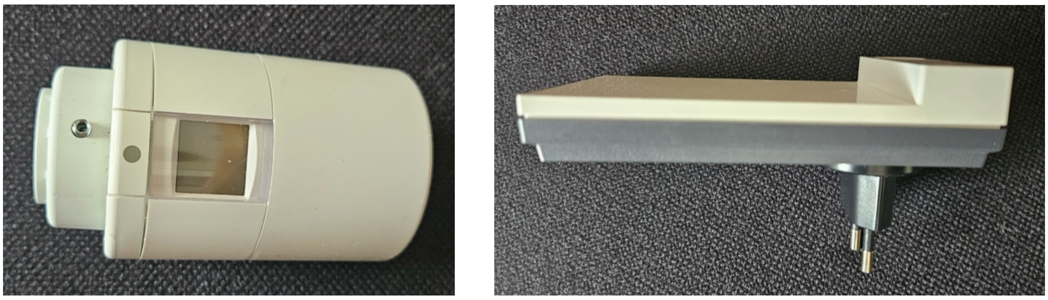

Figure 8 Left: Danfoss Ally™ thermostat. Right: Danfoss signal repeater. Due to the shape of the repeater and the design of Danish plugs, which cause the repeater to protrude significantly from the wall, we have experienced issues with repeaters being unplugged in the schools.

Figure 9 Left: MClimayte Vicki thermostatic head. Center and right: Vicki plexiglass cover.

Figure 10 Test of two different Kerlink LoRaWAN gateways (Kerlink Wirnet iZeptoCell Ethernet 868 MHz on the left, Kerlink Wirnet iFemtoCell LoRaWAN Gateway 868 MHz on the right).

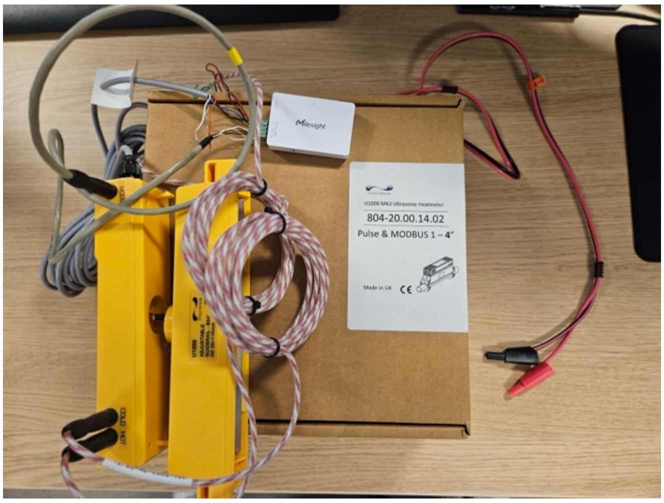

Figure 11 Picture of the Ultrasonic heatmeter U1.000 MK2 Micronics installed in the demos, and Modbus to LoRaWAN converter from Milesight, during testing activities in the CLIMIFY lab.

Hundreds of sensors and actuators (refer to Table 8 for a complete list) have been installed across our demos to monitor various environmental parameters, including indoor air temperature, humidity, CO2 levels, illuminance, occupant presence, and window positions, as well as temperature and relative humidity at window frames. Additionally, in one demo, specific setups involving multiple sensors have been prepared to study how sensor positioning might affect the measurements (see Milestone 4). The demos have also been equipped with BLE beacons to locate occupants, and two out of the three demos have been outfitted with ultrasonic flow and energy meters to monitor energy usage in different parts of the buildings. Smart thermostats from both Danfoss and MClimate have been installed in two of the three demos. Connection to the main meters of the schools in HTK has been established through the HTK municipality. In the Rudersdal school, the main meter and the installed ultrasound meters are accessed through the subcontractor’s digital interface.

Table 2 Components bought and installed in the demos (final number of units acquired might differs).

Component:	Simplified specs	Unit rough price (DKK)	Units acquired by DTU	Units acquired by HTK	Units acquired by Rudersdal
Ultra sonic flow meters U1000MKII-HM with Pulse & Modbus	Inlet and Outlet temperature, Massflow, energy, power.	8241	12	3	3
Indoor climate monitoring Elsys ERS CO2	Temperature, Relative humidity, Carbon Dioxide concentration, Light, PIR	1100	0*	0*	0*
VICKI LoRaWAN incl. Batteries and covers	Set temperature, air temperature, internal piston position,	446	3	105	22 + 60**
Sensative comfort strips	Window position (open/closed), temperature, relative humidity, light	360	20	120	80
Danfoss Gateway	Zigbee proprietary gateway	485			4
Danfoss repeaters	Zigbee proprietary repeater	500	6		
Danfoss eTRVs Ally	Zigbee smart thermostat	225***			60
BLE beacons Kontakt.io		139	72		20
Mclimate sensor-notifier-LoRaWAN	Temperature, Relative humidity, Carbon Dioxide concentration, LED notifier	910	80****		

**We originally planned to buy Elsys indoor climate sensors, but due to delivery problems, we chose to go for MClimate sensor notifiers – Both Demo 1 and Demo 2 were however already equipped with Elsys sensors.*
***We installed the Danfoss Ally system in Demo2, but due to zigbee network problems, we will switch to Vicki LoRaWAN thermostats.*
****Danfoss provided the hardware at half price, to support the project, as promised in the proposal.*
*****Some sensors have been bought also through other internal DTU funding sources.*

Figure 12 Set up of BLE beacons

Figure 13 Left: Installation of MClimate indoor sensors and notifiers. Right: Mclimate LoRaWAN VICKI smart thermostatic valve head with anti-vandalism plastic cover mounted on thermostat

Figure 14 Picture of the first installation of UpSmarting's system at Borgerskolen in Høje Taastrup municipality. On the lefthand side you see UpSmarting's data harvesting box. The yellow device on the right side is the power meter installed to the district heating piping.

UpSmarting executed the physical installation of the heat meters in Borgerskolen (Figure 14). Initially a planning visit was done followed by separate installation and commissioning visits for each system. Totally two data harvesting systems were installed with a total of six power meters. The UpSmarting's system has been configurated to collect data from power meters over a modbus RS485 digital bus. The data is sent to UpSmarting's cloud where it can be accessed in real time. In case of a loss of internet connection the system will continue to save the data locally until the connection is re-established.

5.2.2 Task 2.2 Setup and execution of demonstration of algorithms (WP3) and products (WP4)

In this task, we focused on enabling the live testing of algorithms on demo buildings, expanding mainly the CLIMIFY software's backend. Also, constant communication with demos' owners and managers was ensured, to minimize occupants discomfort during testing activities.

5.2.3 Task 2.3 Data management, and efficiency monitoring and assessment (M1, M5)

In this task, we defined and developed the requirements and specifications for integrating the Center Denmark (CDK) Platform with CLIMIFY systems. We set up data transfers between CLIMIFY and the CDK Platform to support research project objectives and ensure long-term data storage for increased availability and utility.

CDK granted access to its data and analytical tools, including the CDK Platform and Apache Zeppelin, which are used for analyzing indoor climate and smart actuator data. Additionally, work commenced on developing a building model ontology to standardize and streamline data from indoor climate sensors and smart actuators.

This task was foreseeing two Milestones, M1 and M5. Milestone M1 involved defining assessment criteria (energy, comfort, CO2 emissions) based on existing standards, guidelines, and certification processes. We established the assessment criteria for the indoor environment in the HuiL-DEMand project using international and national standards such as EN 16798-1 (ISO 17772-1), TR 16798-2 (ISO 17772-2), and ISO 7730.
Each European country adapts EN16798-1 by creating a normative Annex A. For example, the values from the Danish Annex A in 2022 (time at which the milestone was due) for an office space are included in Table 3. The mentioned standards do not provide criteria for (T)VOC and PM2.5. For these parameters, we used publications from DTU BYG, ICIEE.

Table 3 proposal for an office space: the table also indicates the color code for the different categories that is proposed in the standard, and which we will use by CLIMIFY for the HuiL-DEMand project.

Category-color	PM2.5 µg/m^3	TVOC µg/m^3	CO_2 ppm Above outdoor	CO_2 ppm Outdoor at 400ppm	Rh %	Temperat. Winter C°	Temperat. Sommer C°
I-White	x<10	x<200	x<350	650<x<750	30<x<50	21,0<x<23,0	23,5<x<25,5
II-Green	10<x<25	200<x<500	350<x<580	750<x<980	25<x<60	20,0<x<24,0	23,0<x<26,0
III-Yellow	25<x<60	500<x<1000	580<x<900	980<x<1300	20<x<70	19,0<x<25,0	22,0<x<27,0
IV-Orange		1000<x<3000		1300<x		17,0<x<25,0	21,0<x<28,0
Outside range-Red	60<x		900<x		x<20;70<x	x< 17,0 x > 25,0	x<21,0 x< 28,0
Sources	Suggested criteria, ICIEE	Suggested criteria, ICIEE	EN16798-2	EN16798-2	EN16798-1	EN16798-1	EN16798-1
WELL	x<15	X<500					
WHO	x<25						

In buildings where it is possible to evaluate the indoor temperature according to the adaptive comfort approach used in EN16798-1, typically buildings with no active cooling, we can use this evaluation approach. In this case, the indoor temperature range depends on and varies with a mean outdoor temperature.

Finally, another possibility to evaluate the indoor temperature in buildings, is to use the ISO 7730. This standard defines three different comfort levels, on the basis of the indoor temperature ranges and outdoor temperature ranges (used to define winter and summer season).

For this project, we decided to focus on evaluating:

- Indoor environment (indoor temperature, indoor relative humidity, and indoor carbon dioxide concentration;
- Energy usage (electricity, heating);
- Expenditure for energy;
- CO2 emissions;
- Return temperature to district heating and penalty fees related to this issue.

In regards to Milestone M5 - First assessment of the implemented solutions - we conducted analyses on the indoor climate and energy usage data retrieved through the newly implemented API to evaluate thermal comfort and energy efficiency. We established environmental conditions that define acceptable thermal comfort ranges and those indicative of discomfort, based on recognized standards. Energy efficiency improvements were assessed by comparing the return temperature to the district heating substation and by analyzing the building energy signature (i.e., building heat demand versus outdoor temperature), both before and after implementing the project's solutions. Figure 15 illustrates the distribution of indoor temperatures as a function of outdoor temperatures before and after the installation of new smart thermostatic valves on February 23, 2022. The figure highlights a marked improvement in comfort from February 23 onwards, with an increased number of measurements falling within the designated 'green' comfort area.

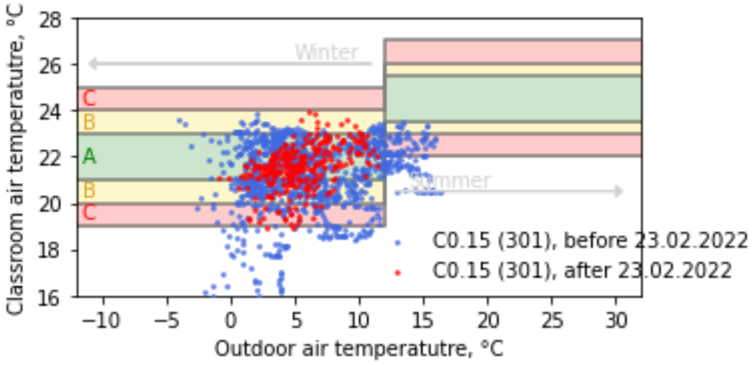

Figure 15 Distribution of indoor-temperature measurements as a function of the outdoor temperature before and after the implementation of the new smart thermostatic valves. Data source: Borgeskolen (Høje Taastrup) - room C0.15 (301).

Evaluating the energy and CO_2 emissions of the demos can be done by comparing the heating energy usage, the primary energy usage, the usage of auxiliary energy (electrical energy usage for pumps, fans and building management system), and the return temperature.

Among the efficiency improvements, also analyzing the values of the return temperature to the district heating (DH) is important. lower return temperature means:

- lower energy usage for the pumps (lower auxiliary energy of the building),
- higher indoor comfort (less thermal asymmetries in the rooms),
- lower energy bill (due to a lower return temperature to the district heating),
- and higher energy efficiency of the district heating network (lower energy losses on the return pipes, and lower electrical energy for the pumping of the water).

Figure 16 illustrates un inefficient operation on the left side, and the correct operation on the right side: Both systems deliver the same amount of heating energy to the building.

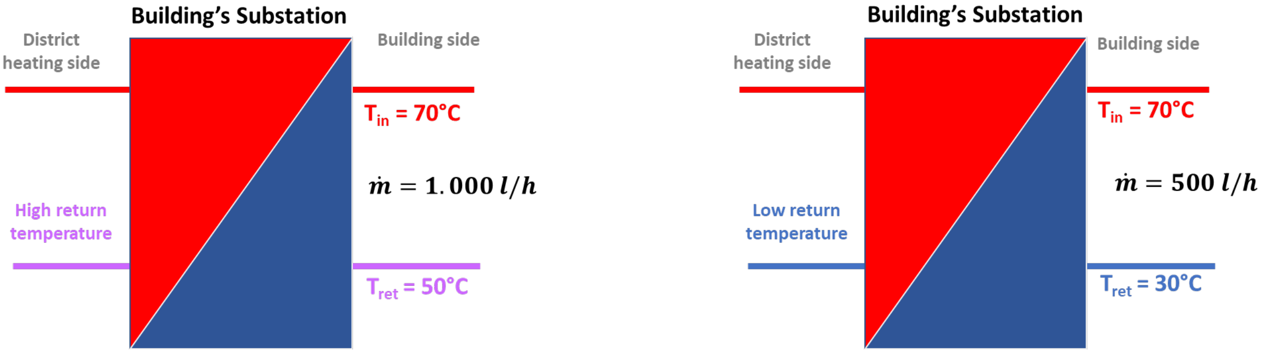

Figure 16 Substations in buildings: Inefficient system with high return temperature on the left, efficient system with low return temperature on the right. The heating energy usage in the buildings, in the above example, is equal. However, the right picture has lower auxiliary energy needs, and the DH network is operated more efficiently.

Exemplary, the return temperature of the substation in Borgerskole, before and after the control enabled by the new valves and the check of the hydraulic system, is illustrated in Figure 17.

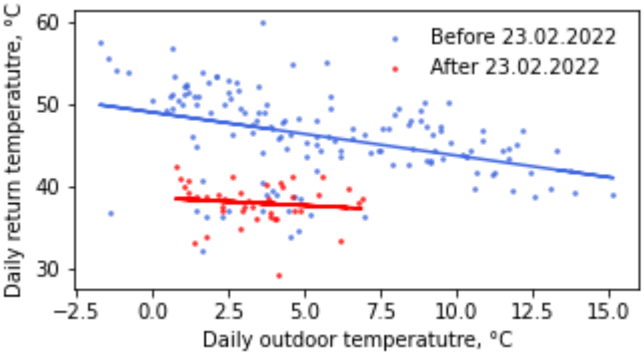

Figure 17 Daily return temperature to the district heating network before and after the control enabled by the new thermostatic valves. Data source: Borgeskolen (Høje Taastrup).

The cost for energy in the DEMO 1 before project start are distributed as following:

- approximately 110.000 DKK are spent for the energy delivered by the district heating
- approximately 12.000 DKK are spent in penalty fees for too high return temperature
- approximately 80.000 DKK per year are spent for electricity, mainly for ventilation, lighting and auxiliary energy.

Within the project, we managed to:

- Stop complains for a too cold environment, without increasing the energy bill (would the temperature had been raised without optimisation, heating cost would have raised by approximately 10%;

- Bring the penalty fee for high return temperature to 0 DKK/year.
- Reduce electricity cost by 10%, mainly due to less auxiliary energy usage and the optimised ventilation system.

By a hardware and software investment investment of approximately 65.000 DKK, and savings for 30.000 DKK per year, we expect return of investment (ROI) of less than 3 years. Reduction of the CO2 emissions of the demos is comparable to their energy savings. However, using flexible tariffs and CO2 signals, CO2 emission could easily be further reduced.

5.3 Results related to WP3, Algorithm Development

The following Milestones are related to this work package and have been achieved:

- M3 First simple algorithm for controlling room set points according to occupants feedback
- M4 First version of fault detection algorithms
- CM2 First integration of the algorithms from WP3 into the products, with consequential first commercialisation of the algorithms.
- CM3 Second integration of the algorithms from WP3 into the products, with consequential commercialisation of the new algorithms.

5.3.1 Task 3.1 Development of fault detection algorithms (M4)

The following milestone has been achieved in this WP: M4 (9) First version of fault detection algorithms

In this task we covered different types of faults:

- Faults related to IoT issues (faults of the sensors and actuators)
- Faults related to building's performance

Regarding the faults related to IoT issues, following issues occurred and their detection has been streamlined:

- Fault #1: the thermostat valve gets stuck in a partially open position when its supposed to be closed.
  Detected by: very high sensor temperature measurements compared to the indoor temperature during periods where the valve is supposed to be closed, caused by hot water flowing into the radiator.
  Solutions: sometimes remote calibration of the thermostat valve can reset it as desired, but often the valve is physically stuck. In that case it is necessary to go to the physical location and either push the piston of the radiator with a tool or replace the thermostat entirely.
- Fault #2: the thermostat becomes infrequent in its messages to the access point.
  Detected by: very irregular communication of the valve with the CLIMIFY platform, the thermostat will often wait hours or even days between sending data and fetch new instructions from users.
  Solution: the thermostat has to be replaced.
- Fault #3: communication completely lost with thermostat.
  Detected by: not being able to communicate with the thermostat for a prolonged period of time, e.g. more than three days. Typically caused by the thermostat being broken.
  Solution: the thermostat has to be replaced, or have its batteries changed.

Besides the seen faults described above, we intentionally installed, in some of the rooms, some extra indoor climate sensors in a position where they would get hit by direct sunlight. We did this to allow DTU studying algorithms to detect, quantify and correct this type of fault.

Faults regarding the performance of buildings, including both indoor environment performance and energy performance, have been analysed by ruled-based algorithms. In the near future, partners of the consortium plan to use the models of rooms and buildings (greybox and blackbox model) to evaluate live performance and trigger alarms to the buildings managers.

5.3.2 Task 3.2 Development of data-driven digital-twins models

In this task, we focused on developing data-driven digital twins for accurately simulating temperature dynamics in classrooms. For a starting point, we decided to aim for a grey-box model made from a system of differential equations, inspired by Bacher et. al. 2011. The sources of contribution to indoor temperature evolution were assumed to include:

- Outdoor temperature
- Solar radiation
- Heating from radiators
- Human occupancy
- Door/window openings

We would then further simplify the model to only cover the first three sources and disregard the human-related inputs. The idea would then be to later on, after obtaining a successful model, extend it with some stochastic component which could cover the latter two sources. In section 5.3.2 we cover the process of selecting a good model structure, before we move on to the estimation of the final model.

Description of location and rooms
The model was developed on data concerning the school Borgerskolen in the Danish city Taastrup. Specifically, we focused on four classrooms of similar size, each equipped with three radiators. Each of the in total 12 radiators were located under a window. Each radiator had a Mclimate thermostat installed, controllable through CLIMIFY. In each classroom, an ELSYS temperature sensor was installed in a central location, typically on the wall near by the blackboard. The rooms are labelled C0.13, C0.15, C1.08 and C1.12, respectively.

Data
We had access to the following data:

Meteorological data from DMI

- Outdoor temperature in 30-minute resolution
- Global horizontal solar radiation in 10-minute resolution

Heat meter data from CLIMIFY via Upsmarting.net

- Forward temperature measurements in 1-minute resolution

Mclimate thermostat data from CLIMIFY, including

- Thermostat sensor temperature in 10-minute resolution
- Thermostat set-point temperature in 10-minute resolution
- Valve position in 10-minute resolution
- Valve max position in 10-minute resolution

ELSYS indoor climate data from CLIMIFY, including

- Room temperature in 5-minute resolution

Note that the individual thermostats were not synchronized with each other, and neither were the ELSYS sensors. All of them had different time-offsets.

We focused on data from two periods, which are in this section referred to as:

- The winter vacation period: 17 Feb to 27 Feb 2023
- The Easter holiday period: 31 Mar to 10 Apr 2023

Data postprocessing

We did some data postprocessing prior to model fitting, sometimes at 5-minute resolution, sometimes at 15-minute resolution. The purpose was to have fully synchronized data, such that every input variable would be available at every observation timestamp. Whenever an observation was not available at a desired timestamp, it was estimated by linear interpolation, except for set-point temperatures, which would be estimated by zero-order hold. For example, if a thermostat reported a set-point temperature of 21 at 07:02:41, then the postprocessing would set the set-point temperature at 07:00:00 to 21, while for e.g. the sensor temperature would be linearly interpolated between the two measurements at 06:52:41 and 07:02:41.

Selection of envelope structure

First, we focused on finding a good envelope model to cover the transfer of heat between the outdoor environment and the indoor environment. For this we used data from January 20 to 23. This period was cloudy, so solar radiation could (for this purpose) be disregarded. Furthermore, we would use the radiator input known from the thermostat data. The starting model structure was:

$$\frac{dT_i}{dt} = \frac{1}{K_1}(T_e - T_i) + \Phi(T_f - T_i)(R_{1,i} + R_{2,i} + R_{3,i})$$

$$\frac{dT_e}{dt} = \frac{1}{K_1}(T_i - T_e) + \frac{1}{K_2}(T_a - T_e)$$

where the parameters to be estimated were (T_{e0}, K_1, K_2, Φ). The initial value for T_i was set to the known initial indoor temperature. The result is seen in Figure 18. Overall, a decent start, however it is seen that the heat loss process during the night is too stiff.

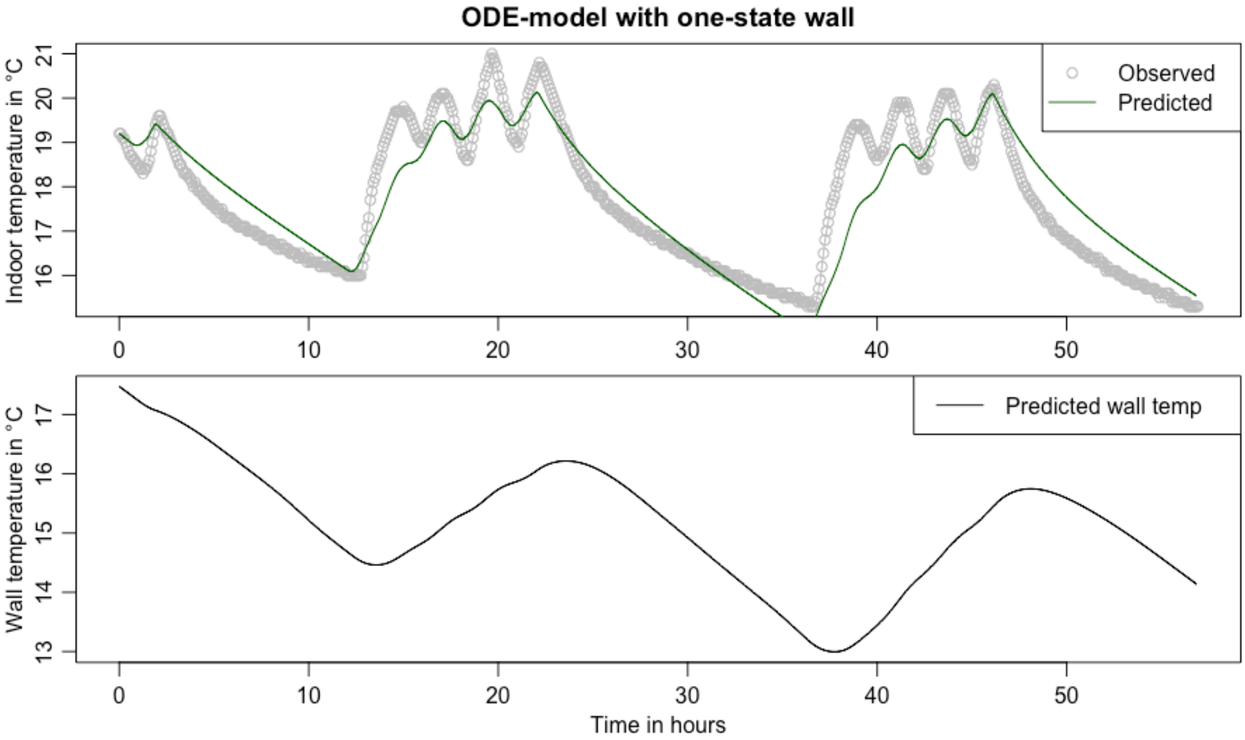

Figure 18: Heat transfer through wall envelope with 1 wall state, using a model based on ordinary differential equations (ODE).

To get a smoother heat loss process, we tried to expand the model to have two wall states, i.e.

$$\frac{dT_i}{dt} = \frac{2}{K_1}(T_{e1} - T_i) + \Phi(T_f - T_i)(R_{1,i} + R_{2,i} + R_{3,i})$$
$$\frac{dT_{e1}}{dt} = \frac{2}{K_1}(T_i - T_{e1}) + \frac{2}{K_1}(T_{e2} - T_{e1})$$
$$\frac{dT_{e2}}{dt} = \frac{2}{K_1}(T_{e1} - T_{e2}) + \frac{1}{K_2}(T_a - T_{e2})$$

The parameters are the same except there are two initial values instead of one. The result is seen in Figure 19, which shows a clearly more accurate temperature decay during nighttime. Still, it looks like there could be some improvement, so we also tried with 3 wall states, however, this did not significantly improve the results, so we decided to stick to 2 wall states going forward.

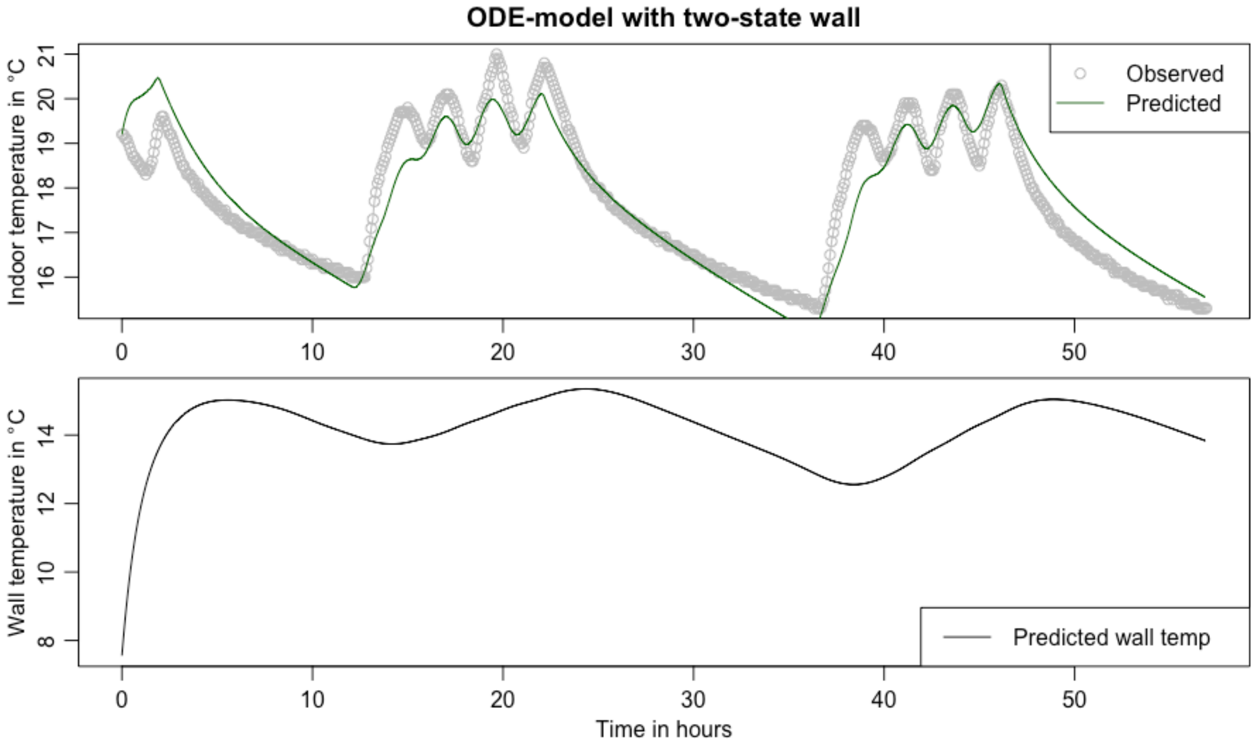

Figure 19: Heat transfer through wall envelope with 2 wall states, using a model based on ordinary differential equations (ODE).

Modelling of contribution from solar radiation

It is well-established that solar radiation has a significant impact on room temperature. The larger the window area, the larger the impact. The raw solar radiation measurements are global horizontal radiation. Some post-processing is done, to split it into direct and diffuse solar radiation, respectively, because the two types of radiation affect the room temperature in different ways. Furthermore, we have been experimenting with two different approaches to capture the effect of the transformed solar input on the room temperature. One approach is data-driven (B-splines) and the other is based on geometry. In the following, the two methods are outlined followed by a comparison of performance, highlighting advantages and drawbacks.

Solar continuation

In the spline method, the solar gain factor function is obtained as a linear combination of a number (= M) of basis functions $B_1, \cdots, B_M$, and hence, the coefficients $\beta_1, \cdots, \beta_M$ determine the shape of the solar gain. Figure 20 shows an example of such a function with 9 basis functions (top), and the resulting spline (middle graph, black curve), given the arbitrary coefficients (0.1, -0.2, 0.4, 0.1, 1.5, 0.05, 0.8, -0.1, 0.2). A spline can be made as flexible and precise as desired by increasing the number of basis functions. This of course also increases the number of parameters to estimate, which makes model identification more difficult and time-consuming. Furthermore, the knot placement can be included in the optimization routine. This again increases the precision and flexibility of the spline at the cost of increased estimation complexity. Keeping in mind that the model already had several parameters in its standard formulation, we chose to preselect fixed knot locations as well as sticking to 9 basis functions. Furthermore, we recognized that both at and around midnight, the contribution from solar is always going to be 0. Therefore, we fixed the coefficients of the outermost two basis functions at either end to 0. These basis functions are marked as dashed lines in Figure 20 (top), and the resulting spline is shown in the bottom graph (orange curve), here with the coefficients (0.0, 0.0, 0.01, 0.2, 1.7, 0.02, 0.8, 0.0, 0.0). Thus, even though we had a spline of order 9, we only had to estimate 5 coefficients, which was evidently faster and more robust.

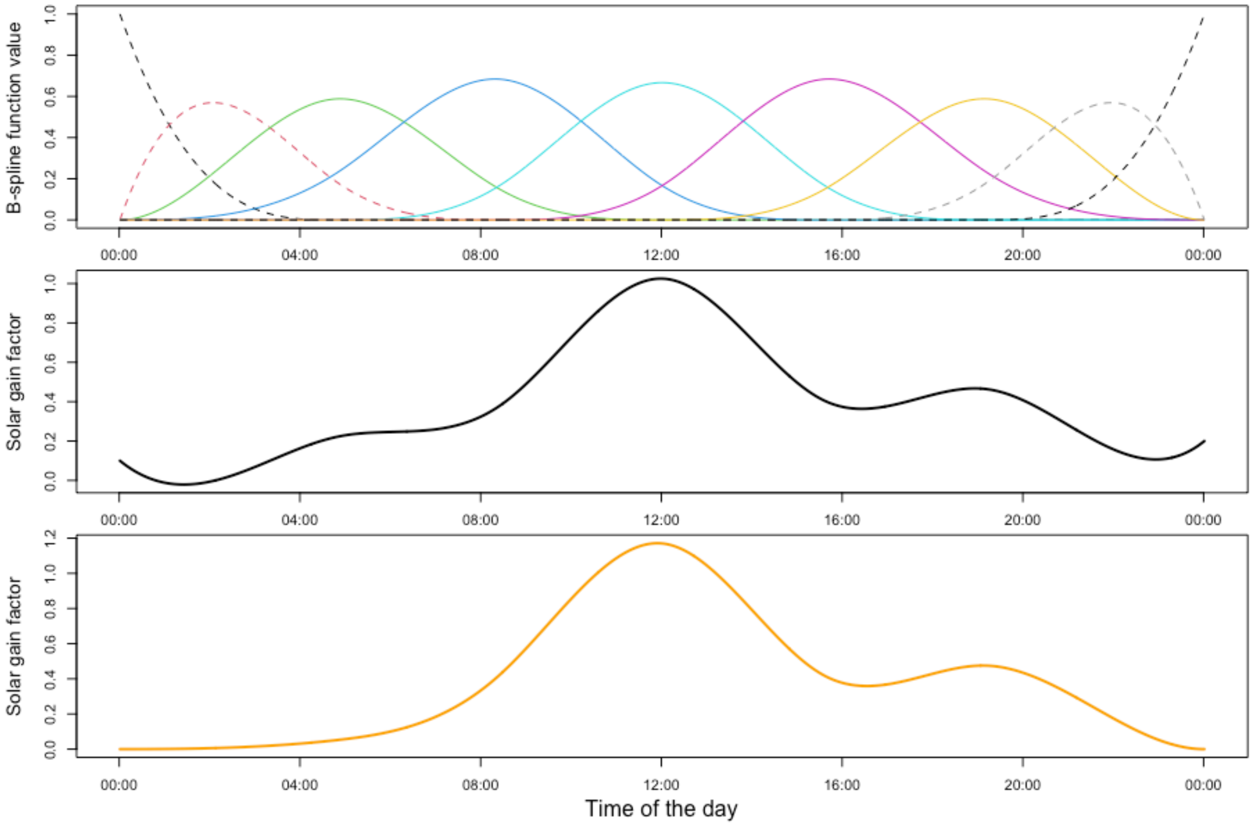

Figure 20: Spline function for solar gain factor. Top: basis functions. Middle: solar spline with all 9 non-zero coefficients. Bottom: solar spline with the first two and last two coefficients fixed to 0.

Thus, our solar gain factor function was the following:

$$S(\tau) = \sum_{i=3}^{7} \beta_i \; B_i(\tau),$$

where τ is the time of the day. The heat contribution from solar power in the model was then initially taken as the product of the solar gain factor and the solar radiation input multiplied with a heat transfer rate, characterized by the parameter K_I:

$$\text{Solar contribution } = \frac{1}{K_I} S(\tau) \cdot I(t)$$

However, later we also took the separation of solar radiation into direct and diffuse radiation into account, and thus had the alternative version:

$$\text{Solar contribution } = \frac{1}{K_I} \left(I_{\text{diff}}(t) \; + \; S(\tau) \cdot I_{\text{dir}}(t) \right)$$

A great advantage of the use of splines for solar gain is that its shape is estimated completely from data, with no prior knowledge about the room at hand being required. Trees and buildings which are blocking the solar path are indirectly taken into account, and so is the orientation of the window surface. However, the spline will be specific to the data period it is fitted to, and as the solar trajectory on the sky changes over the year, a spline fitted to a certain period loses accuracy as time goes by. This may be accounted for by having an adaptive parameter estimation scheme that can keep the solar gain spline up to date, which we want to experiment with in future projects. As an alternative, we implemented a solar gain function based on classical solar modelling theory (Duffie and Beckmann, 1980).

Physical modelling of sun position (geometrical model)

The purpose of implementing a geometrical model for solar gain is that it can be estimated once, and then it works for any day of the year, any location on earth and any window surface orientation. The requirement is of course that information about location and orientation is available (although with a sufficiently large amount of data this information could theoretically be estimated as additional parameters). The full series of equations are not included here, but the main idea is to find the perpendicular component (I_{wv}) of the direct radiation (I_{dir}) onto the window via the angle of incidence (θ_{inc}). The formula is:

$$I_{wv} = I_{dir} * \cos(\theta_{inc})$$

The angle of incidence is calculated by the relation:

$$\cos(\theta_{inc}) = -\sin(\delta)\cos(L)\cos(\gamma_W) + \cos(\delta)\sin(L)\cos(\gamma_W)\cos(\zeta) + \cos(\delta)\sin(\gamma_W)\sin(\zeta)$$

Where the relevant inputs are the declination (δ), the latitude (L), the window azimuth angle (γ_W) and the hour angle (ζ). Clearly the angle of incidence changes over the day due to continuous changes in the hour angle, and over the year due to slow changes in the declination.

A great advantage of using the physical solar radiation model is that it does not have to adapt to changes over the year as the spline method does, because it is automatically included in the well-established equations. However, it needs additional input about the window orientation, which is further complicated if there are windows on more than one side. On the contrary, the spline method can handle any geometrical configuration without prior information because it is purely data-driven. Further elaboration on physical solar calculation is omitted because we ended up choosing the spline method for the practical application.

Split of direct and diffuse gains

It is well established that solar irradiance onto a window comes from two sources: direct and diffuse radiation, respectively. We took the separation into account by using the clearness index k_I, as described in Duffie and Beckmann (1980). The clearness index is the fraction between the observed global horizontal radiation I_{ext} and the extraterrestrial global horizontal radiation I_{gh}:

$$k_I = \frac{I_{gh}}{I_{ext}}$$

When the clearness index has been calculated, the fraction of diffuse radiation for midrange values of k_I is estimated from the following formula (Duffie and Beckmann, 1980):

$$\text{Diffuse fraction} = 0.9511 - 0.1604k_I + 4.388k_I^2 - 16.638k_I^3 + 12.336k_I^4$$

For $k_I > 0.8$, the diffuse fraction is 0.165, and for $k_I \leq 0.22$ it is $1 - 0.09k_I$.

And the complementary fraction is then equal to the direct radiation. With this separation, we extended the model, such that the room would get the full gain from the diffuse radiation, but only the perpendicular (to the window) component of the direct radiation.

Heading input approximations

In reality, the heating power of a radiator depends on the difference between its average temperature and the indoor temperature. The average temperature of the radiator is estimated as the average of the forward and return temperatures. However, in this project, we have only had access to forward temperature data, and have thus used those data to estimate the heat contribution. Note that this doesn't mean the radiator will deliver more heat in the model than in reality, because any too high radiator temperature in the model would be kept in check by fitting a slower heat transfer rate from the radiator to the room.

Furthermore, while we had access to forward temperature data, this was thanks to specially installed heat meters in the delivery system. In a scalable application it might not be realistic to get this data. Therefore, we also implemented a weather compensation curve which infers the forward temperature from the outdoor temperature. This is possible, because the forward temperature is exactly controlled by means of a weather compensation curve. Using the known forward temperature and outdoor temperature data, we estimated an approximate weather compensation curve, which is shown in Figure 21.

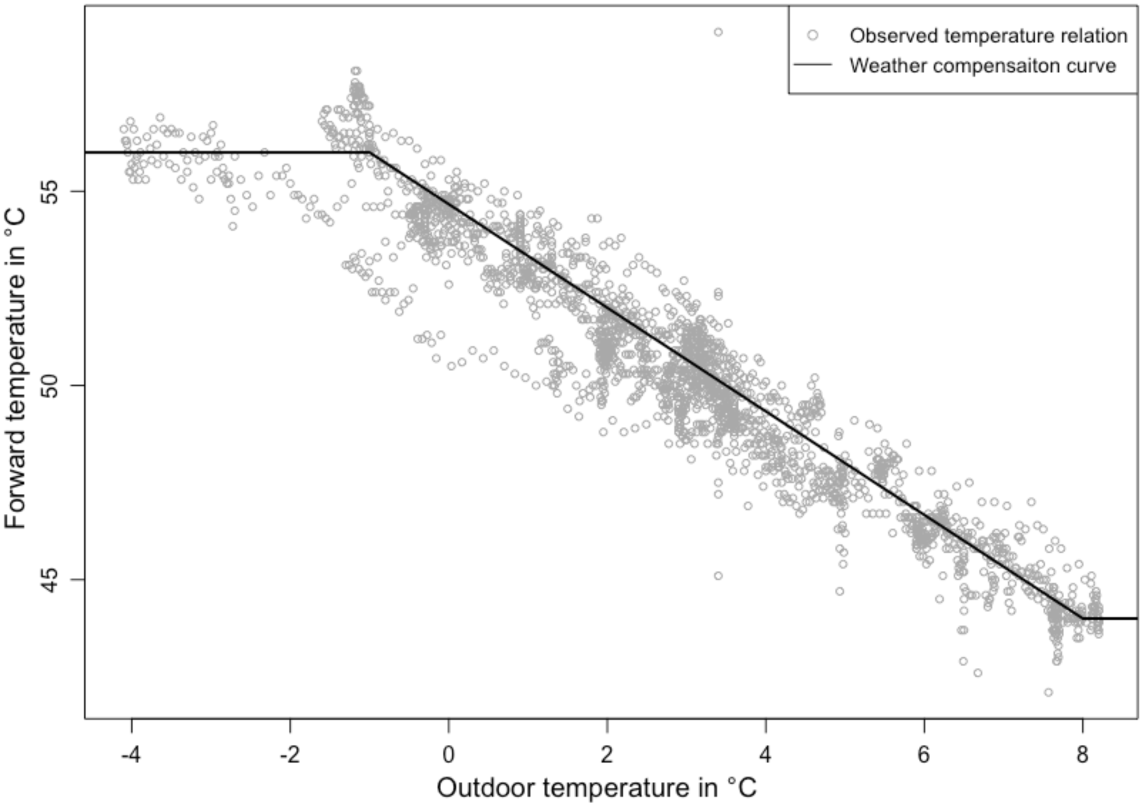

Figure 21: Estimated weather compensation curve for the forward temperature of the district heating supply.

Model of the radiator

In this paragraph we focus on how we modelled the radiator heating input. This is the most important part of the model. Naturally, one of the first things we did was to explore the CLIMIFY data we already had prior to the experimentation period. From inspection it became clear that the indoor temperature T_i was, in every room, behaving in a very specific way with respect to the thermostat sensor temperature T_s and the set-point temperature T_u. While the sensor temperature could be regulated well around the set-point, the indoor temperature would never reach the same levels and always be lower by a couple of degrees. The sensor temperature would also react faster to sudden set-point increments than the indoor temperature. And finally, the indoor temperature would decrease slower than the sensor temperature during non-heating periods. Our interpretation was that the faster heating of T_s is due to the thermostat sensor being very close to the hot water inlet, while the faster cooling of T_s is because the sensor is located close to a window. Meanwhile the indoor temperature sensors are always located further away from both radiators and windows.
In terms of modelling, we got the idea to use the concept of time constants, just like for the heat transfer through walls. The idea was to:

- Have the heat transfer from the radiator to the sensor temperature and to the indoor temperature, respectively, be characterized by each their own time constant.
- Have the modelled radiator only be opened and closed with respect to the sensor temperature, disregarding the actual indoor temperature.

Using these principles, we used the following expression for the valve opening:

$$q(T_s - T_u) = \frac{\mathrm{e}^{-\alpha(T_s - T_u - \beta)}}{1 + \mathrm{e}^{-\alpha(T_s - T_u - \beta)}}$$

Where β is a small offset. The heat contribution from the radiator to the room temperature was then taken as

$$\Phi_i = q(T_s - T_u) \cdot \frac{1}{K_r}\left(T_f - T_i\right)$$

Similarly, the heat contribution from the radiator to the thermostat sensor temperature was taken as:

$$\Phi_s = q(T_s - T_u) \cdot \frac{1}{K_{rs}}\left(T_f - T_s\right)$$

Hence, the first final model structure became the following 4-state model:

$$\begin{aligned}
\frac{dT_s}{dt} &= \frac{1}{K_{1s}}(T_{e1} - T_s) + \frac{1}{K_{rs}} q(T_s - T_u)\left(T_f - T_s\right) + \frac{1}{K_I} S(\tau) I(t) \\
\frac{dT_i}{dt} &= \frac{1}{K_1}(T_{e1} - T_i) + \frac{1}{K_r} q(T_s - T_u)\left(T_f - T_i\right) + \frac{1}{K_I} S(\tau) I(t) \\
\frac{dT_{e1}}{dt} &= \frac{1}{K_1}(T_i - T_{e1}) + \frac{1}{K_2}(T_{e2} - T_{e1}) \\
\frac{dT_{e2}}{dt} &= \frac{1}{K_2}(T_{e1} - T_{e2}) + \frac{1}{K_3}(T_a - T_{e2})
\end{aligned}$$

The location of the states are visualized in the simple graphic in Figure 22 (hot water and solar radiation inputs are not shown).

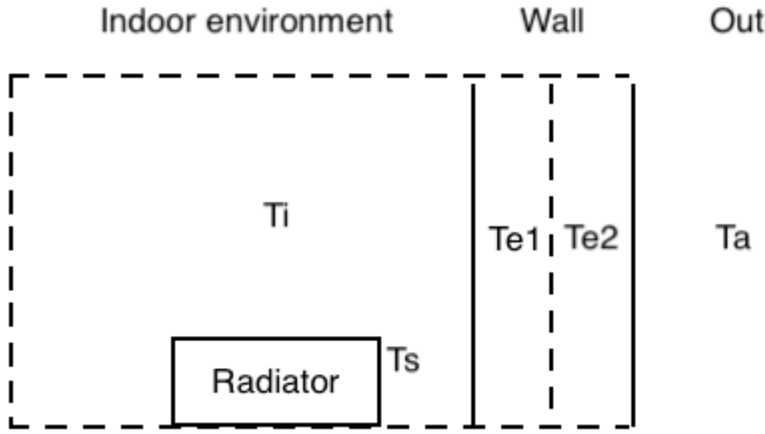

Figure 22: Simple schematic of state-space structure for the grey-box model. The temperature states are Ti (indoor), Ts (thermostat sensor temperature), Te1 (inner part of envelope), Te2 (outer part of envelope). The outdoor/ambient temperature (Ta) is not a state in the model but an input.

Parameter Estimation I – choice of objective function

For parameter estimation we used minimization of least squares. We first attempted to use only the indoor temperature measurements from ELSYS devices, i.e.

$$\hat{\theta} \;=\; \text{argmin}_{\theta} \sum_{t=1}^{N} \left(\hat{T_{\imath}} \;-\; T_i\right)^2$$

If that would be sufficient, it meant we would be able to fit models without any knowledge about what the thermostat was doing or measuring. However, the heating dynamics were not easily identified this way, because the optimization routine would lead towards a scenario where the thermostat opens and closes constantly with absurdly fast and high thermostat sensor heat gains, as is shown in Figure 23. While this works mathematically, it does not reflect the much slower operation and heating of the real valve and radiator. Therefore, we extended the least squares to a weighted version, where deviations from the thermostat sensor temperature are also penalized. We found an equal weighting of the two states to work well (shown in the Results section further down e.g. in Figure 24), i.e.

$$\hat{\theta} \;=\; \text{argmin}_{\theta} \sum_{t=1}^{N} \left[\frac{1}{2}\left(\hat{T_{\imath}} \;-\; T_i\right)^2 + \frac{1}{2}\left(\widehat{T_s} - T_s\right)^2\right]$$

This choice of objective function persisted for the rest of the project period. The optimization routine used was the “nlminb” method in R.

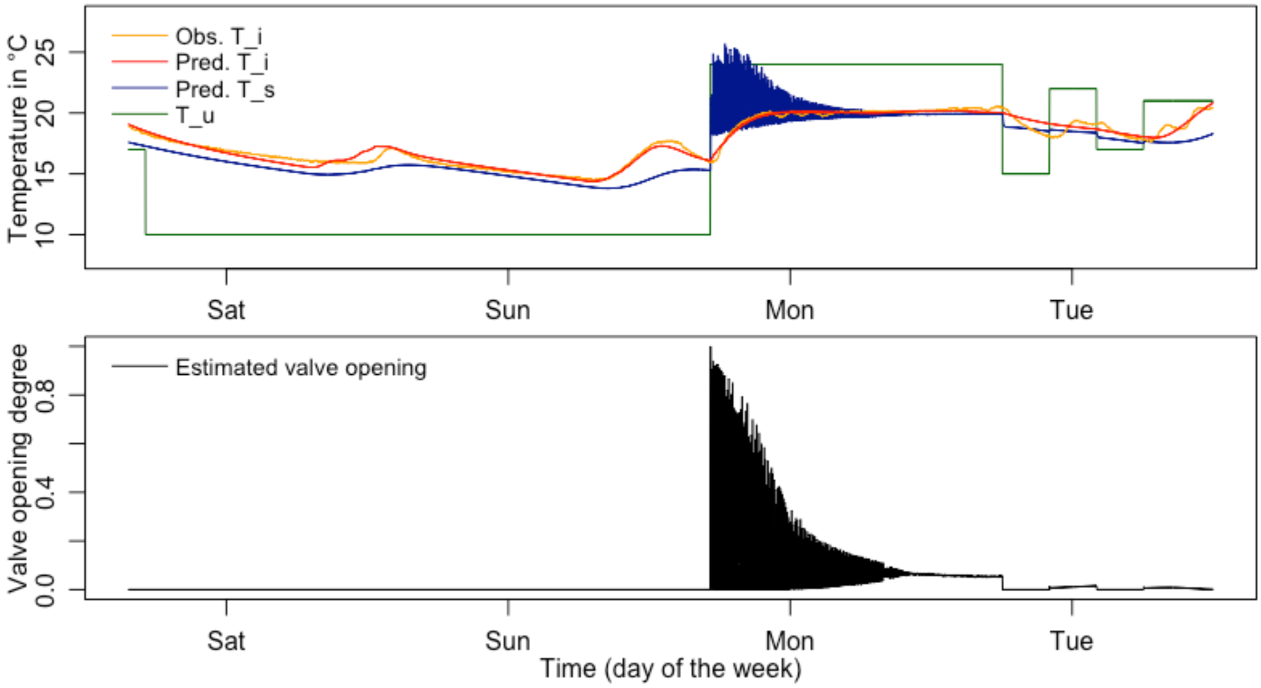

Figure 23: Model fit given only indoor temperatures, while keeping thermostat sensor temperatures unknown. Red: predicted indoor temperature; orange: observed indoor temp.; dark blue: predicted thermostat sensor temp.; green: set-point temp.; black: valve opening.

Results from the Winter Holiday Experiment

The winter holiday experiment took place from 17 Feb 2023 17.00 UTC to 27 Feb 2023 05.00 UTC. Only the most important results are shown. Prior to the experiment we went to the school and ensured that every thermostat was working and reporting properly, replacing the ones which were not. We also made sure all windows were properly closed and the curtains moved to the side for maximal solar impact. During the data collection period, some rooms performed as desired, but we also had examples of thermostats that stopped working. The most successful case was room C0.13, where all three radiators were working and reporting properly throughout the period. The modelling results are shown in Figure 24, which is a full horizon forecast, i.e., we only initialize at the first time point, and then forecast the full period without updating with new information along the way – only using the set point schedule and weather data. The last part of the period is marked with a dark gray background. This period is completely out-of-sample, i.e. its data were not used in the parameter estimation. It is seen that both the indoor temperature and thermostat sensor temperature are forecasted very satisfactory, especially since the last forecasts are a whole week ahead while still very precise (notice for example the temperature increase and subsequent decrease on Feb 26, which is near spot on). It is also interesting to see how the predicted radiator valve opening behavior (Figure 24 middle) has many similarities with the true valve (Figure 24 bottom). They tend to open and close with similar timing. The magnitude is not the same, but it is important to remember that valve opening is just a part of the heating input, there is also scaling with the $1/K_I$ term. The timing of the opening and closing is really what we want to get right, and this model seems to perform promisingly in that aspect.

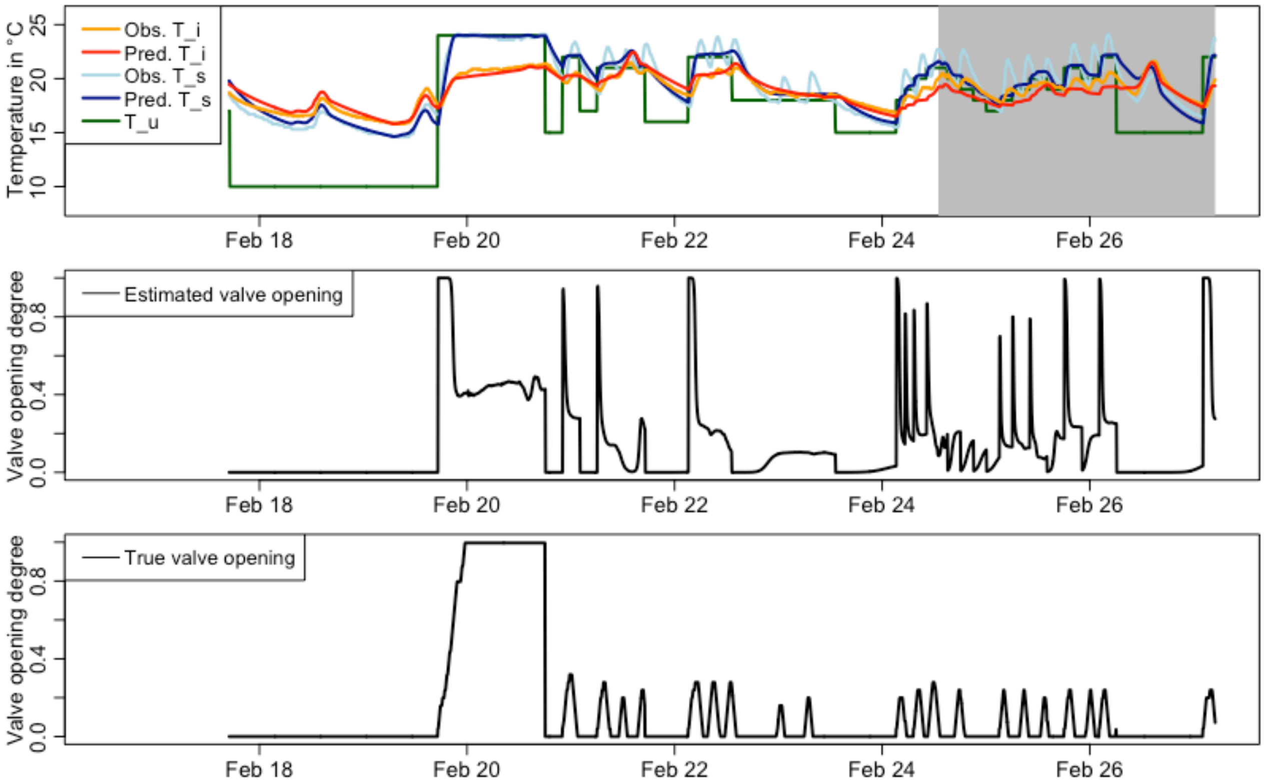

Figure 24: Modelling of room C0.13 for the winter vacation period. Top: full horizon prediction of temperatures + comparison with observations. Middle: estimated valve opening degree (0 = fully closed, 1 = fully open). Bottom: true valve opening for one radiator. Abbrevations: pred = predicted, obs = observed, T_i = indoor temperature, T_s = thermostat sensor temperature, T_u = set-point temperature.

The most problematic example was room C1.08, where one thermostat got stuck in an open valve position early within the period, such that hot water would flow through that radiator for the entire time. This is shown in Figure 26 where “Radiator no. 1” is fully open. This is clear because the sensor temperature (blue) is constantly very hot compared to the indoor temperature (orange), as well as the other radiator sensor temperatures. Yet, the reported valve opening data suggests that the radiator was fully closed, at least for the first part of the time where hot water was clearly blasting through (so obviously it was not fully closed). Hence, it is necessary to be skeptical with any data that comes from an off-behaving thermostat. In contrast, the corresponding data from room C0.13 is shown in Figure 25, where it is seen that all three radiators behave in roughly the same way. In our model, the radiator is interpreted as one large conceptual radiator, so in cases like C1.08 where some radiators work against each other, the model is not able to cover the dynamics. In a well-behaving case like C0.13 however, the assumption that three parallel radiators that operate under the same conditions can be modelled as one collective radiator, is seen to hold well, as shown by the forecasting performance in Figure 24.

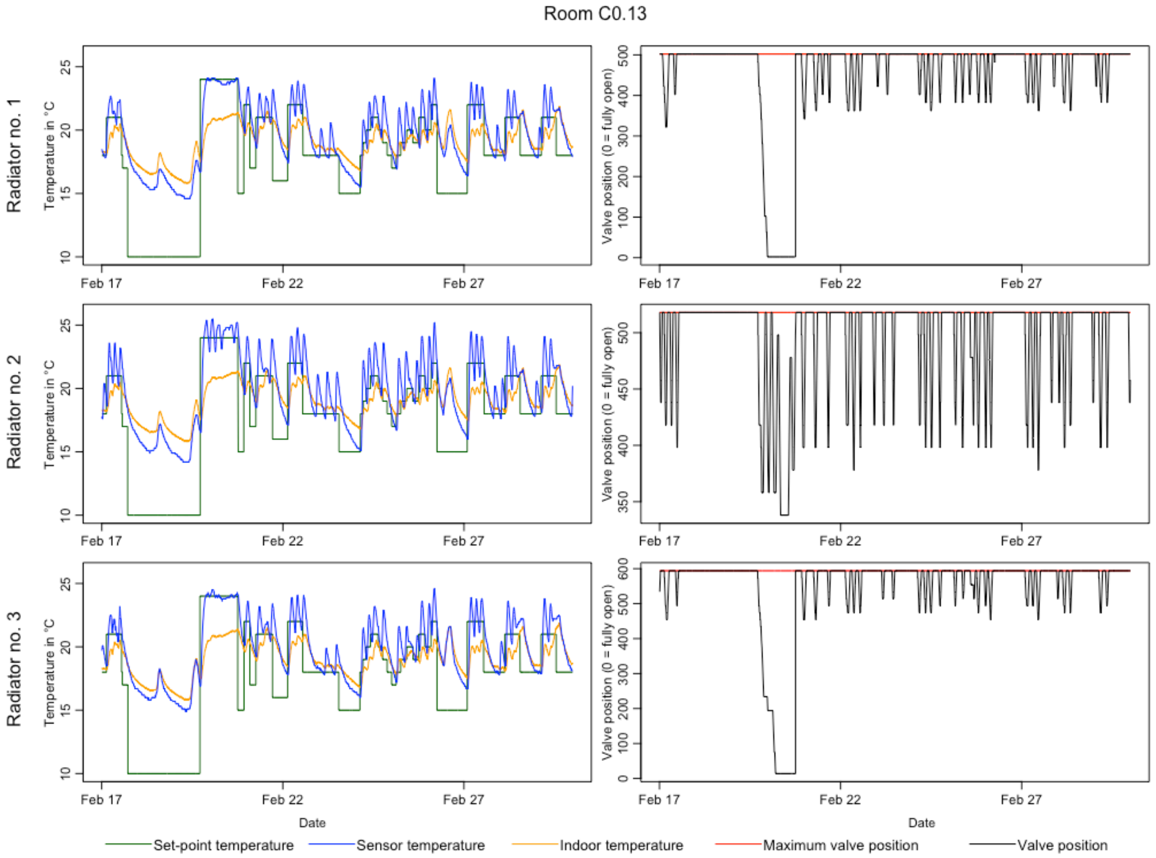

Figure 25: Thermostat data from individual radiators of room C0.13 in the winter vacation.

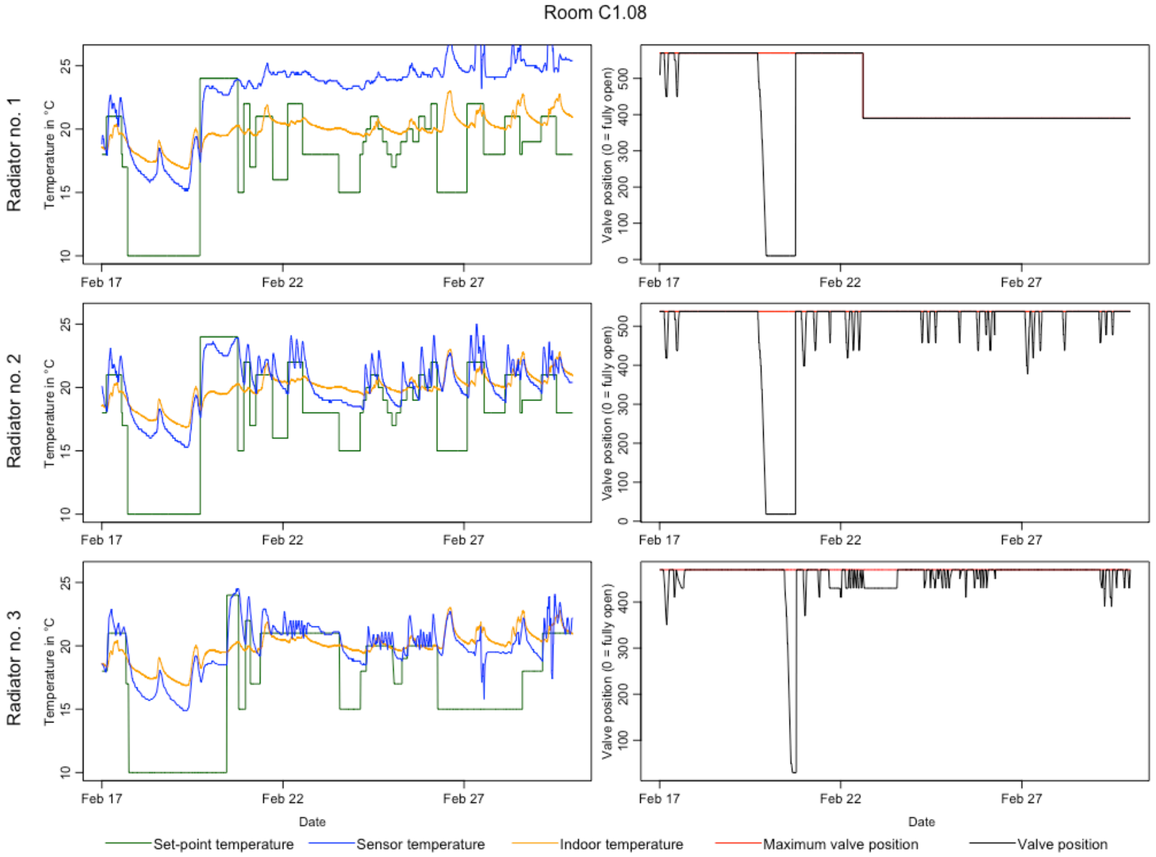

Figure 26: Thermostat data from individual radiators of room C1.08 in the winter vacation.

Results from the Easter Holiday Experiment

The Easter holiday experiment took place from 31 Mar 2023 12:00 UTC to 11 Apr 2023 00:00 UTC. Three out of four rooms behaved well (no broken thermostats), so we fitted a model for each of those rooms successfully. C1.12 had a broken thermostat with constant hot water supply, but it was still possible to fit a model to the room. The results are shown in Figure 27 (see Figure 24 for explanation of colors). All rooms are included here, to give an idea of the variation between rooms. For the reporting of this experiment, we will put some attention on interpretation and analysis of parameters.

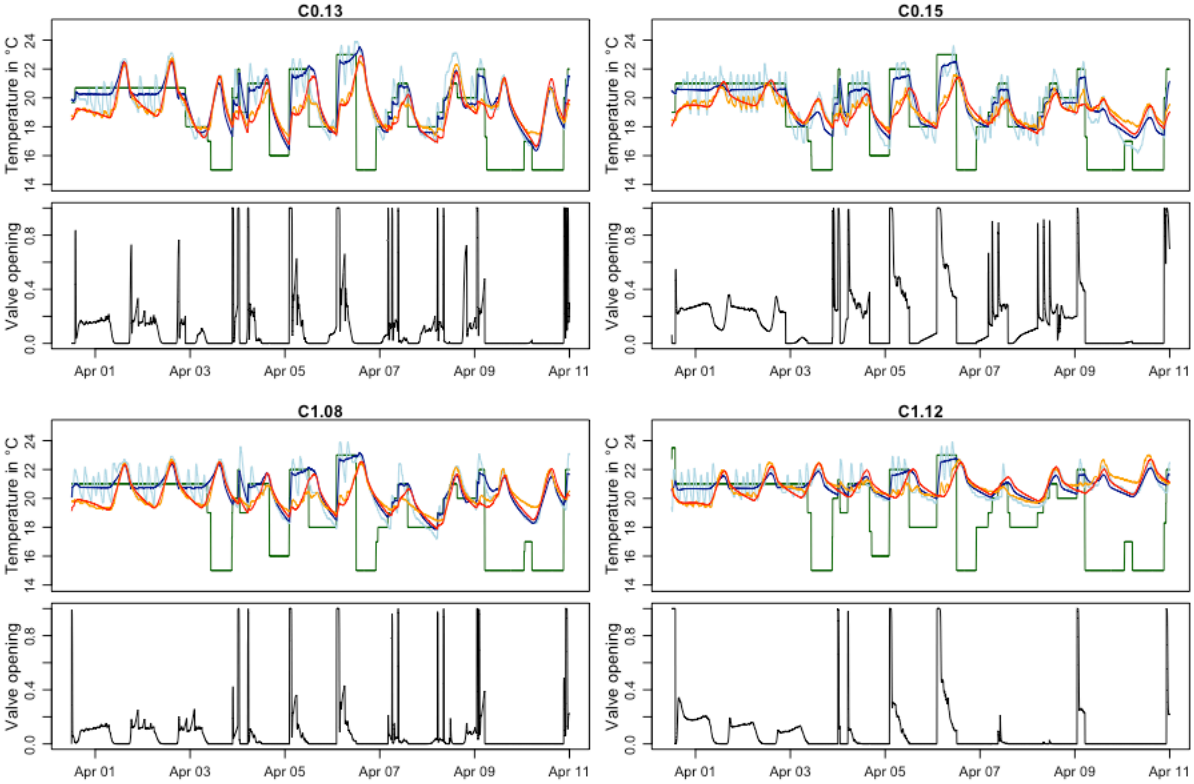

Figure 27: Modelling of the four classrooms C0.13, C0.15, C1.08 and C1.12 during the Easter holiday of 2023. The color references are as in Figure 7.

We then calculated the eigenvalues of the system for the four rooms to understand its general behavior, and they are reported in Table 4. The eigenvalues are time constants, and their magnitude and direction explains where the system is heading over time.

Table 4 Eigenvalues of the 4 classroom models estimated on the Easter data set

	C0.13	C0.15	C1.08	C1.12
τ_s	6.47	3.12	5.85	3.57
τ_1	77.11	122.43	129.35	276.94
τ_2	0.0498	0.0497	0.187	2.12
τ_3	5.12	3.66	4.88	6.30

Here, it is seen that τ_2 is very small for all rooms except for C1.12. If we look at the associated eigenvector for e.g. C0.13, it is equal to (0.0078, 0.0063, -1, 1). The interpretation is that the last two states (the two envelope states) converge to the same temperature very fast (within minutes). The fact that this is a bit slower in the C1.12 model is likely due to the faulty radiator, since it causes the system to behave differently than the model structure describes and thus makes it harder to draw physically meaningful conclusions on. This is a hint, that looking at eigenvalues when comparing rooms can sometimes give a hint that something, in an on the surface well-behaving model, is off (useful if we didn't have access to raw thermostat data).
Later it became clear that this very fast internal wall dynamic actually was an unnecessary burden on the model. In August 2023, a study group analyzed our model and verified that the temperature of the two wall states would indeed converge to the same temperature almost immediately in any given scenario, which made them question the necessity of the extra wall state. The original reasoning had been the smoother temperature decrement curve observed in the early stages of the model development, but soon a new modelling application would come our way, which finally promoted the decision to reduce the working model to have one wall state instead of two. This is elaborated in the next paragraph.

Reduction to one wall state – and final model with comparison between different approaches
Late in the project we got access to a white-box model of a classroom implemented in Modelica. If our model was as generalized as we strived for, we should certainly be able to fit it to data from a white-box model as well. However, this appeared to be very difficult with the current model (with 2 wall states), so we tried to estimate a 1-wall-state model instead, as previously suggested by the study group. In stark contrast to the attempts on fitting the 2-wall-state model, the 1-wall-state model converged easily, and was immediately able to make very accurate forecasts. With this result, naturally, we then went back to the Borgerskolen datasets, and estimated 1-wall-state models for those data as well. The results were good. The forecasts produced by the new reduced models were not significantly worse than those produced by the old 2-wall-state models (which was consistent with the findings about the eigenvalues in the Easter experiment), and therefore we finally concluded that the best model structure for this purpose is a 1-wall-state model, i.e. the following:

$$\begin{aligned}
\frac{dT_s}{dt} &= \frac{1}{K_{1s}}(T_e - T_s) + \frac{1}{K_{rs}} q(T_s - T_u)(T_f - T_s) + \frac{1}{K_I} S(\tau) I(t) \\
\frac{dT_i}{dt} &= \frac{1}{K_1}(T_e - T_i) + \frac{1}{K_r} q(T_s - T_u)(T_f - T_i) + \frac{1}{K_I} S(\tau) I(t) \\
\frac{dT_e}{dt} &= \frac{1}{K_1}(T_i - T_e) + \frac{1}{K_2}(T_a - T_e)
\end{aligned}$$

With all parameters and functions being the same as previously defined, except K_2 is now the time-scale parameter related to the heat transfer between the outdoor environment and the envelope, which was the role of K_3 in the old model.

We compared the different modelling approaches according to the root mean square error (RMSE), as summarized in Table 5. The differences are visualized in Figure 28. Clearly, the models based on splines are better than the model based on physical solar equation, but very similar to each other, thus the physical model should only be used for application where new observations are too infrequent to re-estimate a spline model over the course of the year. According to the RMSE, the 2-wall-state model performs best, but due to the robustness issues associated with having 2 wall states, we are still satisfied with the performance of the 1-wall-state spline models. According to the RMSE, there is a slight gain in forecasting precision from taking the separation of solar radiation into direct and diffuse fractions into account, but it is not much. Overall, the choice of model can depend on the specific application, as all of the models produce good forecasts.

Model name	#Wall states	Solar gain model	Direct+diffuse separation	RMSE
M1	2	Splines	No	0.530
M2	1	Splines	No	0.642
M3	1	Splines	Yes	0.623
M4	1	Physical	Yes	0.783

Table 5: Forecasting performance of temperature models, measured by RMSE.

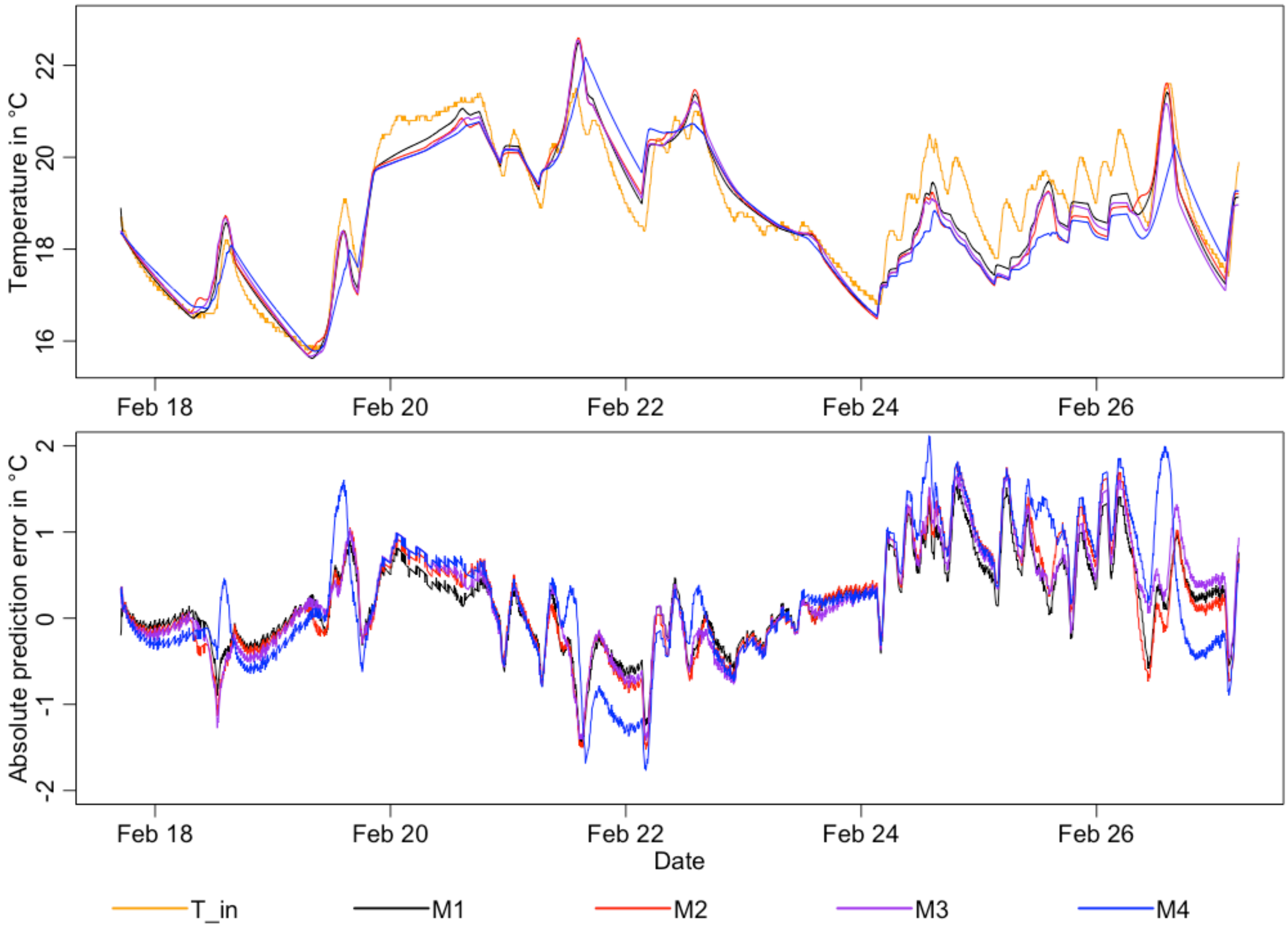

Figure 28: Comparison of the forecasting performance model structures, with full forecast horizon shown. Top: indoor temperature; Bottom: prediction error. Orange/T_in: indoor temperature; Black/M1: two-state wall with solar splines; Red/M2: one-state wall with solar splines; Purple/M3: one-state wall with solar splines + solar separation; Blue/M4: one-state wall with physical solar model.

Parameter Estimation II – robustification

This paragraph serves as important advice for future work with this model class. Over the course of the project many models were estimated, and it was not always guaranteed that the optimization routine converged and an optimal parameter set would be identified. Multiple rounds of manual tweaking, carefully selected initial conditions and strict boundaries was often needed to get to a result. However, with increasing experience we managed to identify the preconditions needed to get a consistently successful parameter estimation.

First, and most importantly, the time-scale parameters such as K_1, K_{1s}, K_r, K_{rs} needed to be bounded from below. If they were not bounded from below, the optimization routine tended to move to a domain with absurdly fast dynamics (temperature fluctuations of several degrees in an instant, similar to Figure 23) without ever leaving that domain again. It is trivial that such fast dynamics do not occur in reality, and it was therefore deemed reasonable to put lower bounds on the K's. As a result, parameters would now be estimated reliably every time, and an interesting detail was that the weighted least squares (the objective function) would under these boundary conditions decrease below what was possible in the unbounded case, already after a few iterations. In other words, correct physical parameters would lead to significantly lower WLS as expected, but the optimization was dependent on a push away from the wrong direction to do so. We found that just putting a lower bound of $K \geq 1$ was enough to get a robust optimization.

Secondly, the optimization was found to be more effective whenever all the strictly positive parameters (the time-scale parameters and the thermostat valve slope parameter) were estimated in the logarithmic domain. The reason for this is that the optimization routine can then more easily explore these parameters on different orders of magnitude, both for small numbers and large numbers. Therefore in some cases utilizing the logarithmic domain allows the optimization routine to get to the right parameter area in significantly fewer iterations than when not utilizing this.

5.3.3 Task 3.3 Occupants detection, classification and modelling

In this task, we focused on the development of models for predicting occupant satisfaction. In order to get data for occupant thermal satisfaction, a measurement campaign was conducted in an office building at DTU where occupants could provide feedback for the thermal environment, through an app on their mobile phone. Occupants would on a voluntary basis answer questions on a 5 point scale. The questions were answered at the convenience of the occupants, but they were encouraged to answer twice per day. The question and the possible answers were:
"How would you like the temperature to be?

1. Much colder
2. Colder
3. No change
4. Warmer
5. Much warmer"

These are ordinal responses and for the further analysis the responses are translated to, Y=-2 if response is "Much colder", Y=-1 if response is "Colder",..., Y=2 if response is "Much warmer". Beside the occupant feed-back a number of other variables was also collected, for the indoor environment the variables were

- Indoor temperature (degrees Celsius, 1h resolution)
- CO_2 concentration (ppm, 1h resolution)
- Humidity (%, 1h resolution)

In addition, some rooms had other measurements, like window opening or multiple sensors, here we only use indoor temperature for the presented models. The data also included numerical values of weather variables, like outdoor temperature and wind speed, and even though these were to some extend explored, those will not be included here since it was not possible to show any significant impact from such variables.

As data preparation all indoor climate variables were estimated at the time of feedback by linear interpolation from the hourly data, and further data was quality assured by removing obvious wrong data records, and repeated feedback (occupant would only be allowed to give 1 feedback per hour). Figure 29 shows an example of feedback and temperature, in general the occupant indicates that it is too warm in the beginning where the temperature is also high, the Christmas holyday is clearly visible (no feedback in from end December through first part of January).

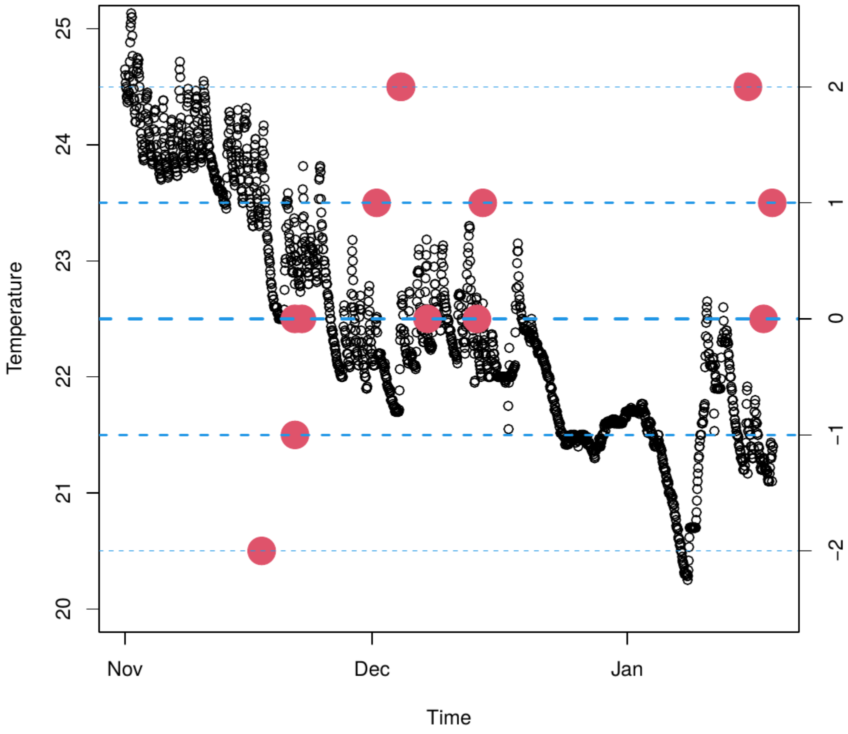

Figure 29: An example of temperature measurements, and thermal feed backs in a room.

The chosen statistical model is a mixed effect proportional odds model, in the logit domain this is a linear model, i.e.

$$\log i\, t\left(P\left(Y_{jt} < i\right)\right) = \theta_i - T_{jt}\beta + u_j\ .$$

Where i (i<2) refer to feedback (“much colder” through “much warmer”), j is the office or the occupant (we have used both in the project), $\theta_i < \theta_{i+1}$ is the separator between feedback levels. T_{jt} is the temperature in office j (or in the office of occupant j) at time t. β is a slope to be estimated, this can be viewed as the thermal sensitivity of the “average” occupant. Finally, u_j is the (random) effect of occupant j, this is not formally a parameter of the model, but will be estimated as part of the general estimation procedure. The random effect is assumed to follow a normal distribution

$$u_j \sim N(0, \sigma^2)$$

Where σ^2 can be viewed as the variation in preference between occupants. The type of models described here are, all though advanced, implemented in fairly standard statistical software packages (we use the R-package tramME), and hence relatively easy to implement.

The complete set of parameters for the model is

$$\theta\ = [\theta_{-2},\ \theta_{-1},\ \theta_0,\ \theta_1,\ \beta,\ \sigma^2]$$

These parameters can be estimated based on the available data and a prior reference curve (i.e. for an occupant not seen by the model), can be defined by

$$\log i\,t\left(P\left(Y_{jt} < i\right)\right) = \theta_i - T_{jt}\beta$$

Where the parameters are estimated from the available data, for an occupant that have seen the data the model is

$$\log i\,t\left(P\left(Y_{jt} < i\right)\right) = \theta_i - T_{jt}\beta + u_j$$

The random effect is replaced by the conditional expectation, $E\left[u_j \middle| Y_j \right|]$, i.e. conditional on all observations from that office/occupant. Using the developed model a comfort curve for each of the offices that participated in the experiment can be estimated, Figure 30 shows the developed models, the diversity of comfort curves is evident from the figure. According to the model the occupant shown at the upper left corner have a high probability of answering that the temperature should be much colder 24 degrees, while the occupant curve shown in the lower right corner predict a high probability of being satisfied at the same temperature.

The preferred temperature for each occupant is estimated based on the individual comfort models in Figure 30, by maximizing the probability of answering that the temperature should not be changed

$$T_{pref,j} = \arg\max_{T} P\left(Y_j = 0 \middle| T, \theta, u_j \right|)$$

the estimated temperature preferences range from 20.3 to 23.9, and these preferences can now be used for controlling the temperature in the individual rooms.
As final remarks it should be noted that the total number of thermal feedbacks is around 170 in total, this implies that statistical power is for identifying further regressors is quite low, and only strong effects can be identified. However, the modelling framework is well suited for further generalizations, and hence as more data becomes available, it is a simple task to test additional hypothesized relations, e.g. that the preference is related to hour of day, or some weather-related variables. In addition, for models as simple as the ones presented here the estimation is fast enough to allow reestimation on e.g. a daily basis and hence being updated as more information become available, both in terms of more occupants and more feedbacks from the individual occupants. In addition, since the number of parameters does not increase with the number of occupants, the computational effort of mixed effect models scales well (i.e. not too fast) with the number of occupants.

Within this task, we also contributed to write a book on occupant behavior: Occupant-Centric Simulation-Aided Building Design: Theory, Application, and Case Studies, Taylor and Francis, edited by L. O'Brian and F. Tahmasebi. Contribution to chapter 6: "Introduction to occupant modeling". Here, we described several modelling approached to simulate/predict occupants' presence and windows opening and closing activities. For this purpose, Mixed effect based models, Markov-Chains based models and logistic regression based models have been thoroughly illustrated.

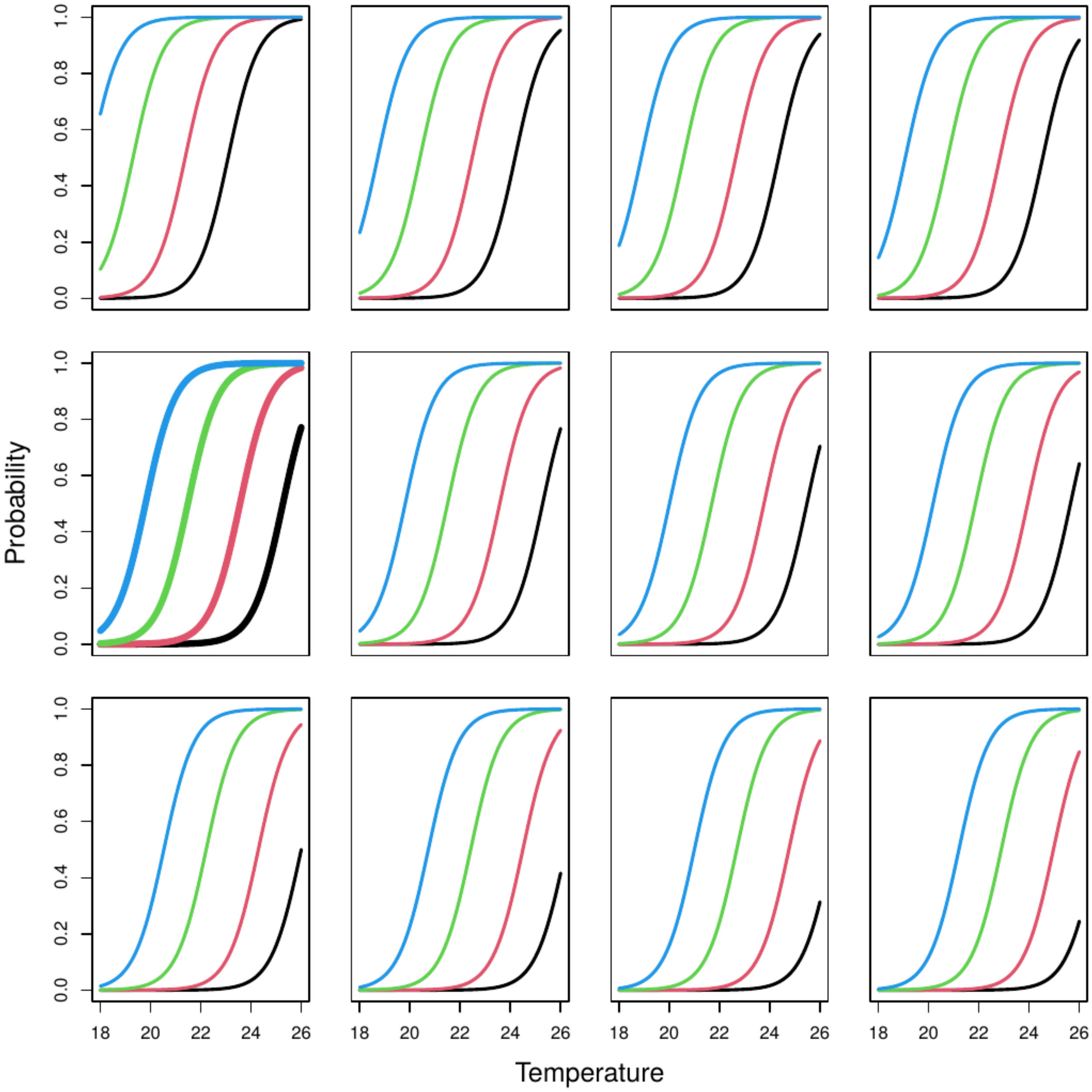

Figure 30: Individual comfort curves for 8 different offices, the curves are ordered from cold preference (upper left corner) to warm preference (lower right corner). The curves highlighted with bold is the prior preference curve.

5.3.4 Task 3.4 Development of MPC algorithms (M3)

In this task, we focused on the design and development of an MPC algorithm to control indoor thermal dynamics. This is done by generating an optimal control signal, as a thermostat setpoint, to the radiator thermostat. This control signal is generated based on considering forecast data and comfort limits of temperature. In the sequel, we describe the designed MPC algorithm.
MPC uses a mathematical model to predict the future behavior of the system over a specified time horizon, N. The model can be linear or nonlinear, depending on the complexity of the system. In this study, the model complexity is high due to the employment of a nonlinear model. For a detailed

description of the model selection and structure, please refer to the previous sections. To simplify the formulation, we discretize the model using the Euler method and write the model in the following compact form:

$$T(k+1) = T(k) + f(T, u, T_a, I_s) \times dt,$$

where $T = [T_i, T_{e1}, T_{e2}]^T$, u is the control input, T_a is the outdoor temperature, I_s is the solar radiation, f is the system of nonlinear differential equations, and dt is the sampling time. This model of the system is then utilized to predict the future evolution of states. The future values of T_a and I_s are provided by a weather station or forecasting method. Current temperature values are used as initial conditions.

Another advantage of MPC over other control methodologies is its capability to handle technical and comfort constraints. The technical limit is the setpoint limit of the thermostat as

$$T_{set_{min}} \leq T_{set}(k) \leq T_{set_{max}},$$

where $T_{set_{min}}$ and $T_{set_{max}}$ are the maximum and minimum setpoint limits, respectively. In addition to the technical limits, there are comfort limits that should be taken into account:

$$T_{i_{min}} \leq T_i(k) \leq T_{i_{max}},$$

where $T_{i_{min}}$ and $T_{i_{max}}$ are the minimum and maximum indoor temperatures, respectively. In order to handle the infeasibility of solving optimization problems, one can employ a slack variable, s, so that relaxes the limit on the indoor temperature. Thus, the comfort limit can be written as

$$T_{i_{min}} - s(k) \leq T_i(k) \leq T_{i_{max}} + s(k),$$
$$s(k) \geq 0.$$

After defining the model and the constraints, it is time to define the cost function. In this study, the goal is to track a reference temperature while retaining the constraints. To this end, we define the cost function as

$$J = \sum_{k=1}^{N} \alpha_1 \left(T_i - T_{ref}\right)^2 + \alpha_2 (u(k) - u(k-1))^2 + \alpha_3 s(k)^2,$$

where T_{ref} is the reference temperature to be followed, and α_1, α_2, and α_3 are the weights of different terms. This cost function consists of three terms. The first term penalizes the deviation of the indoor temperature from the reference temperature, the second term penalizes the rate of change of the setpoint temperature, and the third term penalizes the indoor temperature outside the comfort limit.

In Figure 31, you can see the indoor and outdoor temperatures, setpoint, sensor temperatures, and upper and lower comfort bounds. The comfort bounds for indoor temperature change throughout the day. They are lower at night and higher during the day. From 6 am to 12 pm, the comfort bounds range from 20°C to 23°C. From 12 pm to 2:30 pm, the range is between 21°C and 24°C. After 2:30 pm, the bounds slowly change to a range of 17°C to 19°C for the rest of the day. The setpoint values for temperature control are limited to a range of 10°C to 25°C. Thanks to the MPC design, the indoor temperature remains within these comfort bounds.

Deployment of MPC in real environment

After we had demonstrated the potential of our MPC in a simulated environment, we deployed it in a real environment, namely the four classrooms of Borgerskolen, C0.13, C0.15, C1.08 and C1.12. The MPC was run from an online node on a DTU server cluster, while saving all relevant information in a log file. The full workflow were as follows:

1. Submit MPC job to online node.

2. Load user-defined MPC scheduling parameters: *starting time*, *duration* (length of experiment, in this case 72 hours), *update frequency* (time between new instructions sent to thermostats = 30 minutes), *MPC-horizon* (we experimented with both 1 hour and 24 hours), *list of rooms* (necessary as every room has its own model parameters, see section 5.3.2)
3. Create *overall schedule* to follow for the full duration of the experiment.
4. Create first *access token* for access to the thermostats via the CLIMIFY API (this is done again every time the job has to get data from sensors or communicate with the thermostats).
5. Load *metadata about all thermostats* in the targeted rooms (while an offline substitute may be used here, loading new metadata every time ensured that the setup would automatically adapt to eventual thermostat replacements).
6. Create *log file*.
7. 3 minutes prior to next thermostat instruction, prepare to calculate MPC over the user-defined horizon (3 minutes lead time is used to ensure there is enough time for the MPC to be calculated, as this may take 30-90 seconds).
8. Prepare *input forecasts* for MPC (load weather forecast from ENFOR, compute forward temperature forecast via the weather compensation curve, compute solar input for each individual room via their respective spline parameters).
9. Prepare *temperature reference schedule* (true target temperature and min-max boundaries).
10. *Update model states* with newest temperature measurements from the ELSYS sensors.
11. *For each room, calculate MPC* given the inputs from step 8-10 to find the *optimal series of thermostat set-point temperatures* over the MPC-horizon.
12. At the exact time set by the schedule, send the *first set-point temperature* to all the thermostats in all the rooms (while carefully monitoring if the message is sent successfully to each thermostat. In cases where this fails, additional attempts are made to send the message again, but if it still fails after three attempts, no further attempts are made).
13. If the overall schedule is not completed yet, jump to step 7 (next iteration of the MPC), otherwise, the job is finished.

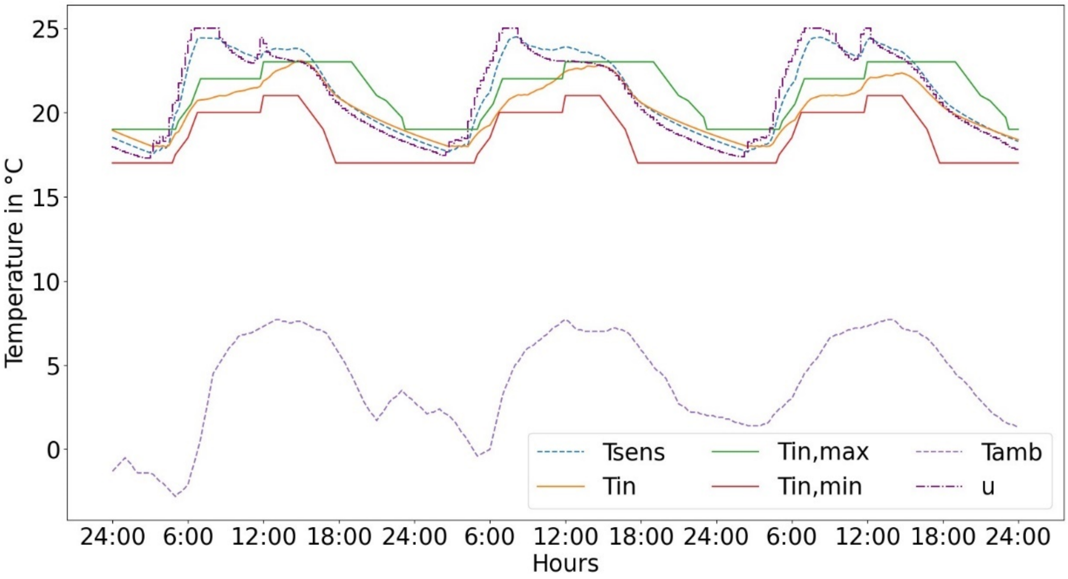

Figure 31: MPC results: indoor temperature (Tin), outdoor temperature (Tamb), setpoint temperature (u), and sensor temperature (Tsens), as well as the upper (Tin,max) and lower (Tin,min) comfort bounds.

In the above, in every iteration of the MPC, the input forecasts, temperature reference schedule, updated model states and optimal series of thermostat set-point temperatures are saved and stored locally for post-run analysis. Information about online communication with the CLIMIFY platform and individual thermostats is stored in the log file.

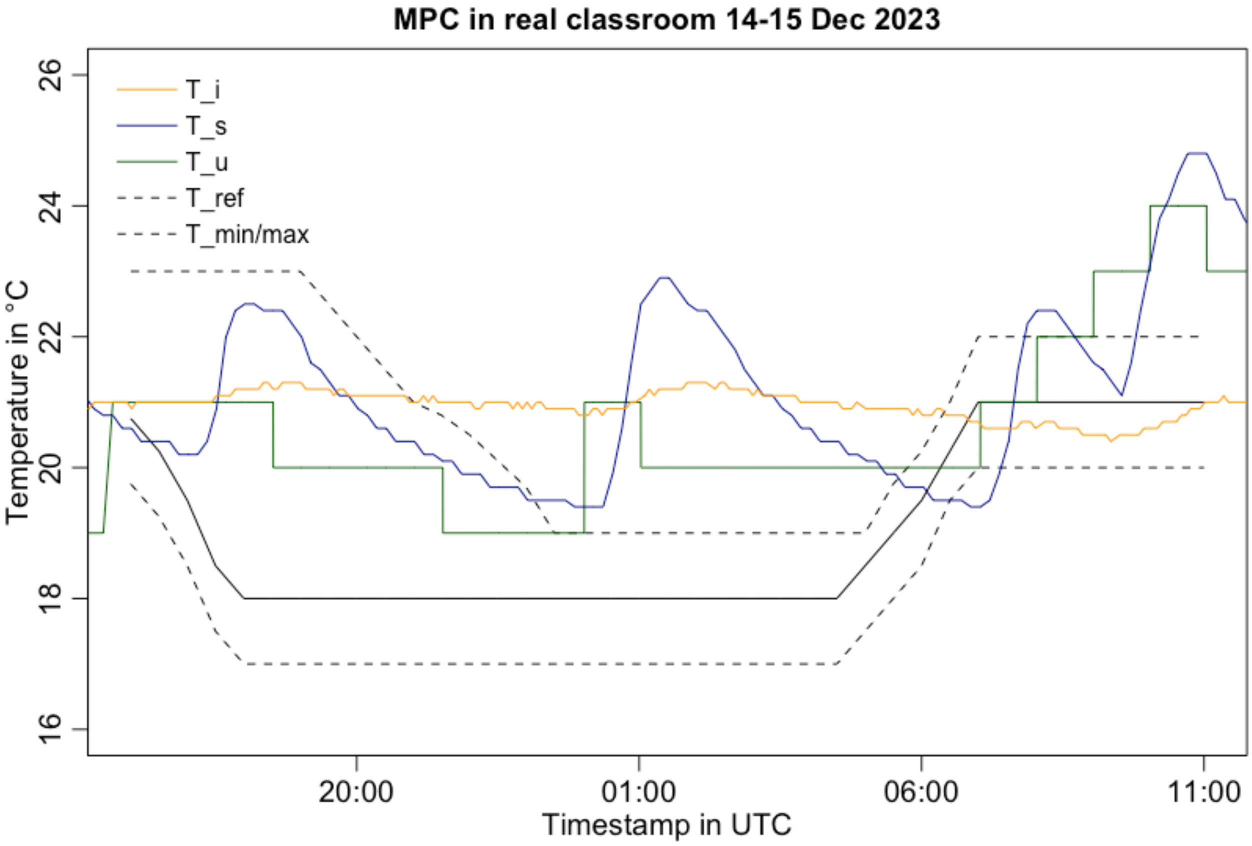

Figure 32: The results of a first attempt in deploying MPC in a real environment, in this case the classroom C0.13 in Borgerskolen. The graph shows the indoor temperature (T_i, orange), the thermostat sensor temperature (T_s, blue), the set-point temperature as it was sent to the thermostats (T_u, green) and the target temperature we are really trying to achieve (T_ref, black) with its boundaries (black dashed lines).

We tested the MPC in the four classrooms C0.13, C0.15, C1.08 and C1.12 of Borgerskolen in the time interval 14 Dec 2023 16:00 UTC to 15 Dec 2023 11:00 UTC. The results of one of the classrooms is shown in Figure 32. The positive outcome was that the MPC was actually running for 19 hours according to the 13-step process outlined above. As it is seen in the figure, it appropriately made the decision to cool down in the afternoon, and heat up in the morning. However, evidently an error occurred around midnight, where the decision was made to turn up the heat, even though the indoor temperature was higher than maximally desired. This happened in all the rooms, so there was likely a bug with the midnight timestamp specifically. A second challenge was associated with the online node we used to run the script from. The actual experiment was supposed to take place for a full week, but even after restarting the experiment in further periods in December, it would still terminate prematurely within less than a day. Yet we find the results to be promising, and we are determined to get rid of those two issues for the next heating season, which should in the end result in an MPC that can match the quality of the simulated environmexnt.

5.3.5 Task 3.5 Integration of variable energy price signals in MPC

In this task, we focused on designing a model predictive controller that takes into account variable energy prices. By utilizing information about energy prices, the controller can be designed to shift energy demand to periods with lower energy prices, ensuring cost efficiency.
The price/penalty signal indicates when the MPC is allowed to use more energy and when it should keep energy demand as low as possible. For example, if the penalty signal is high from 6 am to 10 am and from 4 pm to 8 pm every day, the controller will adjust energy demand to periods outside of these times. This penalty signal will be utilized later in the simulation results.
Similar to the previous MPC design, here we are using the model for the thermal dynamics of the building including the nonlinear function representing the radiator valve movement. In addition, similar technical and comfort constraints are considered. Different from the previous MPC design, the cost function is updated as

$$J = \sum_{k=1}^{N} \beta(k)u(k)^2 + \alpha_2(u(k) - u(k-1))^2 + \alpha_3 s(k)^2,$$

where $\beta(k)$ is the penalty/price signal. This cost function consists of three terms. The first term penalizes the demand during a high penalty period, the second term penalizes the rate of change of the setpoint temperature, and the third term penalizes the indoor temperature outside the comfort limit. In Figure 33, you can observe the indoor and outdoor temperatures, setpoint, sensor temperatures, upper and lower comfort bounds, and the high price period (highlighted in pink). The indoor temperature comfort bounds change throughout the day and are similar to the previous MPC design.

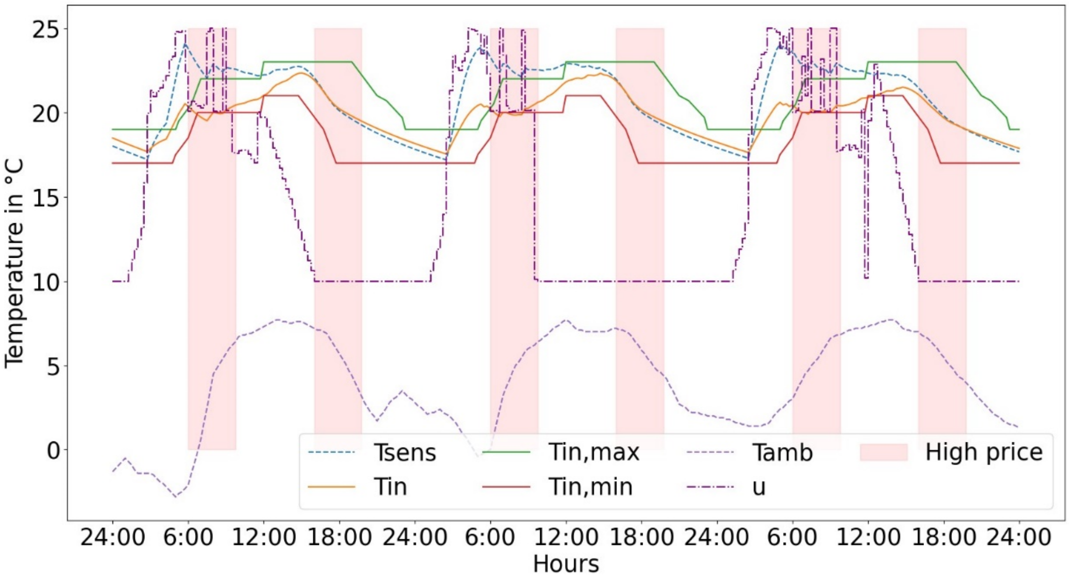

Figure 33: MPC results with penalty/price signal: indoor temperature (Tin), outdoor temperature (Tamb), setpoint temperature (u), and sensor temperature (Tsens), as well as the upper (Tin,max) and lower (Tin,min) comfort bounds. The high price period is highlighted in pink.

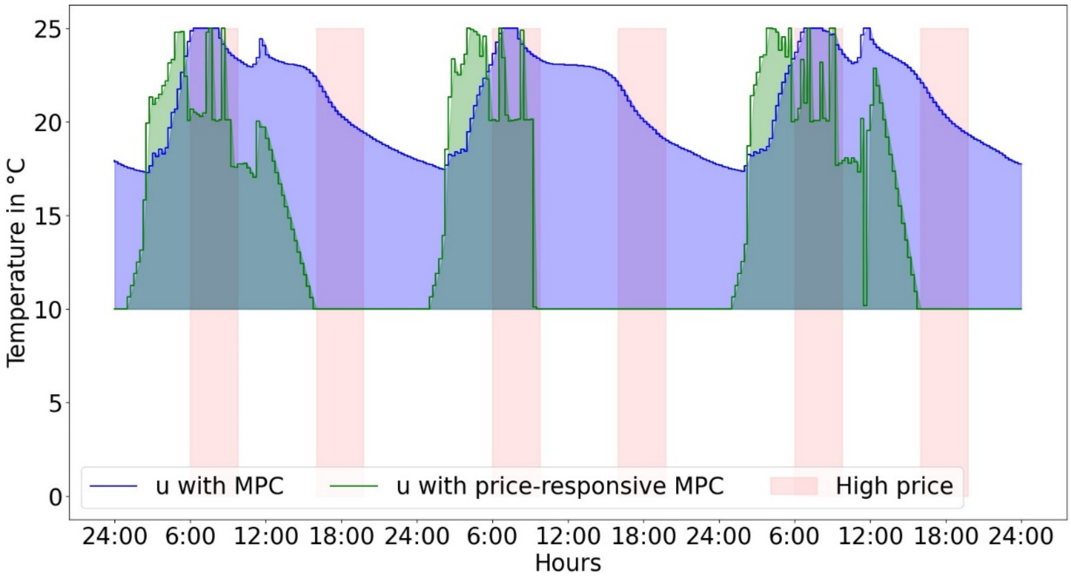

Figure 34: Demand comparison of MPC designs with/without penalty signal. The high price period is highlighted in pink. Set point temperature with original MPC (blue line) and price-responsive MPC (green line) are demonstrated.

The setpoint values are time-dependent and fall within a range of 10°C to 25°C. With the MPC design that considers penalty signals, the demand represented by the setpoint value shifts from the high price period (pink highlighted period) to the low price period. Additionally, the comfort limits are almost always met.
Figure 34 demonstrates the demand, displayed as the setpoint temperature of the thermostats, using two different MPC designs. It is evident that using the MPC design that considers the penalty signal shifts the demand towards the periods with lower penalties/prices.

5.4 WP4 Product Development

The milestone of this work package is Milestone M6 (14), related to the development of FeedMe (2.0), CLIMIFY, and MetFor™, as well as the first version of UpSmarting hardware and software solution for buildings.

5.4.1 Task 4.1 Development of FeedMe (incl. smart wearable/watch app)

FeedMe, a pivotal component of the HuiL-DEMand project, serves as a sophisticated mobile application designed for gathering and integrating user feedback on indoor environmental conditions. This feedback is critical for dynamically adjusting the heating systems in two buildings used as demonstration sites, thereby directly enhancing occupant comfort and energy efficiency. The development of FeedMe has been comprehensive, focusing on user interface improvements, system integration, accessibility, and security enhancements.
Mobile App Enhancements are related to:

1) iOS development:

  - Advanced user interface: The iOS version of FeedMe has been revamped with a focus on enhancing user interaction through a more intuitive and visually appealing design. This includes streamlined navigation menus, quick-access feedback buttons, and a user-friendly dashboard that displays environmental conditions in real-time.
  - Feature-rich updates: New features such as personalized settings for temperature preferences and automated alerts when certain environmental thresholds are reached have been added, making the app not only a tool for feedback but also for personal environmental tracking.

2) Smart watch compatibility:

  - Extended functionality: Integration with smart watches has been deepened to include not only basic feedback capabilities but also notifications and environmental alerts directly to the user's wrist, facilitating immediate responses without the need to interact with a smartphone.
  - Synchronization with health data: FeedMe on smart watches can now sync with other health monitoring apps to provide recommendations for optimal comfort levels based on individual health data such as heart rate and activity levels.

3) BLE beacons for indoor localization:

  - Enhanced accuracy: The deployment of BLE beacons throughout the buildings has been optimized for better accuracy and reliability in indoor positioning, enabling the app to deliver highly specific feedback relevant to precise locations within the buildings.
  - Context-sensitive feedback: With improved localization, FeedMe can now offer context-sensitive adjustments, such as altering room temperatures in specific zones based on the aggregated feedback from occupants within those areas.

4) Integration of FeedMe with CLIMIFY - Feedback visualization:

- Real-time data integration: The visualization tools on CLIMIFY have been upgraded to not only display real-time feedback from FeedMe but also integrate this data with other IoT sensor readings, providing a comprehensive overview of the indoor environment.
- Customizable dashboards: Facility managers and school administrators can customize their CLIMIFY dashboards to highlight key metrics derived from FeedMe feedback, which assists in making informed decisions about environmental adjustments.

5) Integration of FeedMe with CLIMIFY - Data handling and security:

- Robust data encryption: Enhancements in data security include robust encryption protocols to protect all data transmitted between FeedMe and CLIMIFY, ensuring that occupant feedback remains confidential and secure against external threats.
- Compliance and data integrity: Updated compliance measures with international data protection standards ensure that FeedMe's data handling procedures meet rigorous security and privacy requirements. Regular audits and updates keep the system aligned with the latest security practices.

Through these targeted enhancements, FeedMe not only elevates the user experience but also plays a crucial role in the smart management of building environments, demonstrating a significant impact on both comfort and energy consumption. The integration with CLIMIFY ensures that feedback leads to actionable insights, promoting a sustainable and occupant-friendly approach to building management.

5.4.2 Task 4.2 Development of CLIMIFY (data capacity and security, APIs, UI)

CLIMIFY represents the technological core of the HuiL-DEMand project, designed to integrate a broad range of data inputs to optimize building energy management efficiently. The development of CLIMIFY has been extensive, aimed at expanding data handling capabilities, enhancing security features, improving the user interface, and ensuring robust integration through sophisticated APIs.

System capacity and data handling

1. Advanced data integration:
    - Comprehensive API suite: The development of new APIs has facilitated the integration of a wider array of IoT devices and external systems such as Danfoss smart thermostats. These APIs are designed to handle increased data throughput while maintaining high responsiveness.
    - Scalable architecture: To accommodate the growing volume of data, CLIMIFY's architecture has been scaled up. This includes enhancements in the data processing backend to handle real-time data analytics and aggregation effectively.
1. Big data management:
    - Efficient database management: The database architecture has been redesigned to better manage the large volumes of data collected from various sensors and user feedback. This redesign focuses on optimizing data retrieval and storage processes to reduce latency and improve system performance.
    - Data integrity and recovery: New mechanisms have been implemented to ensure data integrity, including advanced error checking and recovery processes. These features ensure that the data remains accurate and reliable, essential for effective building management.

Security enhancements

1. Robust security protocols:
    - Enhanced authentication and authorization: Security protocols within CLIMIFY have been strengthened through advanced authentication mechanisms, including dynamic access controls, which restrict access based on user roles and contexts.
    - Regular security audits: To ensure the ongoing security of the system, regular audits are conducted to identify and rectify potential vulnerabilities, with updates applied seamlessly without disrupting the operational functionality.
1. Compliance with regulations:
    - Adherence to international standards: CLIMIFY complies with global data protection and privacy regulations such as GDPR, ensuring that all data handling practices are legally compliant and meet the highest standards of data security.

User interface (UI) development

1. Intuitive and responsive design:

  - User-centric interface: The UI of CLIMIFY has been redesigned to provide a more intuitive experience, with simplified navigation and a cleaner layout that makes it easier for users to manage and monitor building systems.
  - Interactive data visualization: Enhanced visualization tools within CLIMIFY allow users to interact with data more effectively, including customizable graphs and real-time data feeds that help visualize trends and anomalies.

API development and integration

1. API for external collaboration:
   - Open API development: The open API framework developed for CLIMIFY allows for easier integration with third-party applications and services, fostering a collaborative environment where data can be shared seamlessly across platforms.
   - Secure data sharing: These APIs are secured with the latest encryption standards, ensuring that data shared across platforms is protected against unauthorized access.

Through these comprehensive enhancements, CLIMIFY has evolved into a more robust, secure, and user-friendly platform that significantly contributes to the project's goal of optimizing building energy management. The system's ability to integrate vast amounts of data and convert them into actionable insights is central to its effectiveness in improving energy efficiency and occupant comfort in building environments.

Additional activities executed include:

- We created a Scheduling Application allowing software users such as building managers, facility managers, and occupants to easily create schedules for smart thermostat control through a user-friendly GUI. This enables the creation of multiple schedules and the assignment of different schedules to different locations within the same building. On the CLIMIFY backend, the automated schedule service regularly checks the set points of the thermostats, ensuring higher stability and precise control.
- We developed and integrated a new method of position detection within a building through BLE beacons into the FeedMe app, achieving a more precise and stable detection of occupants in rooms.
- We integrated the installation of BLE beacons into the CLIMIFY hub system, making it easier for building managers to install and manage beacons within the main software application. This improved the overall overview and management of BLE beacons.
- We created a specific function to generate open, shareable links showcasing live measurements for information screens and users without a valid account in the system.
- We added support for energy metering points in the CLIMIFY hub, enabling the visualization of energy usage and production (e.g., from PV systems).

5.4.3 Task 4.3 Development of UpSmarting solution for buildings

In this task, UpSmarting focused on modifying their standard product (a box able to connect, read and write digital signals in existing legacy technical systems) for the adoption of this technology in buildings. They successfully connected their box to streamline data from Ulstrasonic energy flow meters.

5.4.4 Task 4.4 Development of weather forecast algorithms based on IoT weather stations

Using iot weather station for adjusting climate model has been investigated, and cost of suche weather stations was judged to be prohobitive so far. for this reason, ENFOR invested their resources in refining actual models. MetFor™ is a software system for high precision meteorological forecasting in a specific geographic location. The system utilizes multiple weather models as input and finds the optimal weight of each model for the specific location, based on local measurements.

The system was designed using an old and complex core configuration which was tailored for clients in Denmark and the Nordics. All sites were running within the same process, offering low level customization per location and changes to individual sites required an update of the entire system. Development in 2022 and 2023 was focused on making the system more flexible and streamlined, splitting processes across sites and thus offering more custom configurations for clients worldwide with low setup cost. The system is now built using the same core configuration used across ENFOR's software platforms (WindFor™, SolarFor™).

One of the biggest benefits of this development is a more streamlined weather model setup. More weather models can now be included with low effort, offering a custom weather model selection for different regions such that our clients can now benefit from more accurate forecasts from higher resolution regional models if available.

6. Utilisation of project results

6.1 Future utilisation of technological results

6.1.1 DTU

Our grey-box model approach has proved its potential by delivering accurate room-specific indoor temperature forecasts while being simple and generally applicable. The accuracy is especially due to the new way of modelling the interaction between the thermostat and the indoor environment. We expect that this thermostat modelling principle, when published, will be included by research groups in future research projects involving modelling of indoor temperature. Furthermore, it has also been demonstrated that the approach can be integrated in a model predictive control scheme. Hence, research groups who specifically work on optimal control of indoor temperature are likely to use our grey-box-model-MPC approach as a starting point or a benchmark for their own research.

The grey-box-model-MPC results are a proof-of-concept which serves as a first step toward making nightshift setbacks (lowering set-point temperatures deliberately at night to save energy) reliable enough for the society to be willing to implement them in schools, which if fully realized will save energy. Furthermore, if/when dynamic prices on district heating are implemented, then our extended MPC with varying price signals will serve as a solid option for schools to make the most financially robust heating plan without violating comfort constraints.

6.1.2 CLIMIFY

The feedback app FeedMe and the CLIMIFY Hub will be sued and commercialised by CLIMIFY with different customer segments, spacing from municipalities to office buildings. Also, the results and the development will be used in future R&D projects.

6.2 Future utilisation of commercial results

6.2.1 CLIMIFY

The concept of Human-in-the-Loop is the core technology that CLIMIFY want to bring to market. The project has increased CLIMIFY's offer, and has contributed to inspiring us in re-considering our flat price model. Currently, we have a price model that is volume-dependent, while all apps and features are accessible for all customers. In the future, we want to segment our offering, to be able to offer cheaper solutions limited to the actual need of the customer only. Thanks, among others, to this project, our team grew from 4 employees (1.5 full time equivalent) to 8 employees (4,5 full time equivalent). To cover for the co-financing of this project, CLIMIFY's owners have re-invested in the company.
Finally, also thanks to this project, we landed the municipality of Høje Taastrup as a new customer, while the municipality of Rudersdal increased their usage of CLIMIFY drastically.

6.3 Expected market competition

The need for buildings automation is reality for all big buildings in Denmark from January 2025, as outlined and regulated from the building regulation BR18, as long as the investments in automation have an effective return of investment of less than 11 years. For this reason, classical BMS company, the HVAC industry and energy management companies are currently aggressively addressing this market. On top of those players, several startups and scaleups are approaching this market with data-driven tools and an open, digital approach. CLIMIFY is the main partner commercialising the Human-in-the-Loop technologies, therefore, the non-compehensive overview of competitor illustrated in Table 6 is related to CLIMIFY activities.

Table 6 Competitors' analyses

COMPETITOR	**Peculiarities of competitors**	**Main differences with CLIMIFY**
CLIMAID	Vendor neutral monitoring platform, feedback app	CLIMIFY offers indoor localisation of occupants, and apps for smart wearable.
IQ Energy Nordic by Deas	Exclusive reseller of monitoring and control devices Eniscope.	CLIMIFY offers LoRaWAN integration in existing BMS using MBus and ModBus converters.
Neogrid	Intelligent Energy management, flexibility services.	CLIMIFY focus is on occupants comfort and well being: through the app, we make sure occupants are on board, and do not "fight against the system". In this way, we minimise chances for Reboud Effect and Energy Performance Gap.

Roomalyzer	Monitoring visualization app, NB-IOT based sensors.	We use LoRaWAN technology, making long term monitoring (temperature, humidity,. Presence, light, CO2 conc.) cheaper and battery life long-lassting (11 years readings live, every ten minutes).
Vitani	Standard Energy Management Solution with IoT sensors integration	CLIMIFY's focus on occupants.
NorthQ	Hardware (monitoring devices) producers with open APIs and basic visualization software.	CLIMIFY focuses on long terms data evaluation and analyses
ENTO	Data collector with open APIs proposing energy roadmap and control software.	CLIMIFY integrates indoor climate in the IP-MVP metod, assessing buildings performance after a retrofit extremely precisely
IC-METER	Producer of monitoring devices – very basic visualization software[1]	CLIMIFY has an holistic approach, monitoring, analysing, operating.

CLIMIFY unique selling points are listed below:

- ✓ Domain knowledge related to both IoT and Buildings (employees with more than 15 years of experience in those fieldz)
- ✓ platform Feedback app with indoor localization;
- ✓ Seamless integration with nearly any BMS and existing interfaces;
- ✓ Unique, live and past data visualization and evaluation platform
- ✓ User management system for different users types (owner, managers, users, guests, etc.)
- ✓ AI and weather forecast services for optimisation of HVAC systems operations
- ✓ Human in the Loop for proven satisfaction of occupants
- ✓ Possibility to provide flexibility services under a Comfort Guarantee
- ✓ Extremely quick, live data analyses and reporting
- ✓ We execute sensors' installation, when requested by customers
- ✓ We track energy savings according to IPMVP

6.4 Sales Barriers

Advantages of digitalisation and usage of AI in the built environment are clear, yet difficult to convey to a usually conservative industry as the real estate sector. Life-span of IoT equipment is obviously shorter the life span of buildings, and return of investment of any technology applied to buildings should therefore accurately being taken into account. Main sales barriers are therefore mainly connected to an hystorically (and for good reason) conservative industry, who prefer a well-known solution rather than an innovative solution. Yet, the disruptive potential of AI and digitalisation through IoT, on the building-management-system market, just started to show its effects: More and mor esystems are including APIs in their offering, and marketing is focusing increasingly on the openness of systems, rather than on just their performance.
In the particular case of Human-in-the-Loop, there is a second barrier towards market: the misbelieve that you can have either satisfied occupants, or energy savings: the contrary is the true. Many

building owners are scared that a human-in-the-loop solution, satisfying the occupants, might not be the right thing for them, who wants to minimise heating and in general energy cost. Yet, we showed that, in order to save energy, you need to make the occupants satisfied in the first place.
We aim at providing transparent information material to our potential customers, avoiding bold savings and unreachable promises. And we strongly believe that any IoT and AI providers for the building sector should do the same, to avoid jeopardising an otherwise flourishing market.

6.5 Contribution to realisation of energy policy objectives

The project concretely contributes to the energy policy objectives by lowering the energy consumption of buildings, while minimising occupants indoor discomfort. Besides the technical contribution, the algorithms produced, the papers published, and the commercialised solution, this project made very clear one message: If you want to focus on energy savings, focus first on minimising discomfort. Doing so, you will minimise both the direct rebound effect and energy performance gap, which is commonly seen in new and refurbished buildings.

6.6 Use of the results in teaching and dissemination activities

DTU will use the results of this project in dissemination material (papers, conference papers, dissemination journals) in teaching (particularly on special courses and summer courses), and in existing and new IEA EBC annex projects. This project represented a great opportunity to create fundamental knowledge to be used in the upcoming IEA Annex 95.

7. Project conclusion and perspective

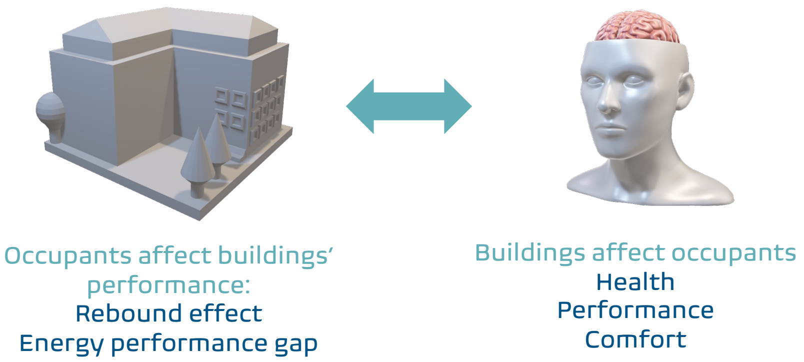

Figure 35 Occupants/Buildings relation

The core conclusion of this project is closely tied to the well-known yet often overlooked fact that while occupants influence building performance, buildings also affect occupants' performance (Figure 35). A truly sustainable building should focus not merely on energy savings—for that, we might simply turn off the HVAC systems—but primarily on the well-being and satisfaction of its occupants. Recent studies have demonstrated that well-ventilated classrooms can reduce the spread of

COVID-19 by over 80% compared to poorly ventilated ones; other research has indicated a performance increase of more than 15% in occupants in buildings with good indoor environmental quality. Thus, focusing solely on buildings' energy usage is a mistake.
One of the key lessons learned from this project is that if the goal is to achieve energy savings, the focus should first be on minimizing discomfort. By doing so, we can reduce both the direct rebound effect and the energy performance gap commonly observed in new and refurbished buildings. With an initial investment of approximately 65,000 DKK in hardware and software, and annual monetary savings of 30,000 DKK, we anticipate a return on investment (ROI) in less than three years. The reduction in CO2 emissions in the demos is proportional to their energy savings. However, by utilizing flexible tariffs and CO2 signals, we could further reduce CO2 emissions significantly.

7.1 Conclusions related to data-driven digital twins

Reliable room-specific grey-box models for indoor temperature were successfully constructed and estimated using data collected from CLIMIFY and DMI. These models were formulated based on ordinary differential equations, incorporating splines to manage solar radiation input and a logistic function to model radiator valves' behavior. It was determined that for this model structure to be robustly identifiable consistently across any room type, it is essential to impose a lower bound on the timescale of the heat dynamics. Additionally, the building envelope should be represented by a single temperature state. The models proved to be sufficiently fast to be integrated into a model predictive control scheme, which was demonstrated effectively in both simulated and real environments.

7.2 Conclusion related to Model Predictive Control

A model predictive controller (MPC) based on building thermal dynamics, integrated with a nonlinear model of a radiator, has been developed. The controller is formulated as a quadratic programming problem, which considers both technical and comfort constraints. The results demonstrate that the MPC effectively utilizes the nonlinear model to maintain thermal comfort throughout the day. Additionally, another MPC has been developed to make the controller responsive to a price signal. This second controller is also formulated as a quadratic programming problem and adheres to the same technical and comfort constraints. The price/penalty signal is represented as a pulse-like signal, with high-penalty periods indicating times when reducing energy demand is preferable. The findings indicate that this new MPC design can shift energy demand to low-penalty periods dictated by the price/penalty signal, without compromising thermal comfort at any point during the day.

7.3 Next steps and future developemnts

The potential of the COMFORT-ID (C-ID) has been demonstrated, highlighting the need to expand its capabilities from thermal comfort alone to encompass the entire spectrum of the indoor environment, including preferences and discomforts related to ventilation, acoustics, lighting, and potentially ergonomics.
Regarding control algorithms, most existing Model Predictive Controllers (MPCs) for building thermal dynamics utilize linear models. In this project, we employed a nonlinear model that includes the radiator's dynamics. Our findings suggest that nonlinear models enhance the MPC's ability to generate accurate control signals, maintaining thermal comfort and improving cost efficiency by optimizing energy demand throughout the day. These outcomes signal a move towards more precise modeling and control strategies.

While a fixed nonlinear model was used in this project, future developments could explore combining system identification methodologies with adaptive model predictive control. This approach would allow for ongoing adjustments to model parameters, enhancing accuracy and adaptability. However, the nonlinear nature of the model introduces complexities in parameter identification, necessitating robustness analysis of the developed MPCs to manage variations in model parameters. MPCs are sensitive to model inaccuracies and external disturbances, which can degrade performance. Therefore, it is recommended to focus on developing a robust model predictive controller that explicitly incorporates model uncertainties and disturbances into its design, ensuring optimal performance even under varying conditions.

Additionally, while traditional approaches depend heavily on system models, learning-based control strategies, such as those using reinforcement learning, offer promising alternatives. These methods are capable of learning system dynamics from a rich dataset and a well-defined reward function. Future research should investigate the application of reinforcement learning control to building thermal dynamics, paving the way for more autonomous and efficient environmental control systems.

8. Appendices

Project description online, and and demo description can be found on:

- www.CLIMIFY.com/solutions
- www.uni-lab.dk

We have published the results on social media, gaining consistent visibility among stakeholders and potential customers, and on technical and scientifical medias, including:

1. Danish Journal: Bjarne W. Olesen, Davide Calì, Christian A. Thilker, Henrik Madsen. Integrering af brugeren i regulering af indeklimaet. HVAC magasinet, Årg. 58, nr. 5 (2022), S. 46, 48-50, 52;
2. Book: Occupant-Centric Simulation-Aided Building Design: Theory, Application, and Case Studies, Taylor and Francis, edited by L. O'Brian and F. Tahmasebi: contribution to chapter 6: "Introduction to occupant modeling". Book under production, chapter is reviewed, contract is signed;
3. Conference paper (paper accepted, presentation in August 2022): Seyed Shahabaldin Tohidi, Davide Cali, Meril Tamm, Joana Ortiz, Jaume Salom, Henrik Madsen, From white-box to grey-box modelling of the heat dynamics of buildings, Building Simulation Nordic 2022;
4. Journal article: Matteo Favero, Jan Kloppenborg Møller, Davide Calì, Salvatore Carlucci. A Human-in-the-loop approach method for occupant-centric building design and operation. Applied Energy.

Other publications are currently either under finalization or in publication phase.