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Sustainable
plus energy
neighbourhoods

WP4 - Flexibility measures in different climate zones & markets

D4.2 CHARACTERIZATION OF THE THERMODYNAMIC PROPERTIES OF THE DEMONSTRATION CASES

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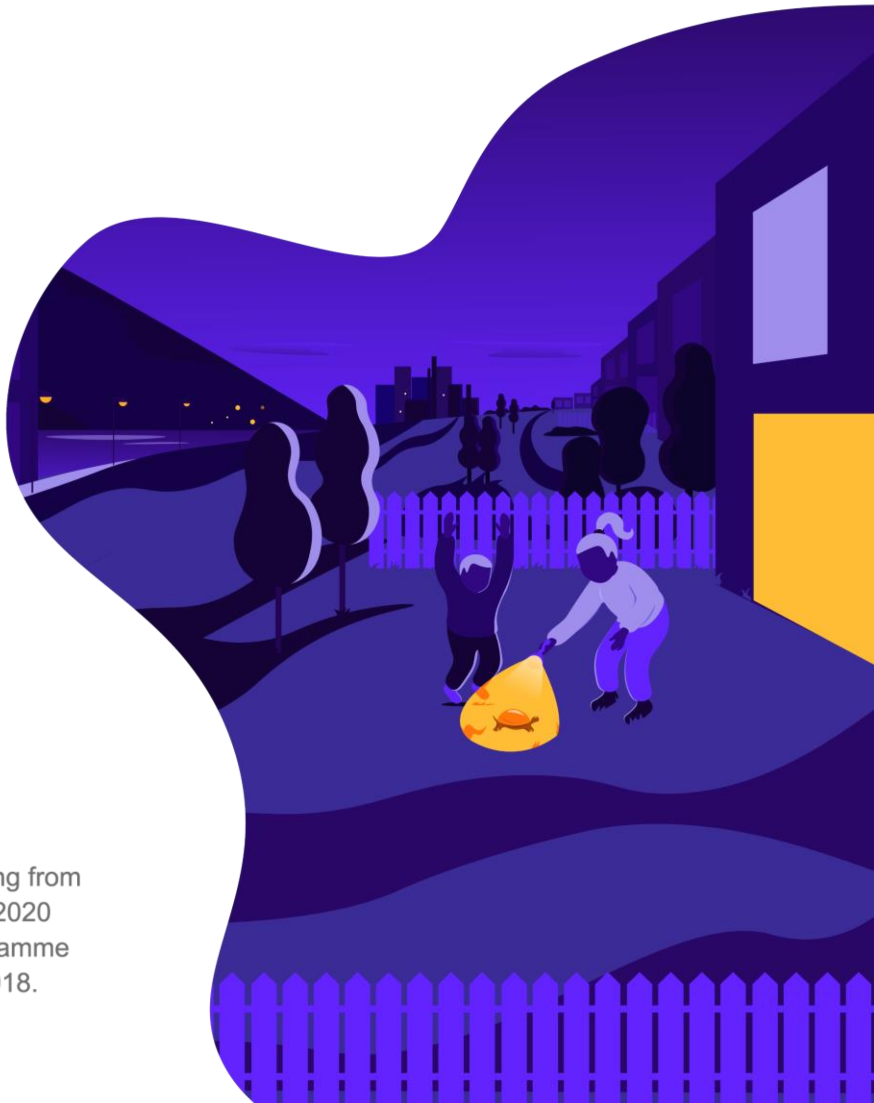

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Executive Summary

The goal of this report is to evaluate the flexibility of each demonstration case, which indicates the capability of reducing costs while providing an appropriate amount of thermal power in each demo. This is done by calculating a so-called flexibility index, as an indicator of cost saving, resulting from employing advanced control strategies.

This report focuses on the HVAC system modelling and controller design: scope of the controller is to provide an optimal schedule for the electricity usage of the HVAC system using predictions, forecasts, and estimation. Specifically, the controller maximizes the electricity consumption of the HVAC system during the periods when the electricity price is lower, and minimize the usage when the price is highest. In addition, the designed controller enables considering the HVAC system constraints and limits to respect occupants' thermal comfort.

Such a controller relies on low dimensional but relatively accurate model of the system. To find an appropriate model, an investigation of various parts of the HVAC system, consists of heat pumps and storage tanks, is required. This provides a proper insight about the setpoints and control parameters necessary for the controller design and modelling procedure. In addition, it determines the constraints and limitations of the HVAC system.

To be able to provide an optimal schedule, the controller requires some information about the future. This information consists of weather, solar irradiation, electricity price, etc. Employing the required forecasts and estimations through some specific horizon, the identified model can predict the future states and outputs, leading to a controller equipped with adequate prediction data. Since the required forecasts are planned to be available via cloud hub, in Tasks 4.4 and 4.5, last year's data is used for the simulation purposes in this report. Based on this set of data, an optimization problem needs to be solved to find the best schedule for electricity consumption of HVAC system such that the costs are minimized while the constraints are satisfied.

As already planned in the proposal, this task is based on white-box models, and not on real measured data. Therefore, the modeling and the control here illustrated are referring to the white box models of the demos. The HVAC system of Norwegian, Spanish and Dutch demos consist of heat pumps and storage tanks, while that of the Austrian demo does not include storage tanks at the time of writing this report (a detail model of the HVAC is currently under developments). Therefore, the objective of the designed controller for the Norwegian, Spanish and Dutch demos are different from the control objective in the Austrian demo. For the Norwegian, Spanish and Dutch demos, the controllers manage to keep storage tank water temperature in a predefined boundary, while the designed controller for the Austrian demo preserves the indoor temperature in a predefined comfort zone. The insights derived from the model identification and controller design procedures in accordance with the provided formulations and descriptions for each demo will guide the activities in Tasks 4.3, 4.4, and 4.5.

In this report, the flexibility potential of each demo is investigated by comparing the results of employing two different control strategies, one with constant penalty signal and the other with time-varying penalty. Using time-varying penalty signal for the electricity consumption encourages the controller to manage electricity consumption by using less energy in the periods where electricity price is high. This leads to an optimal scheduling of electricity consumption. The accumulated energy consumption and the electricity price of the constant and of the time-varying penalty signal are then compared, and an indicator, called flexibility index, is calculated to show the flexibility potential in each demo.

Task description

This task is meant for identifying the thermodynamic properties of each demo and evaluate the flexibility potential of each demo. Within this scope, and for the demos in Spain, Norway and Austria, we implemented the following steps:

1. Finalize the tuning of the grey-box models from T4.1, based on latest and most updated descriptions of the demo sites, and on the latest white-box models simulation results;
2. Identify the characteristic properties of a sample apartment from each demo, including thermal capacity, thermal resistance, time constant, etc. (extracted from the grey-box model);
3. Extend the grey-box model of each demo with grey-box models of the HVAC systems of each demo;

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1. Roles and Responsibilities

Name	Role	Responsibility
DTU	Task 4.2 leader. Coordinator of deliverable contents and edition; Contributor and chapter editor	Modelling and control design, Flexibility calculations; Content's review and edition of deliverable; Coordination
NTNU	Contributor	Demo project description
IREC	Contributor and reviewer	Demo project description, Content's review and edition of deliverable
TNO	Contributor	Demo project description, Modelling and control design, Flexibility calculations
ABUD	Contributor	Demo project description

2. Introduction

Advanced control strategies are vital parts of modern dynamical systems to guarantee stability and enhance performance. These controllers should be designed such that they can provide optimality and high robustness level. Controllers that can provide optimality, generate control signals by solving an optimization problem that aims to minimize or maximize a predefined cost function. Robustness, on the other hand, can be preserved by taking care of disturbances and unmodelled dynamics in the design procedure.

Model predictive controller (MPC) is an advanced control methodology that optimizes a sequence of adjustable variables over a horizon by employing a dynamical model for prediction. It can also handle various types of input, output, and state constraints of the dynamics by formulating them in the optimization problem. Computational complexity of model predictive controllers is relatively high compared to other control methods due to their requirement for numerical optimization algorithms. However, thanks to the advances in the production of powerful processors, this is not a game changer issue anymore. Moreover, solving optimization problem iteratively and considering forecasts make model predictive controller an optimal and robust control approach.

Various types of model predictive control have been proposed in the literature for energy systems. Decreasing energy consumption, load shifting, cost reduction and indoor air quality improvement are some of the topics that this controller has been shown to be efficient. Economic model predictive controller (EMPC) is an MPC that considers dynamic deviations of energy prices and minimizes costs. In this report, an EMPC is employed to minimize the costs by shifting the peak of consumption to low price periods of time. In addition to cost efficiency, this enables supporting the demand side management by shifting the electricity consumption to an appropriate period.

For a model predictive controller to operate properly, a relatively precise model of dynamical system is required. This low-dimensional model predicts the future behavior of the system using information obtained by forecasts and estimation. In this report, HVAC system is going to be controlled to provide cost efficiency. To this end, a low-dimensional model of HVAC system, consist of heat pump and storage tank, is identified using data generated by white-box models. A statistical model is found for the heat pump coefficient of performance (COP), that considers COP as a linear combination of input and output water temperatures of heat pump and ambient temperature. Grey-box (GB) model, which consists of a set of first-order stochastic differential equation (SDE), is also identified to represent the dynamics of water temperature in storage tank. The tank can be modelled as single or multi-layer tank based on the resolution of data. Considering multi-layer tank model resembles the dynamics of tank water temperature accurately, that leads to a more efficient prediction and control. The HVAC systems of Spanish, Norwegian and Dutch demonstration cases contain heat pump and storage tank, responsible for providing water at some specific temperature for domestic hot water (DHW) and heating purposes. Different from the other demos, storage tank is disregarded in the Austrian demonstration case due to the lack of data. This motivates us to design an EMPC that improves cost efficiency while preserving indoor thermal comfort.

To highlight the efficiency of the designed controller, an MPC that is not triggered by the price signal is compared to an EMPC which operates based on the price signal variations. Finally, flexibility index (FI), that indicates the capability of shifting loads using price signals, compares the results of the two optimal control results and describe it by a single percentage. Flexibility index also simplifies the interpretation of this capability for a wider audience, such as end users and decision makers. Simulation results also support our discussion and demonstrate the efficiency of the economic model predictive controller.

This report is organized as follow: description of the apartments of each demonstration case including thermal systems such as heat pumps, storage tanks, setpoints and control parameters are provided in Section 7. Thermodynamic properties of the apartments in each demo are characterized in Section 8. Modelling of HVAC system including heat pump and storage tank models are given in the next section. In Section 10, economic model predictive controller formulations are provided, and the simulation results are demonstrated for each demo. Finally, flexibility index, showing the capability of load shifting in each demo is calculated in Section 11.

3. Description of demos (Introducing HVAC system, setpoints, and control Parameters)

3.1. Spanish demo

Fondo, Santa Coloma de Gramenet Spanish demo neighbourhood.
Climate: Mediterranean

The project is located in Santa Coloma de Gramenet, a city located 4 km from Barcelona, and the demonstration area is placed in a neighbourhood that is involved in an urban regeneration process. The project aims to create open spaces in an existing neighbourhood, refurbishing the buildings of the area and improving habitability of the surrounding buildings.

Figure 1 Illustration of the demo project located in Santa Coloma de Gramenet.

The demonstration site is a newly built urban project, a multi-family building comprising 38 dwellings, 2 commercial premises, and 38 parking spaces.

Gross floor area is 2495 m^2, being the heated floor area 2154 m^2. Figure 2 draws the Barcelona demo site building's elevation section.

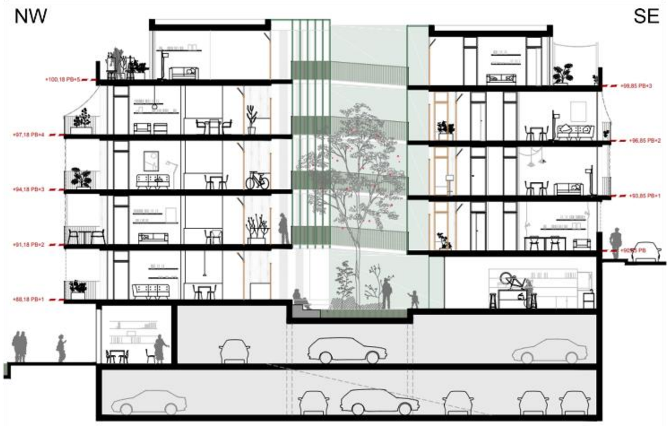

Figure 2 Architectural drawings of floor plan of the Barcelona demo site building's elevation section.

Energy design

The integrated energy design of the building includes both passive and active energy saving solutions.

> Passive systems: Optimized insulation for each facade; inertia of elements; shadows (to control overheating in summer); control the absorbency of materials; and optimal ratio of windows in facades.
>
> Active systems: Centralized heat pump for domestic hot water and heating supplied by photovoltaic panels

The selected technical systems allow to cover the low thermal demands of the building with an innovative and highly efficient solution. Additionally, the building includes a photovoltaic installation to cover the electric needs of the building and to share the excess energy with the neighbourhood. The integrated energy design process has been done based on a multicriteria analysis, considering energy, environmental, indoor comfort, and economic parameters.

HVAC system

In the Spanish demo case three heat pumps on building level will provide heat for space heating and domestic hot water. Each apartment is equipped with a substation heat exchanger, with a heat exchanger for each the DHW and the Heating circuits. On the building, 119 PV-panels are installed to provide power to the heat pumps. The basic layout is represented in Figure 3 and Figure 4.

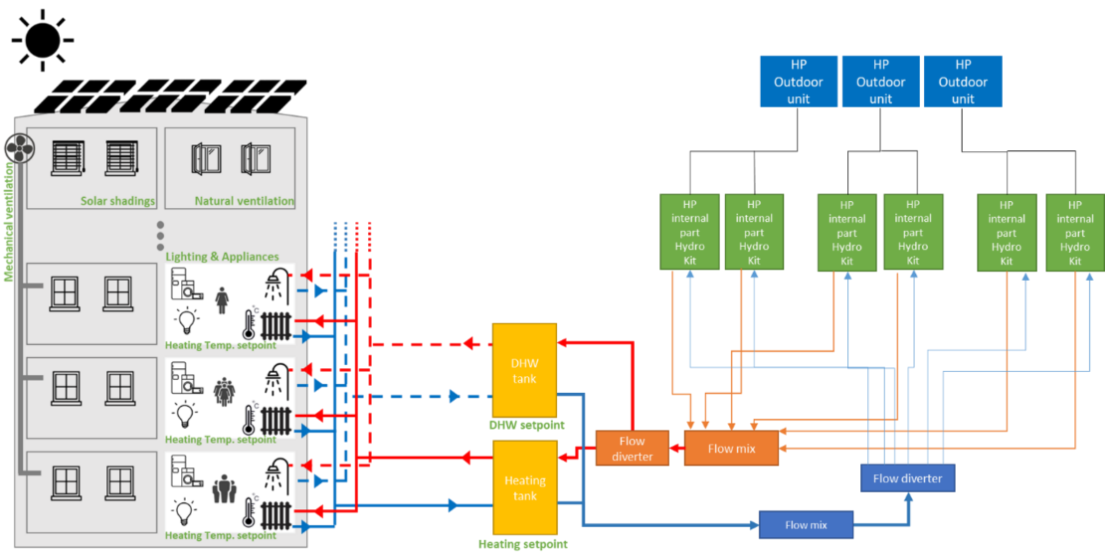

Figure 3 4-pipes Heating and DHW configuration of the air-to-water heat pump system.

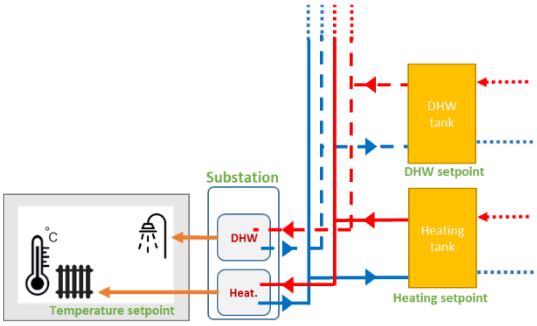

Figure 4 Zoom-in at the apartment level of Figure 3

Figure 5 below shows the detailed HVAC installation.

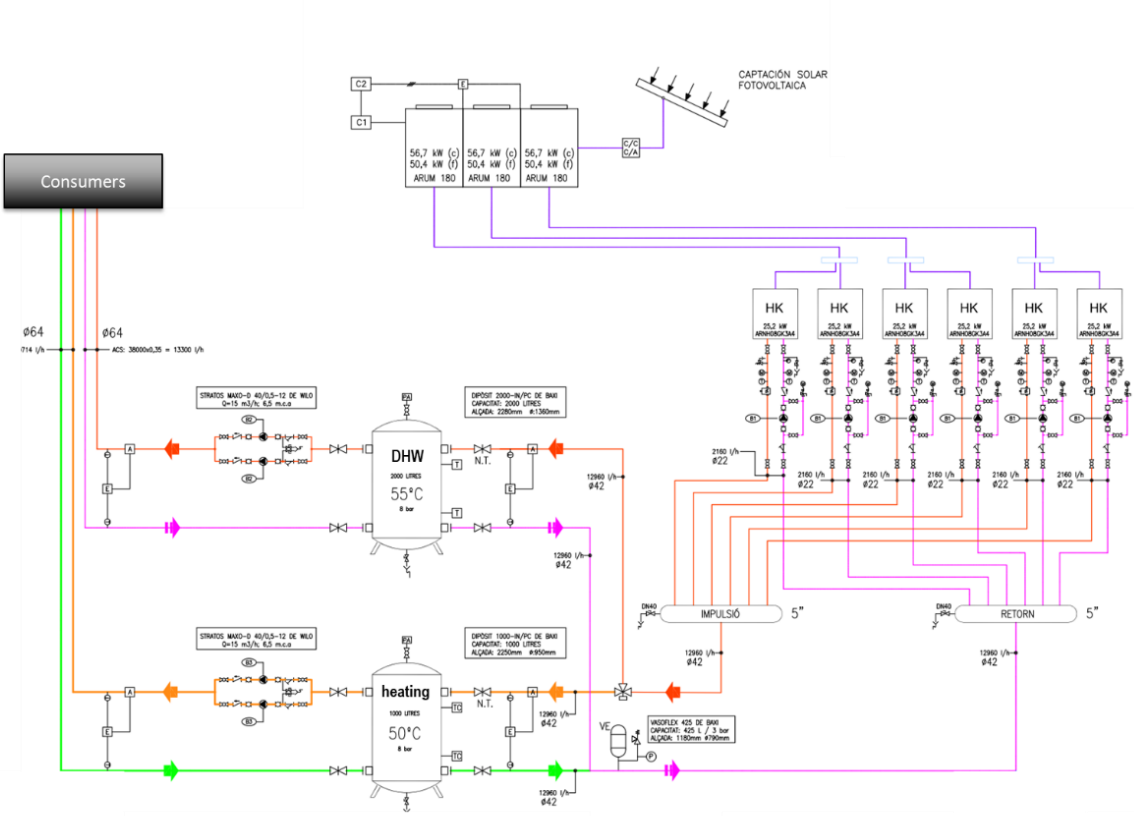

Figure 5 Blueprints of the HVAC system, generation and storage.

SETPOINTS AND CONTROL

The following table summarizes the building equipment and their functions. The devices can either provide readable data, accept setpoint control or both.

Table 1 Building equipments.

	Level		
Function	*District*	*Block*	*Apartment*
Space heating	None	Air-to-water Heat Pump - LG	Substation Heat exchanger - LEAKO
Space cooling	None	None	None

Domestic hot water (DHW)	None	Air-to-water Heat Pump - LG	Substation Heat exchanger - LEAKO
Ventilation	None	None	None
PV-system	None	BAXI - KIT FOTON	None
EV-Charging point	None	EV-Charging point	None
Appliances & electric devices	None	Electric meters	Electric meters

All appliances provide available readings, while controllable appliances are the substation heat exchangers at apartment level, and air-to-water heat pumps at building level.

For control purposes, available readings are sensor data in direction from appliance to the syn.ikia cloud hub. Settings and setpoints are values resulting from the control algorithm that can be pushed from cloud to appliance.

Detail of the available readings and set point control, are in syn.ikia's Deliverable 3.7, appendix A.

Of interest for the space heating and domestic hot water functions of the heat pump, are:

Building level:

- Weather station (readings)
- Heat pump (reading + settings and setpoints)
- DHW water tank (readings+ settings and setpoints)
- Heating water tank (readings+ settings and setpoints)

Apartment level:

- Substation heat exchanger (readings+ settings and setpoints)
- Emitter
- Thermostat (readings+ settings and setpoints)

At building level, the PV system Inverter provides the value of the produced power as an available reading.

3.2. Norwegian demo

The Norwegian demo case is part of a new development in Fredrikstad, called Verksbyen, representing the subarctic European climate. It is the largest development of plus energy houses in Norway, and it has a strong focus on energy sharing and flexibility in the neighbourhood.

<u>Norway</u>
Climatic zone: Subarctic

Figure 6 Illustrations of the Verksbyen demonstration project in Fredrikstad, Norway.

Scope and stakeholders

The demonstration case will be built in Fredrikstad, which is a town located approximately 90 km south of Oslo. The total development consists of more than 1500 dwellings, a kindergarten, a school, and commercial buildings. Two of the residential blocks will be included as demonstration projects in syn.ikia: One block called Panorama with 20 units, and one block called Atrium with 36 units. The apartment blocks are 5-6 storeys high; the Panorama block has a total floor area of 1775 m2, while the floor area of the Atrium block 2779 m2.

Table 2 Key data for the Norwegian Demo Case.

Neighbourhood Number of demo buildings: 2 Number of housing units: 56	Construction Construction start: Fall 2021 Construction end: Summer 2023
Investment cost n/a	Project Developer Arca Nova Bolig AS

The ambition level and possible innovations

The ambition level for energy performance will be plus energy according to the syn.ikia definition. Renewable energy technologies applied in the demonstration case include a ground source heat pump system and building integrated photovoltaics. Special innovations in the demonstration case will be the following:

- Establishing a neighbourhood energy system
- Architecturally integrated PV
- Smart house technology
- Smart charging of electric vehicles (EV charging not designed yet)
- Low carbon design, largely wood-based construction, prefab elements, concrete and steel structure
- Use of recycled materials (recycled construction steel)
- Social sustainability with emphasis on shared spaces and IT platform for energy awareness (not specified yet)

Table 3 Estimated energy need, share of renewables, and energy production.

Estimated energy need	78 kWh/(m^2yr)
Estimated energy need for heating (space and DHW)	45 kWh/(m^2 yr)
Estimated energy need for cooling	0 kWh/(m^2 yr)
Estimated energy need for electricity	15 kWh/(m^2yr) EPB uses
Net delivered final energy	-13 kWh/(m^2 yr) surplus
GHG emissions from energy use	-1,7 kg CO_2-eq/(m^2 yr) negative
Renewable energy generation	51 kWh/(m^2 yr)
Share of renewables	100%
Types of renewables	Photovoltaics, Ground source heat pump
Energy storage : sizes and strategies	DWH, ground, building structure
Smart metering/home automation systems and systems for feedback to the users	FutureHome system
Set point for heating and cooling	Heating: 21 ˚C, Cooling: n/a

The Panorama building is compact and well-insulated. The roof is oriented towards the south (with PV panels). The window and door area of the heated area (BRA) is 22%. The balconies have an enclosed part that increases the period of use and functions as a buffer space.

The building envelope's thermal properties should align with the Norwegian Building Code TEK17 and Passive-house standard – NS3700:2013 (Criteria for passive houses and low energy houses – Residential buildings) except for the building component – internal floors.

Designed thermal properties of the building envelope (Panorama building)
U-values [W/m^2K]:

- exterior wall = 0.1
- roof = 0.08
- external floor = 0.13
- internal floor = 0.50
- windows and doors = 0.83
- normalised thermal bridge factor = 0.03

Infiltration (n50): 0.6 ACH

The heating system is a centralized water-borne floor heating system that distributes thermal energy to the apartment from the main energy distributor, and the medium is water. There is no cooling system planned; this will be handled with ventilation, windows opening and shading. The thermal energy is supplied from a ground source heat pump. Peak load is covered by district heating. Each room has a thermostat.

The domestic hot water system is also centralized, where DHW is distributed to the different apartments.

The ventilation system is based on decentralized air-handling units. Each apartment has its ventilation unit with heat recovery. Balanced ventilation with supply in bedrooms and living rooms, and exhaust(forced) in kitchen and bathrooms

The occupants control the thermostat set-points in their apartments. The simulations were performed with a heating set point: 21℃ with night setback: 19℃

PV panels will be installed on roofs and suitable south-facing facades.

3.3. Austrian demo

The Austrian demo is a new residential development in Salzburg. It is a greenfield development located on the outskirts of the city in a quiet area with mostly multifamily houses.

The development consists of 17 new buildings and refurbishment of 2 already existing buildings. Most of the buildings are multi-residential, half of the dwellings will be social housing units and half will be sold on the market. There will also be a Kindergarten and a zone managed by social aid and service organization "Caritas".

The project is developed by "Heimat Österreich" together with the City of Salzburg and many other contributors. In addition to achieving the syn.ikia goals, the project aims to achieve the Austrian 'klimaaktiv certification' and many other project specific goals that are fixed in a quality agreement. Illustrations and overview plans of the development can be seen in Figure 7 and Figure 8.

Figure 7 Illustration for the continental case in Austria GNICE.

Figure 8 Overview for the continental case in Salzburg, Austria GNICE.

As there are refurbished, and also newly built buildings in the development, HVAC systems and therefore control parameters and setpoints also differ. For the purpose of the MPC, the system of the newly built area is described.

Gross floor area of the project is 25 062 m^2 and the heated area 17 367 m^2.

Thermal properties of the buildings are collected in Table 4.

Table 4 Description of building thermal properties in continental case in Salzburg, Austria GNICE.

Heated floor area		W/m^{2}K
Envelope	Wall	0,12-0,15
	Slab on ground	0,18
	Roof	0,10
	Windows	0,8-1,20
	Glass to wall ratio	~35 %
	Infiltration rate	1,5 ach

Besides the robust envelope design, the development incorporates shading as well to reduce energy consumption, and elevate comfort levels.

<u>HVAC system:</u>

The Austrian case uses the waste heat from sewage water coming from the buildings. Sewage water is lead through a heat-exchanger before letting it out in the sewer. With an approximately 17.5 °C temperature, this provides a great source of heat for the development. Since heating cannot be satisfied with only using this source of heat, a geothermal heat pump is installed to complement the system.

During the year, heat from waste water is preferred as a primary option, and whenever there is need, the geothermal heat pump switches on. This heating system is a central system catering for all 17 buildings in the development.

Although in the design, hot water is stored in a central water-tank, in the current white-box model there is no water tank present.

PV panels are planned on every building roof, however, due to extensive greening of the roof area, for PV purposes only around 30% of the roof can be utilized.

However, in the actual simulated model, the heat tank is not considered. Conceptual drawing of the first white-box model created based on the HVAC system model. This first version of the white box (Figure 9) model did not consist of the utilization of waste heat from sewage water:

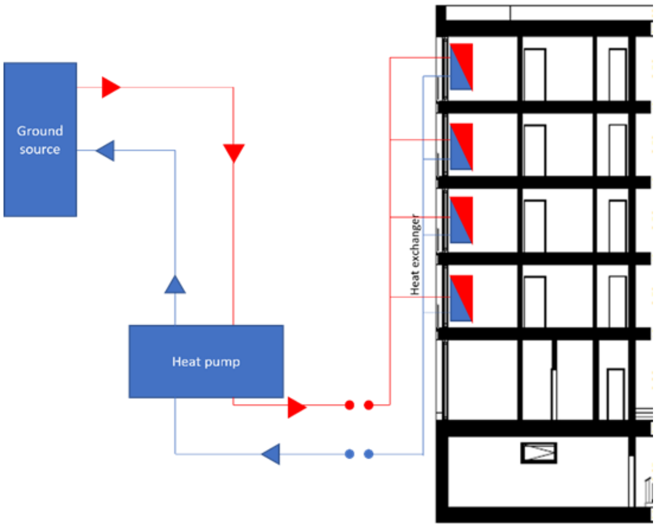

Figure 9 Conceptual drawing of the HVAC system modelled in the white-box model.

The updated white box model contains the waste heat from the sewage water coming from the development. In conceptual drawing shows the updated model:

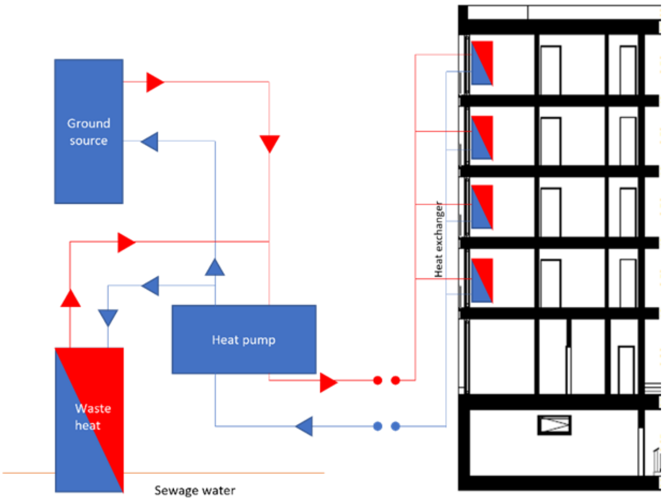

Figure 10 Conceptual drawing of the HVAC system modelled in the updated white-box model.

SETPOINTS AND CONTROL

Table 5 below summarizes the equipments and their functions.

Table 5 Summarizing equipments and their functions in the development in Austria.

	Level		
Function	***District***	***Block***	***Apartment***
Space heating	Waste heat from sewage complemented with GSHP	None	Heat-exchanger
Space cooling	None	None	None
Domestic hot water	Waste heat from sewage complemented with GSHP	None	Heat-exchanger
Ventilation	None	None	None
PV-system	None	PV panels	None
EV-Charging point	None	None	None
Household appliances	N/A	N/A	Electric meters

In the buildings there is mechanical ventilation in most common spaces, and natural ventilation in smaller apartments. Currently there is no cooling planned in any of the buildings.

The control parameters can be seen below in Table 6:

Table 6 Summarizing parameters for the development in Austria.

Heating set point		20°C
Heating setback		18°C
Control	Room temperature control	

3.4. Dutch demo

The Dutch demo is a new apartment building located in Uden in the South of the Netherlands. The apartment complex consists of 39 one- and two-bedroom apartments divided in two wings of three floors. The construction phase started in 2021 and the building was completed in April 2022.

Figure 11 Architectural impression of the demo project in Uden.

Figure 12 Status realization in March 2022.

The ambition level for energy performance is plus energy use for the building related energy uses. Per January 2021, the design is finalized. The design consists of:

Passive systems:

- Good insulation (high thermal resistance (Rc))
  - Façade: Rc = 6.1 m^2K/W
  - Roof: Rc = 8.1 m^2K/W
  - Floor: Rc = 5.1 m^2K/W

- Airtight building ($q_{v;10}$ value < 0.3 $dm^3/s/m^2$ at 10 Pa)[1]
- Triple glazing (U_w = 1.0 W/m^2K)
- Doors (U = 1.2 W/m^2K)

Active systems:

- Individual ground source heat pumps for space heating. space cooling and domestic hot water in each apartment
- Floor heating and cooling
- Mechanical exhaust ventilation with CO_2 sensor
- PV on the roof

The equipment is schematically presented in Figure 13.

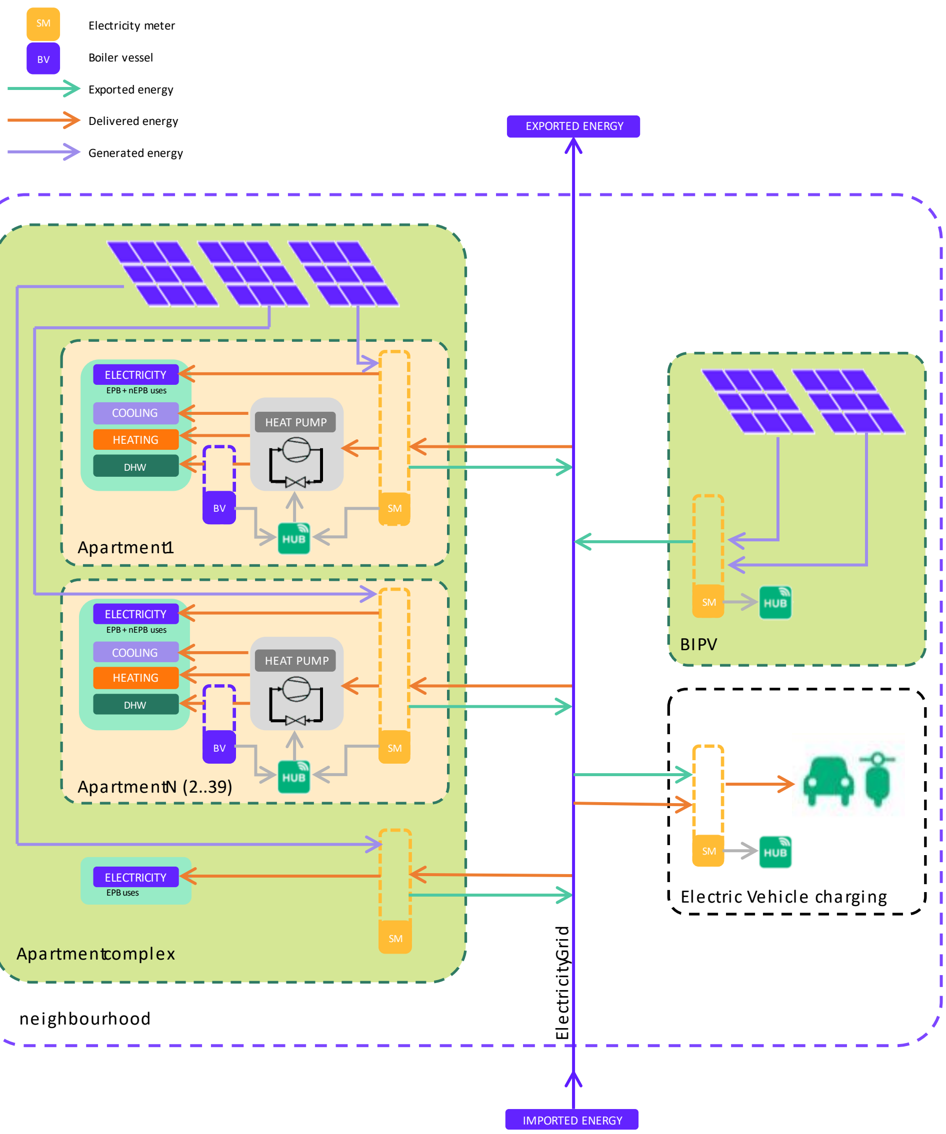

Figure 13 Equipment schematic.

[1] Air tightness of a building, indicated by $q_{v,10}$, means the air volume flow (q_v) that arises through the cracks and seams that are located between the various building parts in the building envelope at a pressure difference of 10 Pa. Divided by the usable floor surface of a building the specific $q_{v,10}$ is obtained ($dm^3/s/m^2$ at 10 Pa).

Apart from neighbourhood level PV and electric vehicle charging, each apartment has individual PV panels and an individual ground source heat pump used for heating and cooling and domestic hot water.

The heat pump is both used for domestic hot water production and floor heating/cooling. The heat pump can only be on/off controlled. Domestic hot water production and floor heating/cooling are mutually exclusive.

4. Characterization of the Thermodynamic Properties of Apartments

The thermodynamic properties consist of time constant, settling time, total thermal resistance, total heat capacity, total HLC-value (heat loss coefficient, also called heat transfer coefficient (HTC) or UA-value) of the building, etc. can be obtained using the grey-box model found in the Task 4.1. The grey-box models consist of a set of first-order stochastic differential equations and can be equivalently described by the electrical circuits including resistors and capacitors (RC). These simplified low-dimensional models are capable of representing thermal behaviours required for prediction and control purposes. Example of an RC model including interior, heater, solar, envelope and ambient dynamics are given in Figure 14. The parameters of this circuit are provided in *Table 7*.

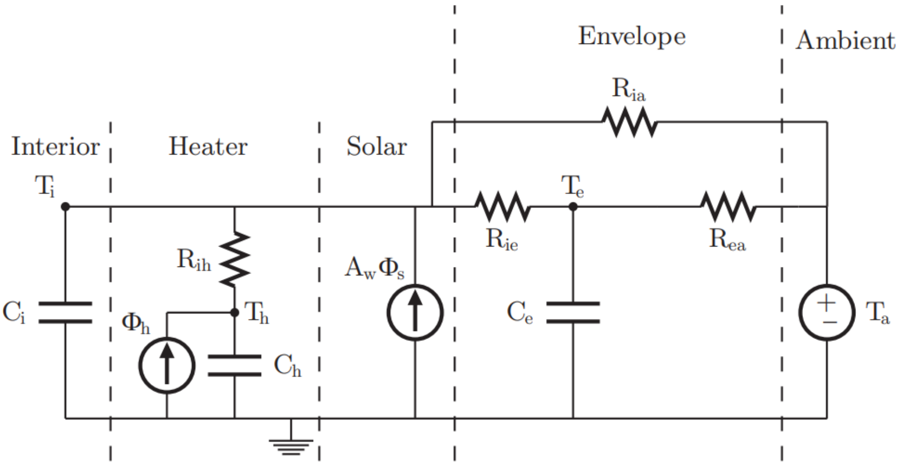

Figure 14 An example of an electric circuit equivalent to the thermal dynamics of a building [1].

An optimization problem [2] is being solved to identify the parameters of the grey-box model [1], [3]. Computer software CTSM-R can be used to solve the optimization problem and estimate the parameters simultaneously [4]. The optimization algorithm is based on maximizing the likelihood between the selected model and the given data. This optimization is based on a hypothesis test that finds out if the model is able to represent the dynamics without some of the parameters. That is the reason why some of the models are simpler that the others.

Table 7 Grey-box model parameter definition.

C_i	Interior heat capacity	kWh/K
C_e	Building envelope heat capacity	kWh/K
C_h	Heating system capacity	kWh/K
R_{ie}	Thermal resistance between interior and the building envelope	K/kW
R_{ea}	Thermal resistance between building envelope and the ambient	K/kW
R_{ia}	Thermal resistance between interior and the ambient	K/kW
R_{ih}	Thermal resistance between interior and heating system	K/kW
A_w	The effective window area of the building.	m^2

T_i	Interior temperature	K
T_e	Building envelope temperature	K
T_h	Heater temperature	K
T_a	Ambient temperature	K
Φ_h	Heat input	kW
Φ_s	Solar irradiance	kW/m^2

Building envelope isolation properties can be identified using heat transfer coefficient [5], [1], that is a summation of normalized heat flow rate due to ventilation and transmission:

$$\alpha_{UA} = \frac{1}{A_{use}}\left(\frac{1}{R_{ie} + R_{ea}} + \frac{1}{R_{ia}}\right) \tag{1}$$

where R_{ie}, R_{ea} and R_{ia} are defined in *Table 7* and A_{use} is the useful floor area. Time constant, that is an indicator of how fast the dynamics respond, can be calculated by using the following formula:

$$\tau_i = \frac{1}{|Re\{\lambda_i\}|}, \tag{2}$$

Where $Re\{.\}$ indicates the real part of the eigenvalue and λ_i stands for the ith eigenvalue of the state matrix. As a rule of thumb, $T_{set} = 4\tau_i$ is the time that the dynamics reach to their steady state. The thermodynamic properties of apartments in each demo are calculated using the simplified low-dimensional grey-box models.

4.1. Spanish demo

Using statistical analysis and the generated data from the Spanish demo white-box, the best structure for the grey-box model is found as

$$\begin{aligned} C_i dT_i &= \left(\Phi_\mathrm{h} + A_w\Phi_s + \frac{T_e - T_i}{R_{ie}}\right)dt + \sigma_i d\omega_{i,} \\ C_e dT_e &= \left(\frac{T_i - T_e}{R_{ie}} + \frac{T_a - T_e}{R_{ea}}\right)dt + \sigma_e d\omega_e, \\ Y_k &= T_{i,k} + e_k, \end{aligned} \tag{3}$$

where Y_k is the measured interior temperature. To represent the stochastic behaviour of the heat dynamics, we introduce ω_i and ω_e as standard Wiener processes, where σ_i^2 and σ_e^2 are the incremental variances of the Wiener processes. The deterministic part of the model can be considered as the following RC circuit given in Figure 15.

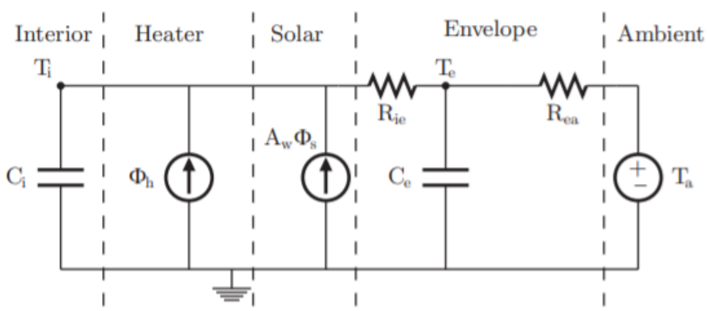

Figure 15 RC circuit representing the thermal dynamics of the Spanish demo.

The estimated values of the parameters of the grey-box model for the Spanish demo are found as $R_{ea} = 59.08\ K/\mathrm{kW}$, $R_{ie} = 2.3\ K/\mathrm{kW}$, $C_e = 2.4\ \mathrm{kWh}/K$, $C_i = 0.1\ \mathrm{kWh}/K$ and $A_w = 1\ m^2$ using CTSM-R. Time constant of the model can be calculated by using (2), with the state matrix

$$\begin{bmatrix} \frac{-1}{R_{ie}C_i} & \frac{1}{R_{ie}C_i} \\ \frac{1}{R_{ie}C_e} & \frac{-1}{C_e}\left(\frac{1}{R_{ie}} + \frac{1}{R_{ea}}\right) \end{bmatrix}, \tag{4}$$

of the grey-box model (3). Using the estimated values and the given formulas, an estimation of thermodynamic properties of the Spanish demo is provided as: $\tau_1 = 0.22\ h$, $C_{total} = 2.5\ \mathrm{kWh}/K$, $R_{envelope} = 61.38\ K/kW$ and $\alpha_{UA} = 0.36\ W/(m^2K)$ for an apartment of size $45.4\ m^2$.

4.2. Norwegian demo

Applying the procedure of identifying grey-box model from white-box, the grey-box of apartments in the Norwegian demo has been found as

$$\begin{aligned} C_i dT_i &= \left(\frac{-T_i + T_\mathrm{h}}{R_\mathrm{ih}} + \frac{-T_i + T_e}{R_{ie}} + A_w \Phi_s\right) dt + \sigma_i d\omega_i, \\ C_\mathrm{h} dT_h &= \left(\frac{T_i - T_\mathrm{h}}{R_\mathrm{ih}} + \Phi_\mathrm{h}\right) dt + \sigma_h d\omega_h, \\ C_e dT_e &= \left(\frac{T_i - T_e}{R_{ie}} + \frac{T_a - T_e}{R_{ea}}\right) dt + \sigma_e d\omega_e, \\ Y_k &= T_{i,k} + e_k, \end{aligned} \tag{5}$$

where Y_k is the measured interior temperature. Also, ω_i, ω_h and ω_e as standard Wiener processes with σ_i^2, σ_h^2 and σ_e^2 as the incremental variances of the Wiener processes are introduced to represent the stochastic behaviours. The deterministic part of the model can be considered as the following RC circuit.

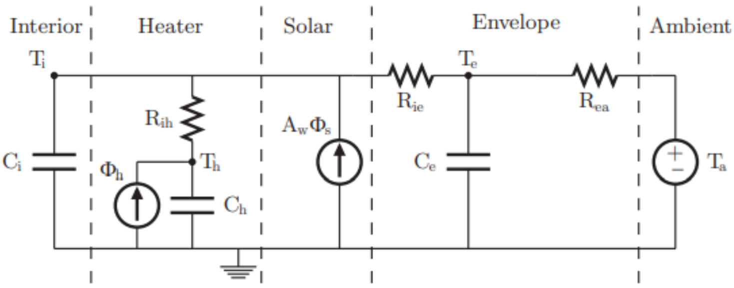

Figure 16 RC circuit representing the thermal dynamics of the Norwegian demo.

The estimated values of the parameters of the grey-box model for the Norwegian demo are $R_{ea} = 99.7\ K/\mathrm{kW}$, $R_{ie} = 0.94\ K/\mathrm{kW}$, $R_{ih} = 0.13\ K/\mathrm{kW}$, $C_e = 21\ \mathrm{kWh}/K$, $C_i = 2.3\ \mathrm{kWh}/K$, $C_h = 0.76\ \mathrm{kWh}/K$ and $A_w = 3.82\ m^2$. Using (5), the state matrix can be obtained as

$$\begin{bmatrix} \frac{-1}{R_h C_i} - \frac{1}{R_{ie}C_i} & \frac{1}{R_{ih}C_i} & \frac{1}{R_{ie}C_i} \\ \frac{1}{R_{ih}C_h} & \frac{-1}{R_{ih}C_h} & 0 \\ \frac{1}{R_{ie}C_e} & 0 & \frac{-1}{R_{ie}C_e} - \frac{1}{R_{ea}C_e} \end{bmatrix}, \tag{6}$$

for time constant calculations. Using the estimated values and the given formulas, the thermodynamic properties of the Norwegian demo is provided as: $\tau_1 = 0.07\ h$, $\tau_2 = 2.5\ h$, $C_{total} = 23.3\ \mathrm{kWh}/K$, $R_{envelope} = 100.64\ K/kW$ and $\alpha_{UA} = 0.13\ W/(m^2K)$ for an apartment of size $76\ m^2$. In this study, dominant states' time constants are considered, and the other time constant is disregarded.

4.3. Austrian demo

CTSM-R is used to estimating the parameters of the grey-box model for the Austrian demo as

$$\begin{aligned} C_i dT_i &= \left(-\frac{T_i - T_\mathrm{h}}{R_\mathrm{ih}} - \frac{T_i - T_e}{R_{ie}} + \frac{T_a - T_i}{R_{ia}} + A_w\Phi_s\right)\mathrm{dt} + \sigma_i d\omega_i, \\ C_\mathrm{h} dT_h &= \left(\frac{T_i - T_\mathrm{h}}{R_\mathrm{ih}} + \Phi_\mathrm{h}\right)\mathrm{dt} + \sigma_h d\omega_h, \\ C_e dT_e &= \left(\frac{T_i - T_e}{R_{ie}} + \frac{T_a - T_e}{R_{ea}}\right)\mathrm{dt} + \sigma_e d\omega_e, \\ Y_k &= T_{i,k} + e_k, \end{aligned} \tag{7}$$

where Y_k is the measured interior temperature. Also, ω_i, ω_h and ω_e as standard Wiener processes with σ_i^2, σ_h^2 and σ_e^2 as the incremental variances of the Wiener processes are introduced to represent the stochastic behaviours. The other parameters are defined in *Table 7*. The deterministic part of the model can be considered as the following RC circuit.

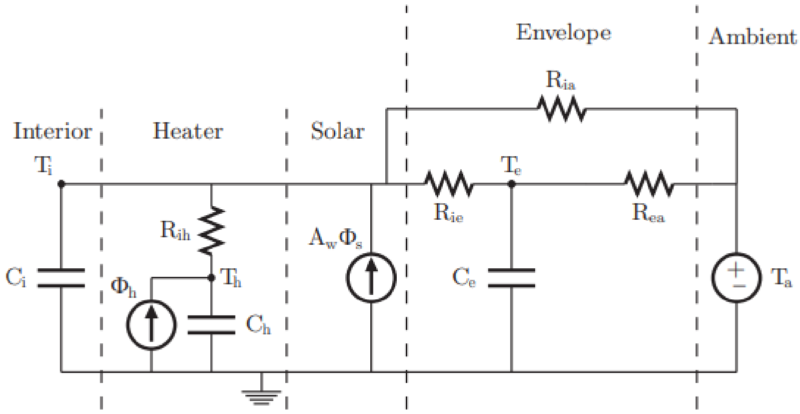

Figure 17 RC circuit representing the thermal dynamics of the Austrian demo.

The parameters are identified such that maximizes the likelihood of the measured data and the model output. The estimated values of the parameters of the grey-box model for the Austrian demo are $R_{ia} = 14.98\ K/kW$, $R_{ih} = 0.1\ K/kW$, $R_{ea} = 26.4\ K/kW$, $R_{ie} = 41\ K/kW$, $C_i = 14.5\ \mathrm{kWh}/K$, $C_h = 0.5\ \mathrm{kWh}/K$, $C_e = 0.1\ \mathrm{kWh}/K$ and $A_w = 12.9\ m^2$. State matrix is also found using the dynamics of (7) as

$$\begin{bmatrix} \frac{-1}{R_{ih}C_i} - \frac{1}{R_{ie}C_i} - \frac{1}{R_{ia}C_i} & \frac{1}{R_{ih}C_i} & \frac{1}{R_{ie}C_i} \\ \frac{1}{R_{ih}C_h} & \frac{-1}{R_{ih}C_h} & 0 \\ \frac{1}{R_{ie}C_e} & 0 & \frac{-1}{R_{ie}C_e} - \frac{1}{R_{ea}C_e} \end{bmatrix}. \tag{8}$$

Using the estimated values and the given formulas, the thermodynamic properties of the Austrian demo is provided as: $\tau_1 = 0.4\ h$, $\tau_2 = 1.6\ h$, $C_{total} = 15\ \mathrm{kWh}/K$, $R_{envelope} = 12.25\ K/kW$ and $\alpha_{UA} = 1.47\ W/(m^2K)$ for the building of size $55.24\ m^2$. In this study, dominant states' time constants are considered, and the other time constant is disregarded.

4.4. Dutch demo

Employing the same procedure as the previous demos, the best model for the Dutch demo is found as

$$\begin{aligned} C_i dT_i &= \left(\frac{-T_i + T_\mathrm{h}}{R_\mathrm{ih}} + \frac{-T_i + T_a}{R_{ia}} + A_{w,W}\Phi_{s,W} + A_{w,E}\Phi_{s,E}\right)dt + \sigma_i d\omega_i, \\ C_\mathrm{h} dT_h &= \left(\frac{T_i - T_\mathrm{h}}{R_\mathrm{ih}} + \Phi_\mathrm{h}\right)dt + \sigma_h d\omega_h, \\ Y_k &= T_{i,k} + e_k, \end{aligned} \tag{9}$$

where Y_k is the measured interior temperature. Also, ω_i, ω_h and ω_e as standard Wiener processes with σ_i^2, σ_h^2 and σ_e^2 as the incremental variances of the Wiener processes are introduced to represent the stochastic behaviours. The other parameters are defined in *Table 7*. The deterministic part of the model can be demonstrated as a RC circuit in Figure 18.

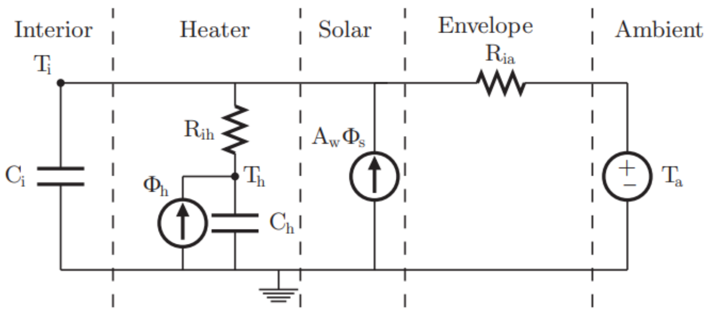

Figure 18 RC circuit representing the thermal dynamics of the Dutch demo.

the estimated values of the parameters of the grey-box model for the Dutch demo are $R_{ia} = 6.84\ K/kW$, $R_{ih} = 0.1\ K/kW$, $C_i = 18.25\ \mathrm{kWh}/K$, $C_h = 3.78\ \mathrm{kWh}/K$, and $A_w = 36.18\ m^2$. State matrix is also found using the dynamics of (9) as

$$\begin{bmatrix} \frac{-1}{R_{ih}C_i} - \frac{1}{R_{ia}C_i} & \frac{1}{R_{ih}C_i} \\ \frac{1}{R_{ih}C_h} & \frac{-1}{R_{ih}C_h} \end{bmatrix}. \tag{10}$$

Using the estimated values and the given formulas, the thermodynamic properties of the Spanish demo is provided as: $\tau_1 = 0.3\ h$, $C_{total} = 22.03\ \mathrm{kWh}/K$, $R_{envelope} = 6.84\ K/kW$ and $\alpha_{UA} = 0.44\ W/(m^2K)$ for East/West section of the first floor with size $332\ m^2$.

4.5. Summary

This section briefly provides the grey-box model, as a prominent modelling approach required for the control and optimization purposes, of each demo and introduces some thermodynamic properties of each demo based on the estimated model. This type of model is found based on the data, generated from the white-box model of each demo, and some physical aspects of the system. An optimization problem, managing to maximize the likelihood of data and model output, needs to be solved. Thus, this leads to optimal parameter estimations. Then, some statistical methods have been used to find the best structure among many existing ones. This procedure has been described briefly in [3]. Statistical methods equip the designer with some tool to choose among various existing models. Thus, the difference between the structures is based on the statistical properties of the estimated models.

It should be noted that the obtained models are low-dimensional and are required to provide predictions for the controller. So, unlike white-box models, grey-box models may not be able to resemble in-detail thermal properties of the apartments. However, based on the existing information about the thermal properties, it is seen that the envelope resistance calculated from the grey-box model ($6.84\ K/kW$) and the mean of the envelope resistances of Duch demo apartment ($6.4\ K/kW$) are close. Also, the calculated heat transfer coefficient ($0.13\ W/(m^2K)$) of the Norwegian demo looks pretty close to its real value ($0.1 - 0.13\ W/(m^2K)$). The calculated thermal properties extracted from the grey-box model of each demo are collected in Table 8.

Table 8 Thermal properties generated from grey-box models of each demo.

	τ, h	C_{total}, kWh$/K$	$R_{envelope}, K/kW$	$\alpha_{UA}, W/(m^2K)$
Spanish demo	0.22	2.5	61.38	0.36
Norwegian demo	0.07, 2.5	23.3	100.64	0.13
Austrian demo	0.4, 1.6	15	12.25	1.47
Dutch demo	0.3	22.03	6.84	0.44

5. HVAC Modelling

In this section, appropriate models of the HVAC systems of each demo are introduced. This model will be used in the model predictive controller design.

5.1. Spanish demo

The HVAC system of the Spanish demo consists of three heat pumps and two tanks. The tanks store thermal energy for domestic hot water and heating system. Since the produced thermal power by the heat pump is related to the input and output water temperature and the ambient temperature, coefficient of performance (COP) of heat pumps are considered as,

$$COP = 3.364 - 0.0095\, T_{out\ from\ HP} - 0.0095\, T_{in\ to\ HP} + 0.047\, T_{amb}, \tag{11}$$

where $T_{out\ from\ HP}$ and $T_{in\ to\ HP}$ are the temperature of output and input water of the heat pump and T_{amb} is the ambient temperature. Then the produced thermal power by the heat pump is calculated as: $Q_{HT} = Q_{el} * COP$. It is noted that the COP formula is found by employing the least squares method, that fits a linear function to the data.

Since a single measurement for the water temperature in each tank is provided, the model for domestic hot water and heating tanks are considered as single-layer tanks in the grey-box modelling procedure. Applying the procedure for finding grey-box from white-box data leads to the following grey-box model for the heating tank as

$$\begin{gathered} dT_{HT,1} = \left(\alpha_{HT} Q_{HT} - \beta_{HT}\, Q_{load,HT} + \zeta_{HT}\left(T_{HT,2} - T_{HT,1}\right)\right) dt + \sigma_1\, dw_1, \\ dT_{HT,2} = \left(\kappa_{HT}\left(T_{HT,1} - T_{HT,2}\right) - \gamma_{HT}\left(T_{HT,2} - T_{amb}\right)\right) dt + \sigma_2\, dw_2, \\ Q_{HT} = Q_{el} * COP, \\ y_{HT_k} = T_{HT,1_k} + e_k, \end{gathered} \tag{12}$$

where Q_{HT} is the delivered thermal power by the heat pump to the heating tank, and Q_{load} is the delivered thermal power from heating tank to the building. Heat loss between the heating tank and the ambient (T_{amb}) is considered as well ($\gamma_{HT}\left(T_{HT,2} - T_{amb}\right)$). Also, w_1 and w_2 are standard Wiener processes, and σ_1 and σ_2 are the incremental variances of Wiener processes, and $\alpha_{HT}, \beta_{HT}, \eta_{HT}, \kappa_{HT}, \zeta_{HT}$ and γ_{HT} are the parameters that needs to be estimated. The output of the model (y_{HT_k}) is the temperature of the tank, with measurement error, e_k.

The parameters are estimated by solving an optimization problem that leads to maximum likelihood in CTSM-R [4]. The estimated parameters of the deterministic part of the model are given in Table 9.

Table 9 Estimated parameters of heating tank.

α_{HT}	β_{HT}	ζ_{HT}	κ_{HT}	γ_{HT}
$4.74\ K/J$	$4.74\ K/J$	$4.023\ s^{-1}$	$2.34\ s^{-1}$	$0.02\ s^{-1}$

It can be observed that the error between the model outputs and the data represents similar properties as the ones for the white noise, which is an indicator of properly estimated model [2]. These results are shown in Figure 19.

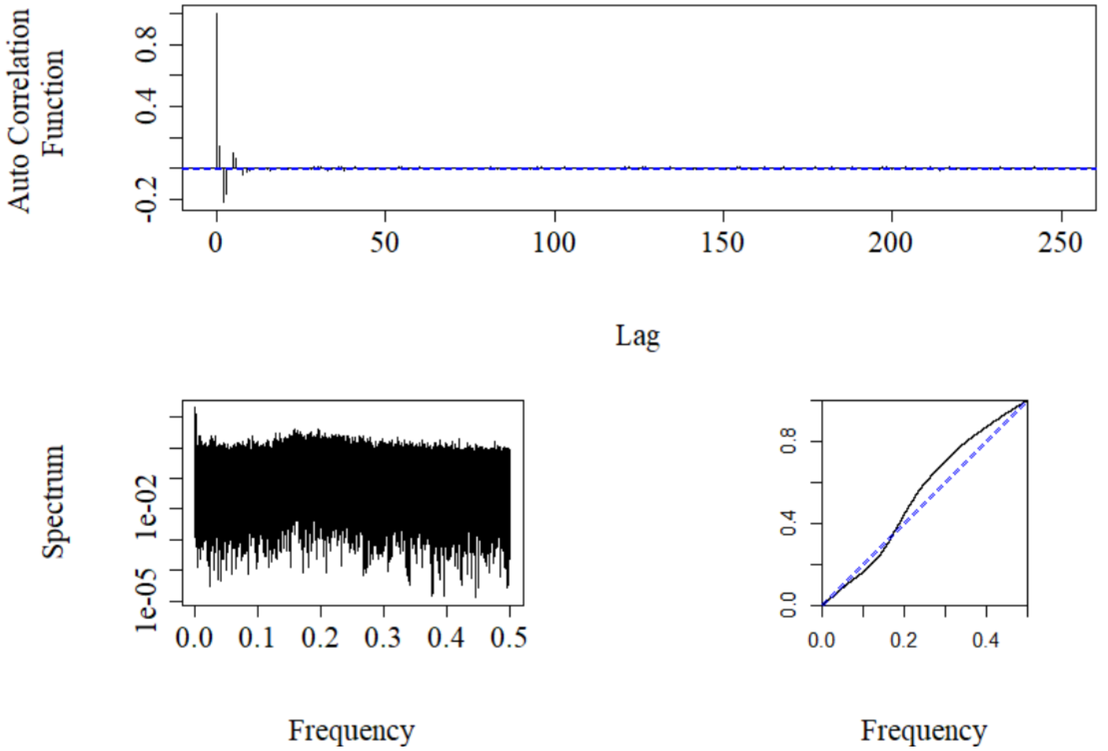

Figure 19 Statistical properties of one-step-ahead error of the heating tank temperature. The top panel shows that the error is almost uncorrelated in time. The bottom panel demonstrates that the spectrum of the error is uniformly spread across the frequencies, and the cumulative periodogram, is close to a straight line.

Applying the same procedure leads to the following grey-box model for the domestic hot water (DHW) tank as

$$\begin{aligned} dT_{DHW,1} &= \left(\alpha_{DHW} Q_{DHW} - \beta_{DHW}\, Q_{load,DHW} + \zeta_{DHW}\left(T_{DHW,2} - T_{DHW,1}\right)\right) dt + \sigma_1\, dw_1, \\ dT_{DHW,2} &= \left(\kappa_{HT}\left(T_{DHW,1} - T_{DHW,2}\right) - \gamma_{DHW}\left(T_{DHW,2} - T_{amb}\right)\right) dt + \sigma_2\, dw_2, \\ Q_{HT} &= Q_{el} * COP\,, \\ y_{DHW_k} &= T_{DHW,1_k} + e_k, \end{aligned} \tag{13}$$

where Q_{DHW} is the delivered thermal power by the heat pump to the domestic hot water tank, and Q_{load} is the delivered thermal power from domestic hot water tank to the building. Heat loss between the DHW tank and the ambient (T_{amb}) is considered (($\gamma_{DHW}\left(T_{DHW,2} - T_{amb}\right)$). Also, w_1 and w_2 are standard Wiener processes, and σ_1 and σ_2 are the incremental variances of Wiener processes, and α_{DHW}, β_{DHW}, η_{DHW}, κ_{DHW}, ζ_{DHW} and γ_{DHW} are the parameters that needs to be estimated. The output of the model (y_{DHW_k}) is the temperature of the tank, with measurement error, e_k.

The parameters are estimated by solving an optimization problem that leads to maximum likelihood in CTSM-R. The estimated parameters of the deterministic part of the model are given in Table 10.

Table 10 Estimated parameters of DHW tank.

α_{DHW}	β_{DHW}	ζ_{DHW}	κ_{DHW}	γ_{DHW}
$2.57\ K/J$	$2.57\ K/J$	$1.59\ s^{-1}$	$0.001\ s^{-1}$	$0.01\ s^{-1}$

It can be observed that the error between the model outputs and the data represents similar properties as the ones for the white noise, which is an indicator of properly estimated model. These results are shown in Figure 20.

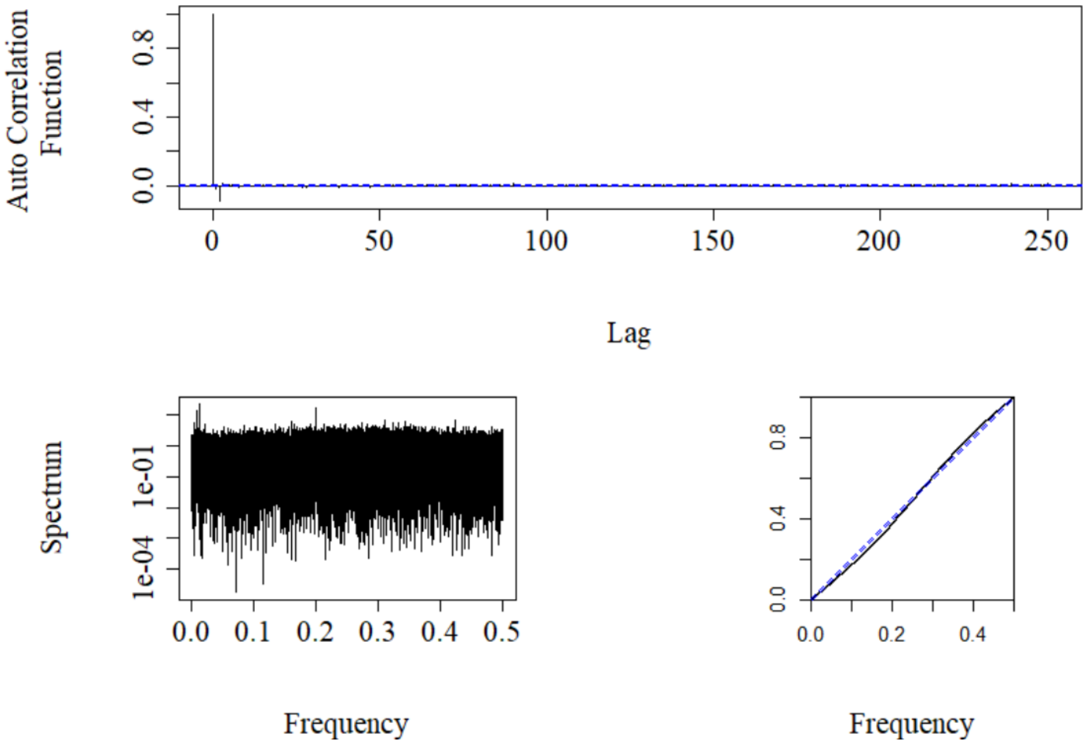

Figure 20 Statistical properties of one-step-ahead error of the domestic hot water tank temperature. The top panel shows that the error is almost uncorrelated in time. The bottom panel demonstrates that the spectrum of the error is uniformly spread across the frequencies, and the cumulative periodogram, is close to a straight line.

5.2. Norwegian demo

The HVAC system of Norwegian demo consists of a ground source heat pump and a tank that provides the required hot water and space heating. The heat pump consumes electrical energy and produces thermal energy considering coefficient of performance (COP) of heat pump,

$$COP = 4.6 - 0.0065\, T_{out\ from\ HP} - 0.033\, T_{in\ to\ HP} + 0.0057\, T_{amb}, \tag{14}$$

where $T_{out\ from\ HP}$ and $T_{in\ to\ HP}$ are the temperature of output and input water of the heat pump and T_{amb} is the ambient temperature.

The white-box model of the tank has five layers. To simplify the control procedure, the model is reduced to a two-layer model in grey-box, top and bottom layers. After analysing various model structures and applying model validation methods, a two-state model for each layer is proposed. The proposed model for the ith layer is given as

$$\begin{gathered}
dT_{i,1} = \left(\alpha_i\, Q_{in} - \beta_i\, Q_{load} - \eta_i\, Q_{mix,1} - \zeta_i Q_{mix,2}\right)dt + \sigma_{i,1}\, dw_{i,1}, \\
dT_{i,2} = \left(\kappa_i\left(T_{i,1} - T_{i,2}\right) - \gamma_i\left(T_{i,2} - T_{amb}\right)\right)dt + \sigma_{i,2}\, dw_{i,2}, \\
y_k = CT_k + e_k, \\
\dot{m} = \dot{m}_{in} - \dot{m}_{out}, \\
Q_{mix,1} = \dot{m}\left(T_{top,layer} - T_i\right), \\
Q_{mix,2} = \dot{m}\left(T_i - T_{bottom,layer}\right),
\end{gathered} \tag{15}$$

where Q_{in} is the thermal power from the heat pump to the tank, Q_{load} is the delivered power from tank to the building, Q_{mix} is the power transferred between the layers, and $Q_{loss} = \gamma_i\,(T_{i,2} - T_{amb})$ is the power loss from tank to ambient. Also, $w_{i,1}$ and $w_{i,2}$ are standard Wiener processes, and $\sigma_{i,1}$ and $\sigma_{i,2}$ are the incremental variances of Wiener processes, and α_i, β_i, η_i, κ_i, ζ_i and γ_i for $i = \{1, 2\}$ are the parameters that needs to be estimated. The output of the model (y_k) is the temperature of each layer, with measurement error, e_k, and $T_k = \left[T_{1,1},\ T_{1,2}, T_{2,1}, T_{2,2}\right]^T$ and $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$. The parameters are estimated by solving an optimization problem that leads to maximum likelihood in CTSM-R. The estimated parameters of the deterministic part of the model are given in Table 11.

Table 11 Estimated parameters of the storage tank.

α_1	α_2	β_1	β_2	η_1	η_2	ζ_1	ζ_2	κ_1	κ_2	γ_1	γ_2
0.001 K/J	0.0046 K/J	0.001 K/J	0.0046 K/J	0 K/J	0.0037 K/J	0.014 K/J	0 K/J	0.0035 s^{-1}	0.0526 s^{-1}	0.0004 s^{-1}	0.00024 s^{-1}

It can be observed that the error between the model outputs and the data represents similar properties as the ones for the white noise. These results are shown in Figure 21 and Figure 22.

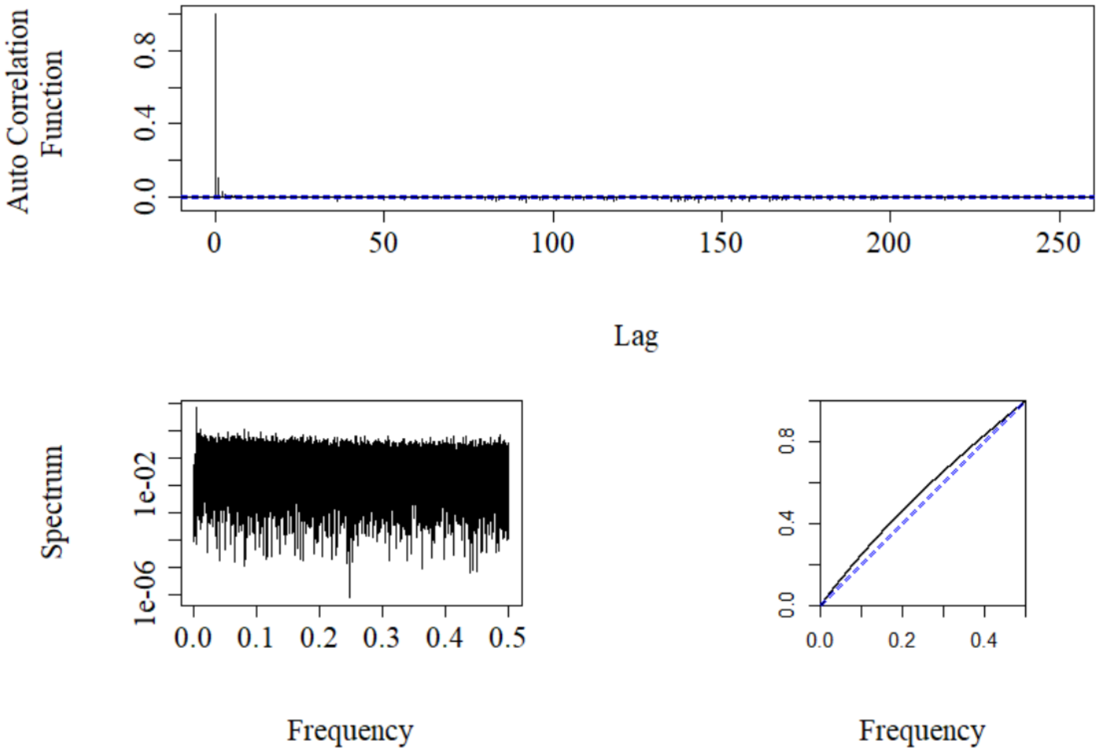

Figure 21 Statistical properties of one-step-ahead error of the first output. The top panel shows that the error is almost uncorrelated in time. The bottom panel demonstrates that the spectrum of the error is uniformly spread across the frequencies, and the cumulative periodogram, is close to a straight line.

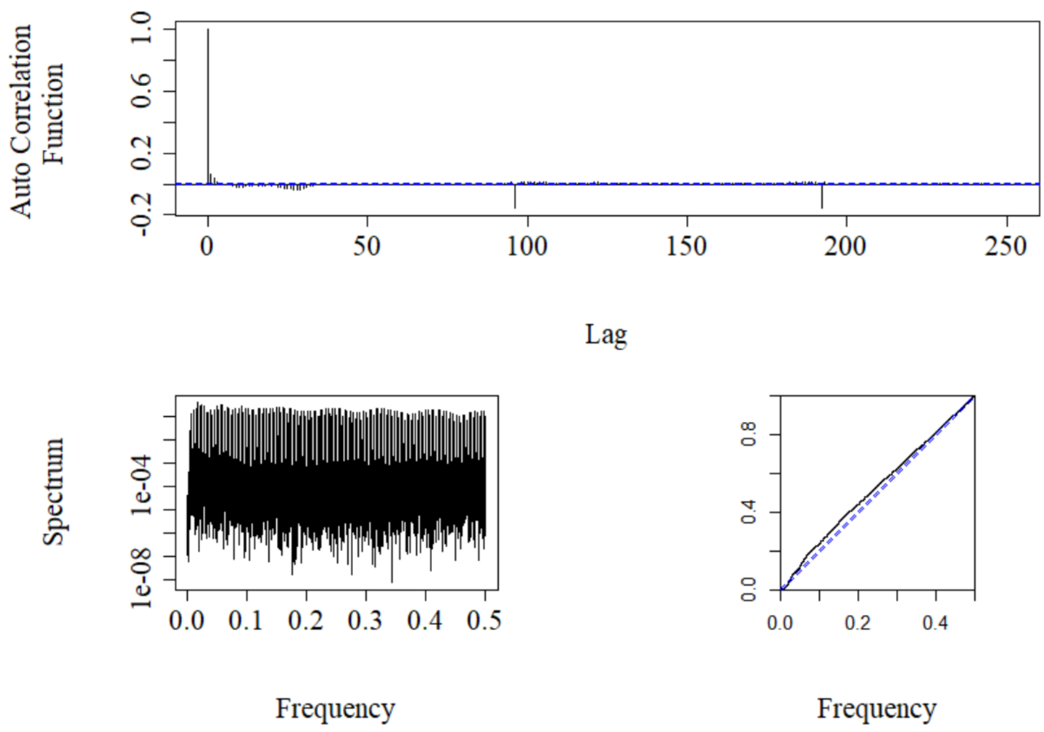

Figure 22 Statistical properties of one-step-ahead error of the second output. The top panel shows that the error is almost uncorrelated in time. The bottom panel demonstrates that the spectrum of the error is uniformly spread across the frequencies, and the cumulative periodogram, is close to a straight line.

5.3. Austrian demo

The HVAC system of the Austrian demo does not have a storage tank, so heat pumps deliver the power directly to the building. Coefficient of performance (COP) of heat pumps are found using data as

$$COP \;=\; 8917 - 222.5\, T_{out\ from\ HP} \;-0.43\, T_{in\ to\ HP} -\; 0.026\, T_{amb}, \tag{16}$$

where $T_{out\ from\ HP}$ and $T_{in\ to\ HP}$ are the temperature of output and input water of the heat pump and T_{amb} is the ambient temperature. The heat pump provides the required heat for the apartment. The grey-box model of an apartment in Austrian demo is given in (7). Figure 23 demonstrates that the error between the output of the grey-box and the white-box model data is almost uncorrelated in time, its spectrum is uniformly spread across the frequencies, and the cumulative periodogram is close to the straight line.

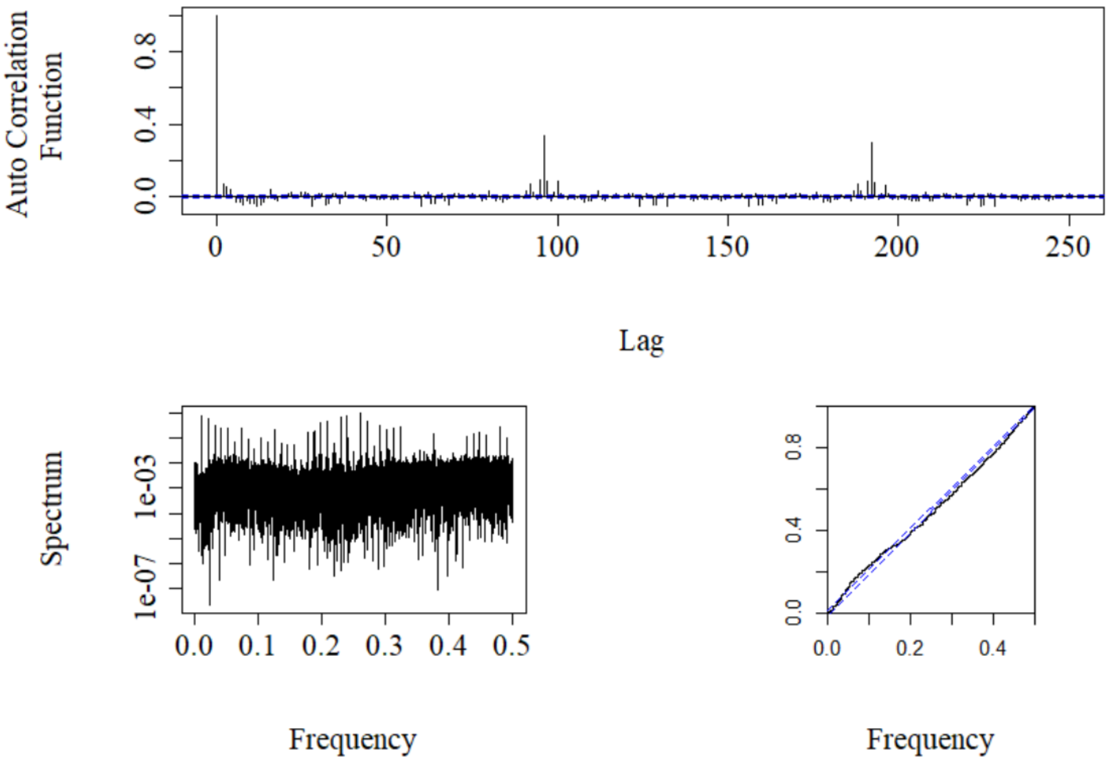

Figure 23 Statistical properties of one-step-ahead error of the indoor temperature. The top panel shows that the error is almost uncorrelated in time. The bottom panel demonstrates that the spectrum of the error is uniformly spread across the frequencies, and the cumulative periodogram, is close to a straight line.

5.4. Dutch demo

In the Dutch demo apartment the thermal behaviour of the HVAC equipment is modelled based on a hybrid (physics & data driven) dynamical model. The geometry and physical properties of the floors, roofs, walls, doors and windows are provided by the building constructor. This information is described in the international standardized gbXML format.

The geometry of the building and all physical parameters can be inspected using public gbXML viewers, see Figure 24.

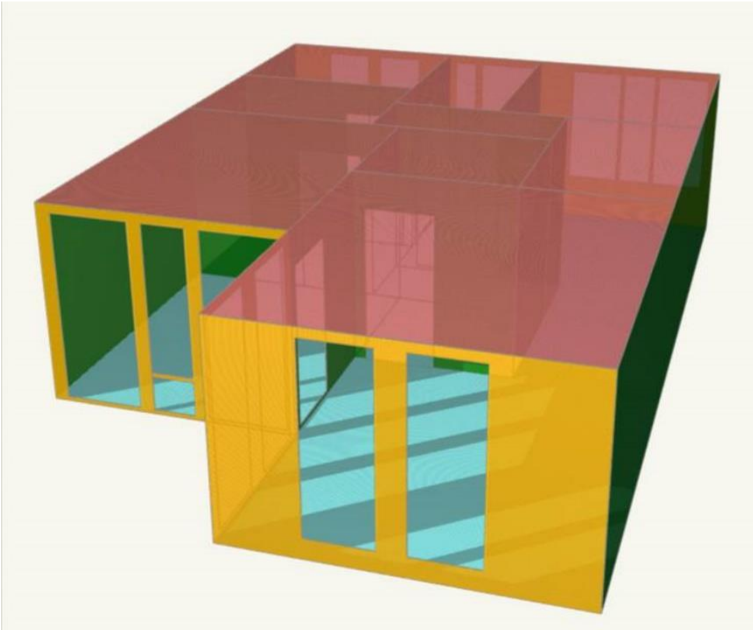

Figure 24 gbXML viewer of one of the individual apartments.

The gbXML model is used to automatically generate a dynamic physics-based network model for all thermal zones. The dynamic response of zone temperatures is computed including:

- External conditions: outside temperature, solar radiation, wind, neighbour temperatures
- Heat transfer through walls, floors, roofs, windows
- Forced and unforced ventilation
- HVAC equipment model (heat pump, floor heating system, pumps, heat exchangers, boiler)
- Equipment control
- Occupant behaviour (absence, room temperature setpoint, window use, tap water use, appliance heat production)

Defining a temperature state vector T for all nodes in the network (zones, internal wall nodes, external nodes) the model can be symbolically described as a first order vector differential equation:

$$C\frac{dT}{dt} = HT + \sum_i Q_i \, , \tag{17}$$

Where T is the node temperature vector, C a vector of node capacities, H is a heat admittance matrix and Q_i the set of all heat inputs to a node by solar radiation, ventilation, equipment, appliances.

The equipment model (plant loop) describes the heat pump, boiler, floor heat exchanger, fluid transport pumps and ground source.

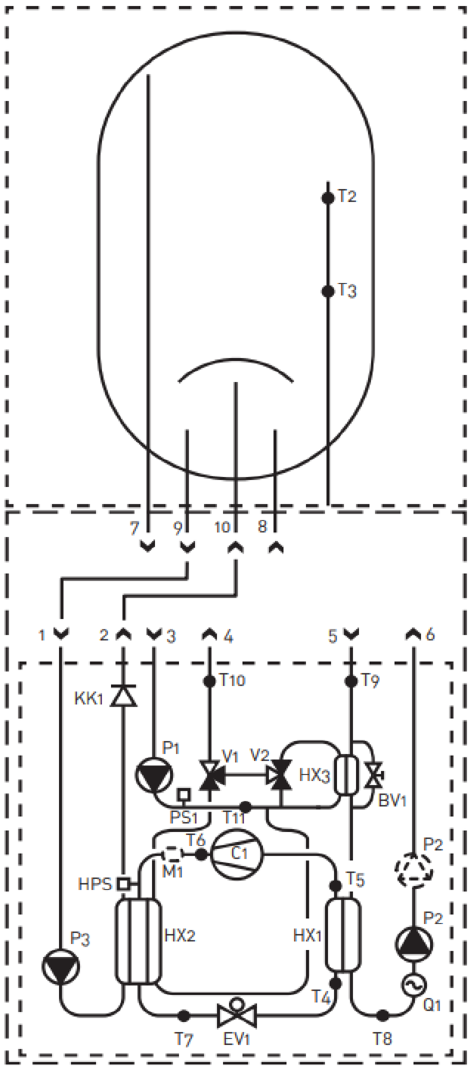

Figure 25 Apartment heat pump and boiler system. The boiler has two temperature sensors T2,T3. Flows 5 and 6 are coupled to the floor heating system, flows 3 and 4 to the ground source.

The heat pump and boiler are modelled by physical relations. The heat pump is modelled by a steady-state model and the boiler is modelled as a stratified layer dynamical model.

The heat pump and boiler models were tuned to match the dynamic behaviour measured in experiments with the heat pump/boiler system in the TNO lab.

6. Model Predictive Control

Model predictive control (MPC) is an advanced control strategy, capable of using a model to predict the future outputs and calculating control signals by minimizing a predefined objective function. Considering various types of constraints and relatively simple implementation are the main two benefits of employing MPC. Economic model predictive controller is employed to minimize electricity costs.

Tunning of model predictive controllers is challenging and sometimes time-consuming. For instance, finding a proper horizon, weighting matrix and slack variable boundary require designer's experiment and adequate amount of time. This section introduces the model prediction control formulation for each demonstration case.

6.1. Spanish demo

It is required that the MPC minimizes the electricity cost and satisfying the power and temperature constraints. To this end, the optimization problem, consists of objective function and equality and inequality constraints, should be defined as:

$$
\begin{aligned}
&\underset{P_{el},\ S}{\text{minimize}} \sum_{j=0}^{N-1} c_{el} \times P_{el} + c_{con}^{T} S \\
s.t.\quad &\dot{T}_{HT,i}(t) = f\left(T_{HT,i}(t), Q_{HT}, p(t)\right), \quad i = 1,2 \\
&\dot{T}_{DHW,i}(t) = f\left(T_{DHW,i}(t), Q_{DHW}, p(t)\right), \qquad i = 1,\ 2 \\
&Q_{in} \ = \ COP\left(T_{HP,in}, T_{HP,out}, T_{amb}\right) \times \ P_{el} \\
&0 \leq \ P_{el} \leq \ P_{el,max} \\
&T_{HT,1} \leq \ T_{HT,max} + s_1 \\
&T_{DHW,1} \leq \ T_{DHW,max} + s_2 \\
&T_{HT,1} \geq \ T_{HT,min} - s_1 \\
&T_{DHW,1} \geq \ T_{DHW,min} - s_2 \\
&p(t) \ = \ (T_{amb}, Q_{load})
\end{aligned}
\tag{18}
$$

where, N is the control horizon, c_{el} is the penalty signal based on the daily electricity price, and c_{con} the cost of breaking the temperature constraints using the vector of slack variables, S. The equality constraints are the tank and heat pump models, and the inequality constraints are the limitations for the electricity and temperatures of the tanks. $T_{HT,max}$ and $T_{HT,min}$ are the maximum and minimum allowable temperatures of heating tank, and $T_{DHW,max}$ and $T_{DHW,min}$ are the maximum and minimum limits of domestic hot water tank temperatures. $P_{el,max}$ is the maximum electricity usage.

Simulation results are provided to demonstrate the efficiency of the designed controller. Two scenarios are considered in the simulations: 1) the penalty signal is constant, 2) time varying penalty signal. Figure 26 and Figure 27 show the system results for the two above mentioned scenarios for five hours of control horizon. The top panels show the temperatures of the two tanks. The next panel demonstrate the electricity power consumed by the heat pumps. It is seen in the 2nd scenario that heat pumps consume more electricity and thus heat up the tank temperatures during the periods with low penalty signal.

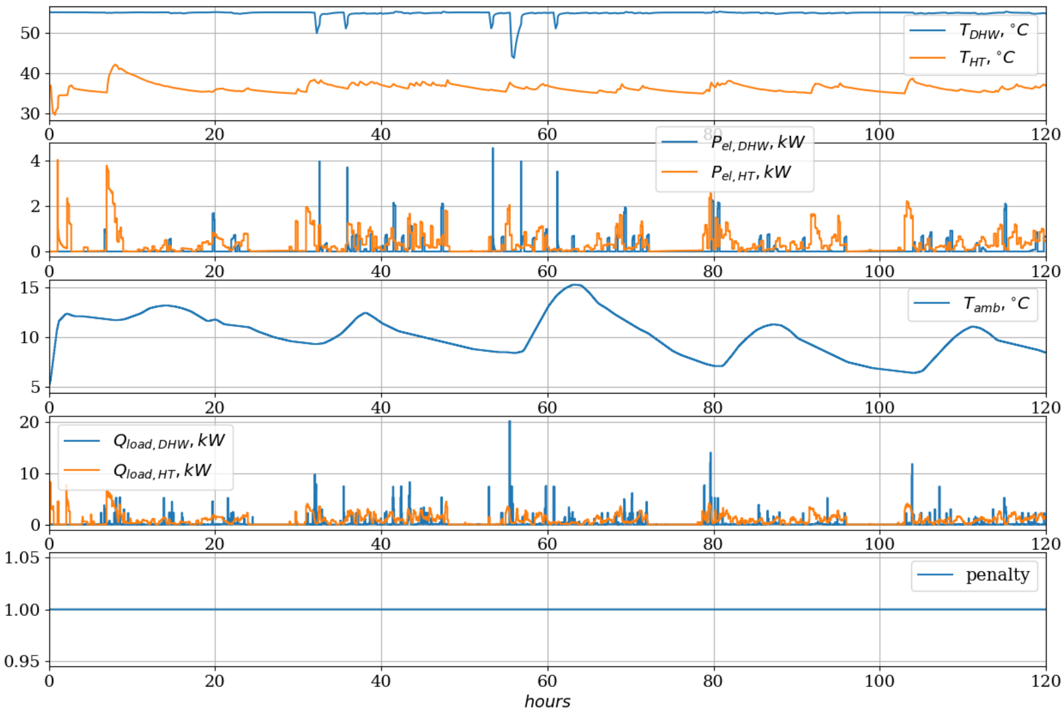

Figure 26 Simulation results of MPC using constant penalty signal. Top panel shows the water temperature in the DHW and heating tanks. The second panel demonstrated the electricity consumption to control the water temperature of each tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

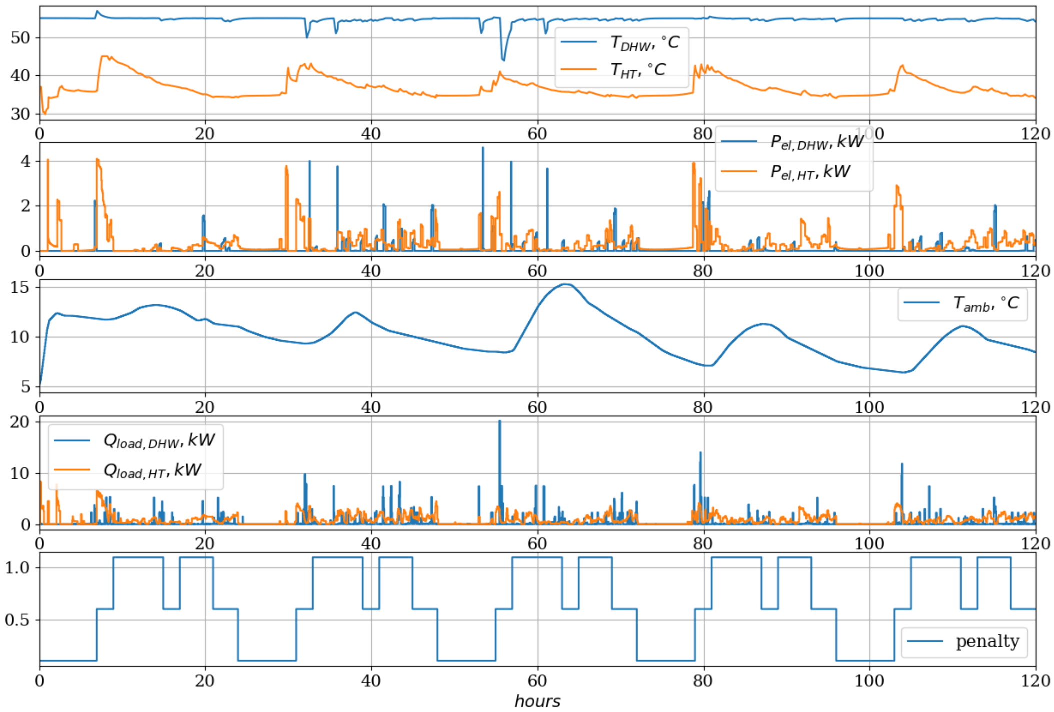

Figure 27 Simulation results of MPC using time varying penalty signal. Top panel shows the water temperature in the DHW and heating tanks. The second panel demonstrated the electricity consumption to control the water temperature of each tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

To find the penalty signal, first, the daily electricity price is monitored, and the mean of daily electricity price is found. Then, the mean of daily price is normalized between 0 and 1, and finally, the idealized penalty signal is proposed. Figure 28 illustrates the real mean and normalized daily electricity price signals, and the penalty signal.

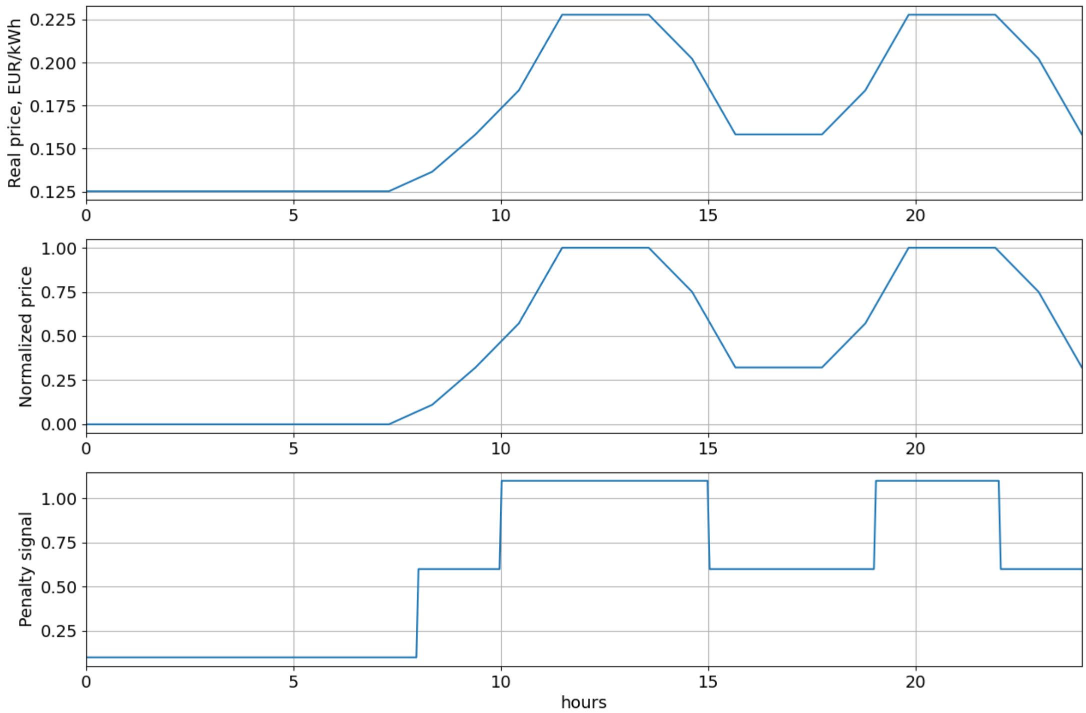

Figure 28 Determination of price signal for the Spanish demo. The top panel shows the mean of daily electricity price in 2021-2022. The second panel demonstrates the normalized price signal between zero and one. The third panel shows the idealized version of the normalized signal that is used as penalty signal.

Annual simulation is provided to show that the designed controller works in all seasonal conditions. The results using constant and time-varying penalty signals and one hour control horizon can be found in Figure 29 and Figure 30, respectively.

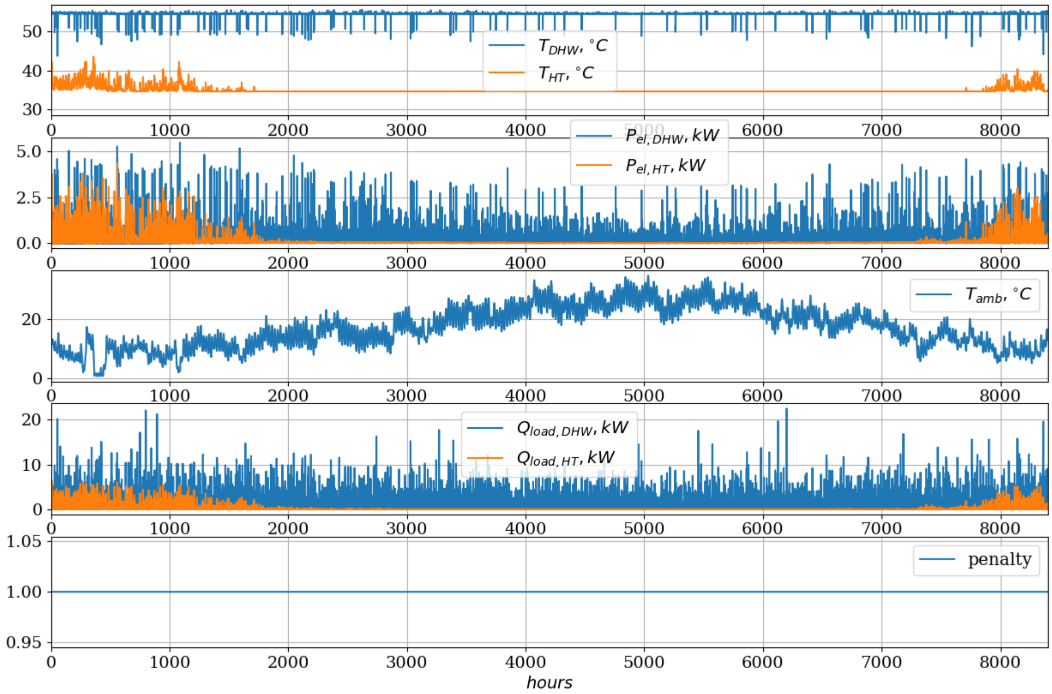

Figure 29 Annual simulation results of MPC using constant penalty signal. Top panel shows the water temperature of domestic hot water and heating tanks. The second panel demonstrated the electricity consumption to control the water temperature of tanks. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

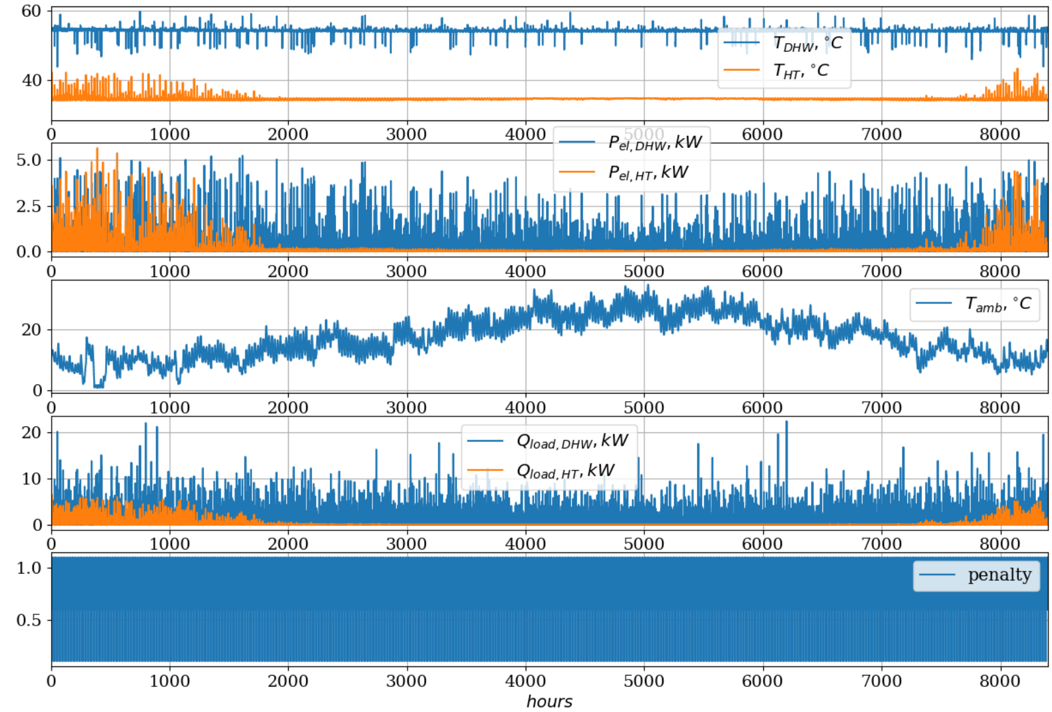

Figure 30 Simulation results of MPC using variable penalty signal. Top panel shows the water temperature of domestic hot water and heating tanks. The second panel demonstrated the electricity consumption to control the water temperature of tanks. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

6.2. Norwegian demo

Model predictive controller is used to minimizes the electricity cost and satisfying the power and temperature constraints of the Norwegian demo. To this end, the optimization problem, consists of objective function and equality and inequality constraints, are defined in the form of the economic model predictive controller as:

$$
\begin{aligned}
&\underset{P_{el},\ s}{\text{minimize}} \sum_{j=0}^{N-1} c_{el} \times P_{el} + c_{con} \times s \\
&s.t. \qquad \dot{T}_{i,1}(t) = f\big(T_{i,1}, T_{i,2}, Q_{in}, p\big), \\
&Q_{in} = COP\big(T_{HP,in}, T_{HP,out}, T_{amb}\big) \times P_{el}, \\
&0 \leq P_{el} \leq P_{el,max}, \\
&T_{i,1} \leq T_{i,1_{max}} + s, \\
&T_{i,1} \geq T_{i,1_{min}} - s, \\
&\mathrm{p(t)} = (\mathrm{T}_{amb}, \mathrm{Q}_{load}, \dot{m}), \\
&i = 1, 2
\end{aligned}
\tag{19}
$$

where, N is the control horizon, c_{el} is a weight, penalizing when the electricity price is high, and c_{con} is a weight to penalize large values of slack variable, s. The equality constraints are the tank layers' and heat pump models, and the inequality constraints are the limitations for the electricity and temperatures of the tank layers. $T_{i,1_{max}}$ and $T_{i,1_{min}}$, where $i = 1, 2$, are the maximum and minimum allowable temperatures of each layer of the tank, respectively. $P_{el,max}$ is the maximum electricity consumption.

Simulation results are given to illustrate the efficacy of the control design. Two scenarios are considered in the simulations: 1) the penalty signal is constant, 2) time varying penalty signal. Figure 31 and Figure 32 show the system results for the two above mentioned scenarios. It can be observed that the controller forces the heat pump to produce more energy during the periods of low electricity price in the 2nd scenario.

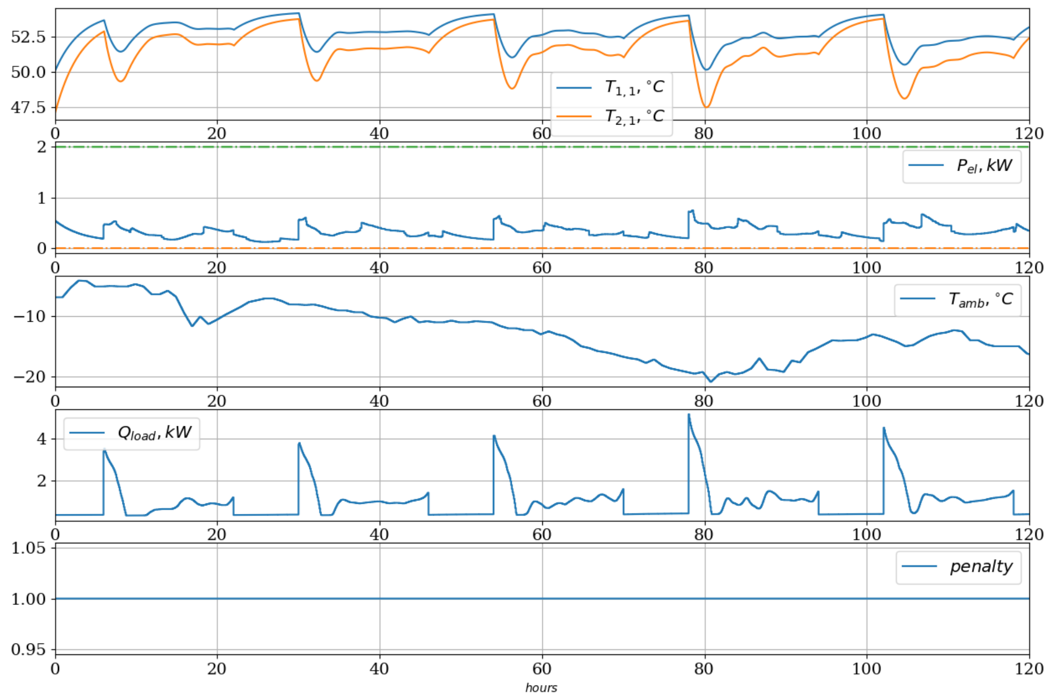

Figure 31 Simulation results of MPC using constant penalty signal. Top panel shows the water temperature of two layers of the tank. The second panel demonstrated the electricity consumption to control the water temperature of tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

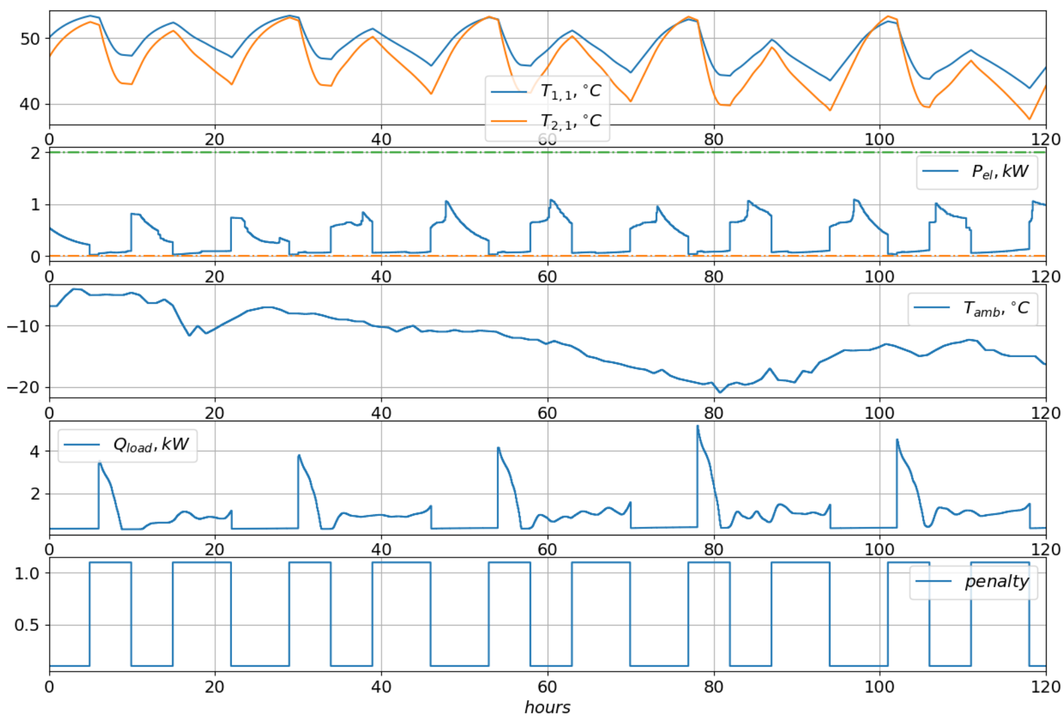

Figure 32 Simulation results of MPC using variable penalty signal. Top panel shows the water temperature of two layers of the tank. The second panel demonstrated the electricity consumption to control the water temperature of tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

To find the penalty signal, first, the daily electricity price is monitored, and the mean of daily electricity price is found. Then, the mean of daily price is normalized between 0 and 1, and finally, the idealized penalty signal is proposed. Figure 33 illustrates the real mean and normalized daily electricity price signals, and the penalty signal.

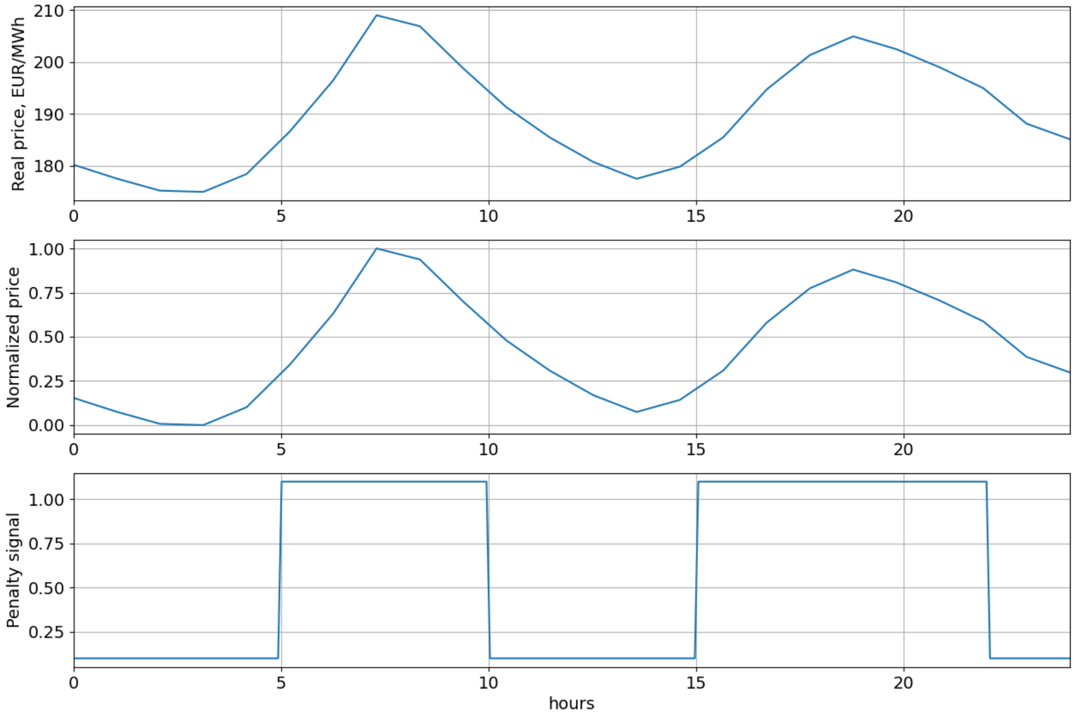

Figure 33 Determination of price signal for the Norwegian demo. The top panel shows the mean of daily electricity price in 2022. The second panel demonstrates the normalized price signal between zero and one. The third panel shows the idealized version of the normalized signal that is used as penalty signal.

Annual simulation is provided to show that the designed controller works in all seasonal conditions. The results using constant and time-varying penalty signals can be found in Figure 34 and Figure 35, respectively.

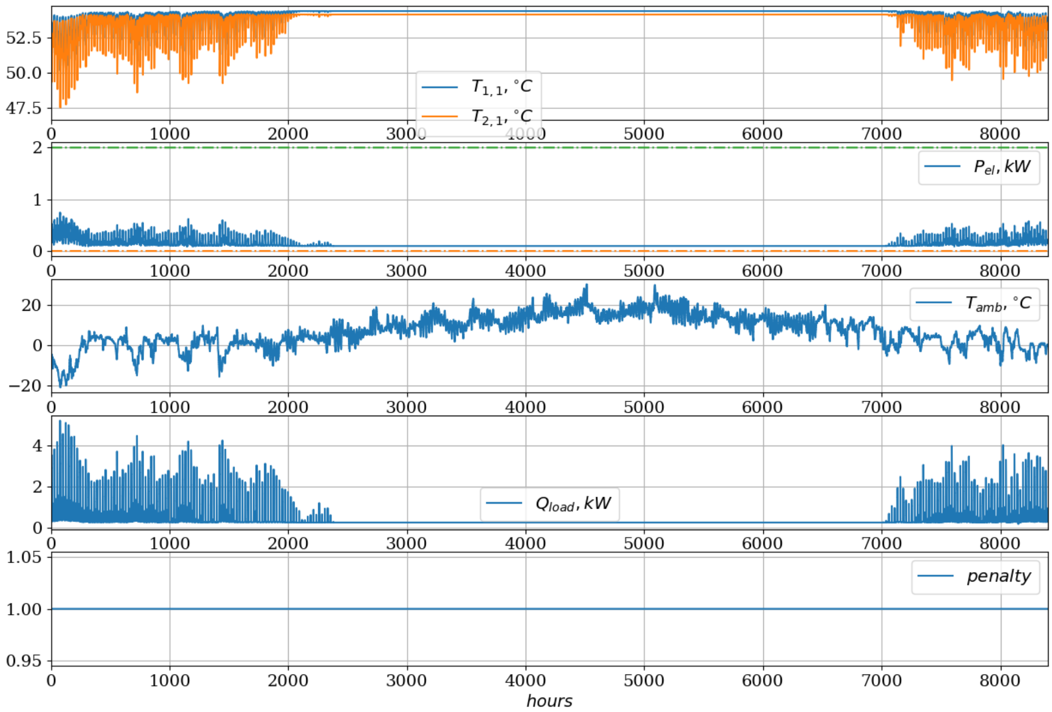

Figure 34 Annual simulation results of MPC using constant penalty signal. Top panel shows the water temperature of two layers of the tank. The second panel demonstrated the electricity consumption to control the water temperature of tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

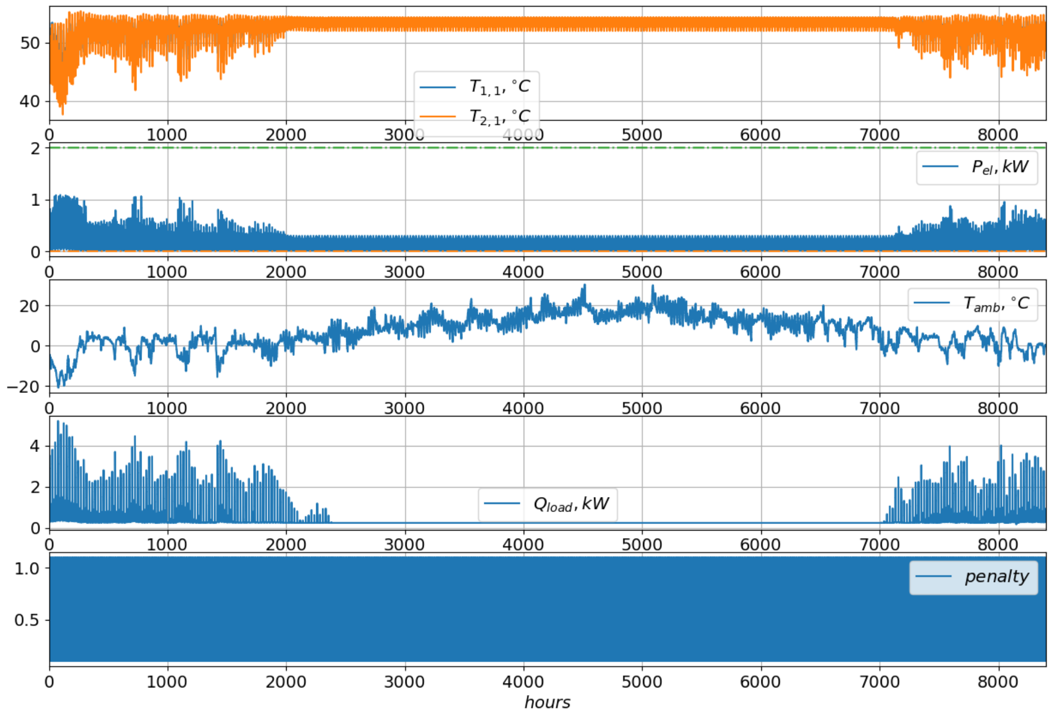

Figure 35 Annual simulation results of MPC using time-varying penalty signal. Top panel shows the water temperature of two layers of the tank. The second panel demonstrated the electricity consumption to control the water temperature of tank. The ambient temperature is provided in the third panel. Requested load of each tank and the penalty signal are shown in the fourth and fifth panels, respectively.

6.3. Austrian demo

Model predictive controller is used to minimizes the electricity cost while keeping the indoor temperature in a predefined bound. To this end, the optimization problem, consists of objective function and equality and inequality constraints, are defined in the form of the economic model predictive controller as:

$$
\begin{aligned}
&\underset{P_{el},\ s}{\text{minimize}} \sum_{j=0}^{N-1} c_{el} \times P_{el} + c_{con} \times s \\
&s.t. \quad \dot{T}(t) = f(T(t), Q_{in}, p(t)), \\
&T = [T_i, T_h, T_e]^T \\
&\Phi_h = COP(T_{HP,in}, T_{HP,out}, T_a) \times P_{el} \\
&0 \leq P_{el} \leq P_{el,max} \\
&T_i \leq T_{i,max} + s \\
&T_i \geq T_{i,min} - s \\
&p(t) = (T_a, \Phi_s)
\end{aligned}
\tag{20}
$$

where, N is the control horizon, c_{el} is the penalizing signal based on the electricity price, and c_{con} is to penalize indoor temperatures close to the limits using slack variable, s. The equality constraints are the apartment and heat pump models, and the inequality constraints are the electricity consumption and indoor temperature limitations. $T_{i,max}$ and $T_{i,min}$ are the maximum and minimum indoor temperatures leading to a thermal comfort, and $P_{el,max}$ is the maximum electricity consumption by the heat pump. An appropriate solver is implemented that lea to binary signals for on/off control of the heat pump.

Considering two scenarios, one with a constant penalty signal and the other one with a time varying penalty signal, simulation results demonstrate the efficacy of the controller design. Figure 36 and Figure 37 show the system results for the two above mentioned scenarios. The controller keeps the temperatures between 20℃ and 21℃ while using less electricity during certain periods in a day. The time varying penalty signal is chosen arbitrarily for the simulation purposes since the electricity price data provided by Austrian demo is constant.

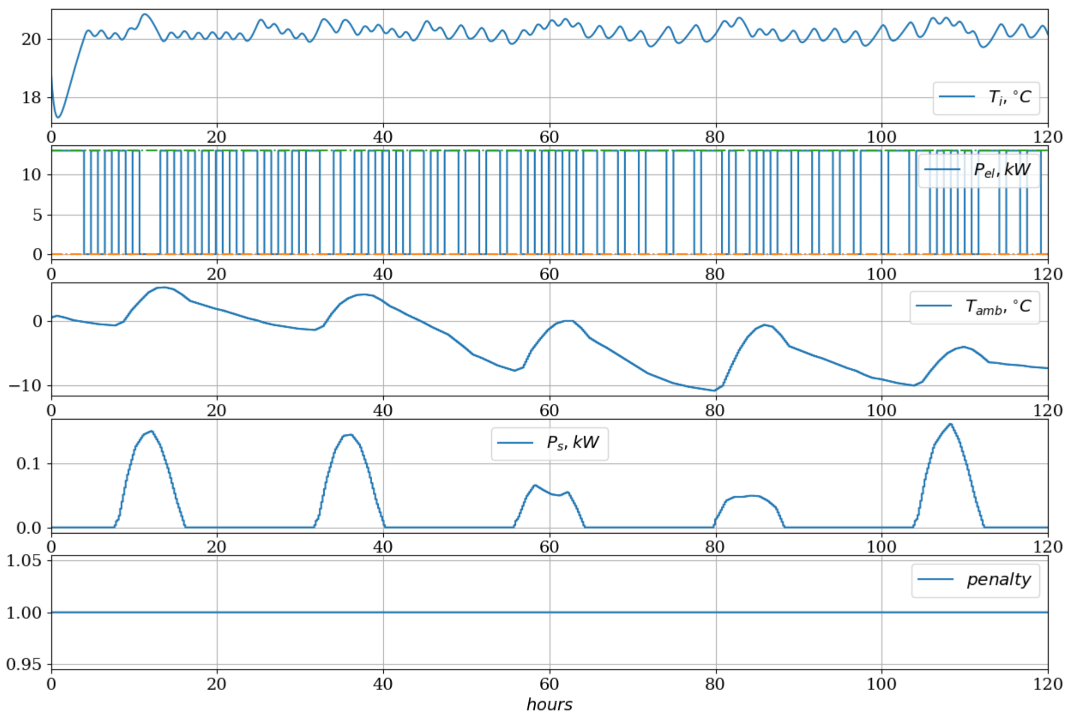

Figure 36 Simulation results of MPC using constant penalty signal. Top panel shows the indoor temperature. The second panel demonstrated the on/off control signal of the heat pump. The ambient temperature is provided in the third panel. The solar irradiation and the penalty signal are shown in the fourth and fifth panels, respectively.

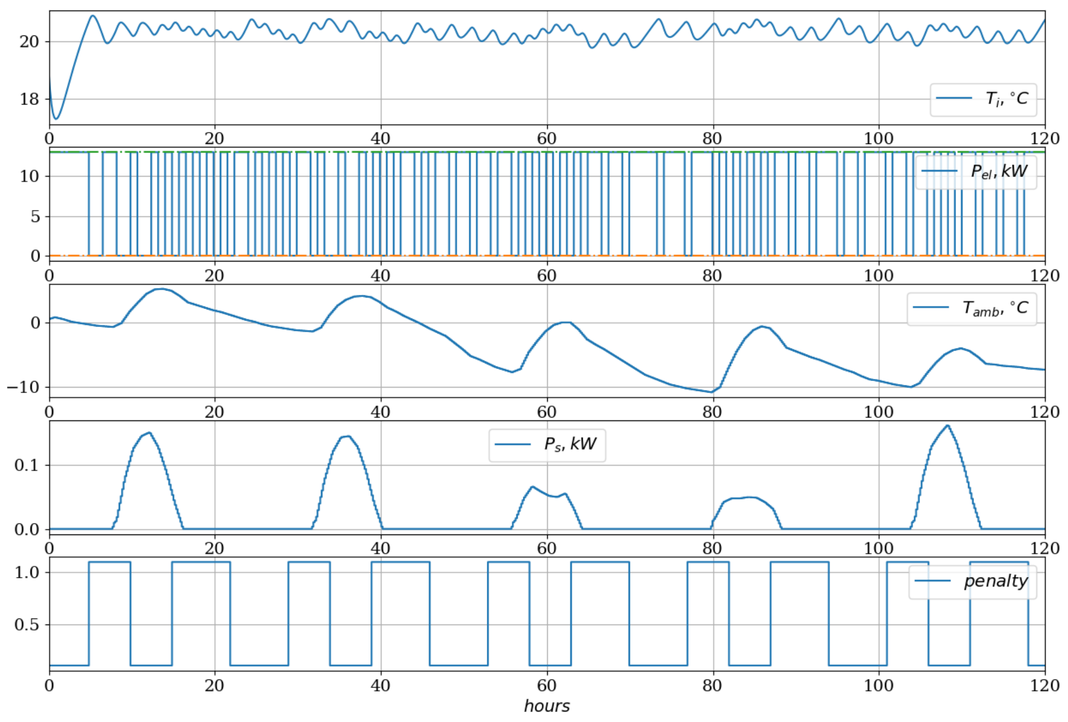

Figure 37 Simulation results of MPC using time varying penalty signal. Top panel shows the indoor temperature. The second panel demonstrated the on/off control signal of the heat pump. The ambient temperature is provided in the third panel. The solar irradiation and the penalty signal are shown in the fourth and fifth panels, respectively.

Annual simulation is provided to show that the designed controller works in all seasonal conditions. The results using constant and time-varying penalty signals can be found in and, respectively.

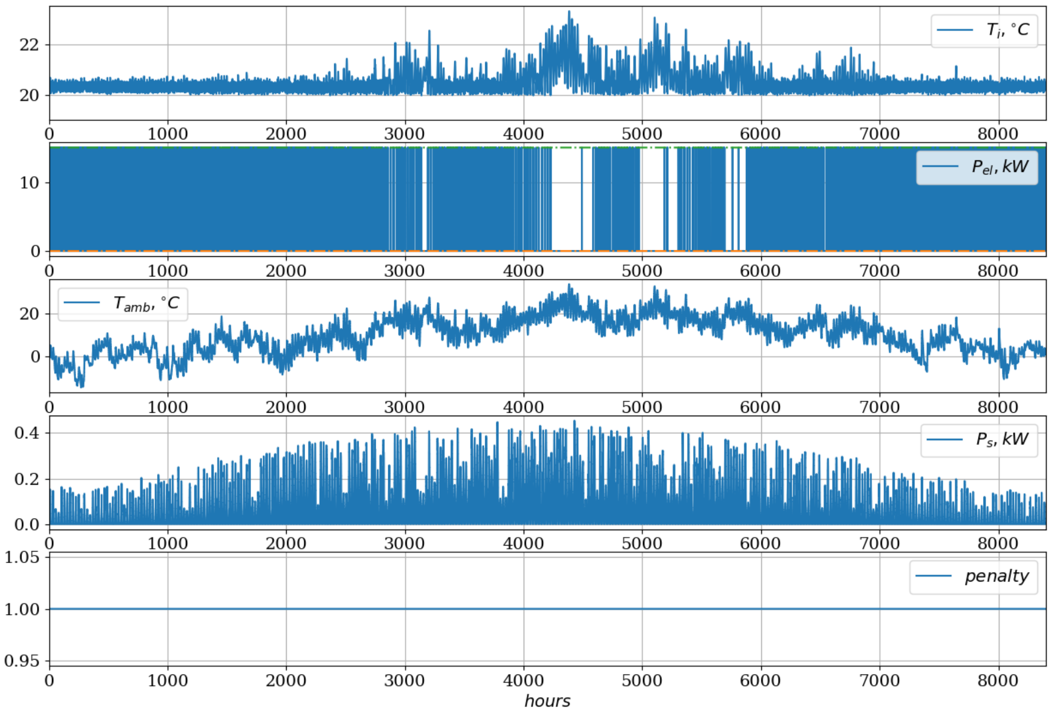

Figure 38 Annual simulation results of MPC using constant penalty signal. Top panel shows the indoor temperature. The second panel demonstrated the on/off control signal of the heat pump. The ambient temperature is provided in the third panel. The solar irradiation and the penalty signal are shown in the fourth and fifth panels, respectively.

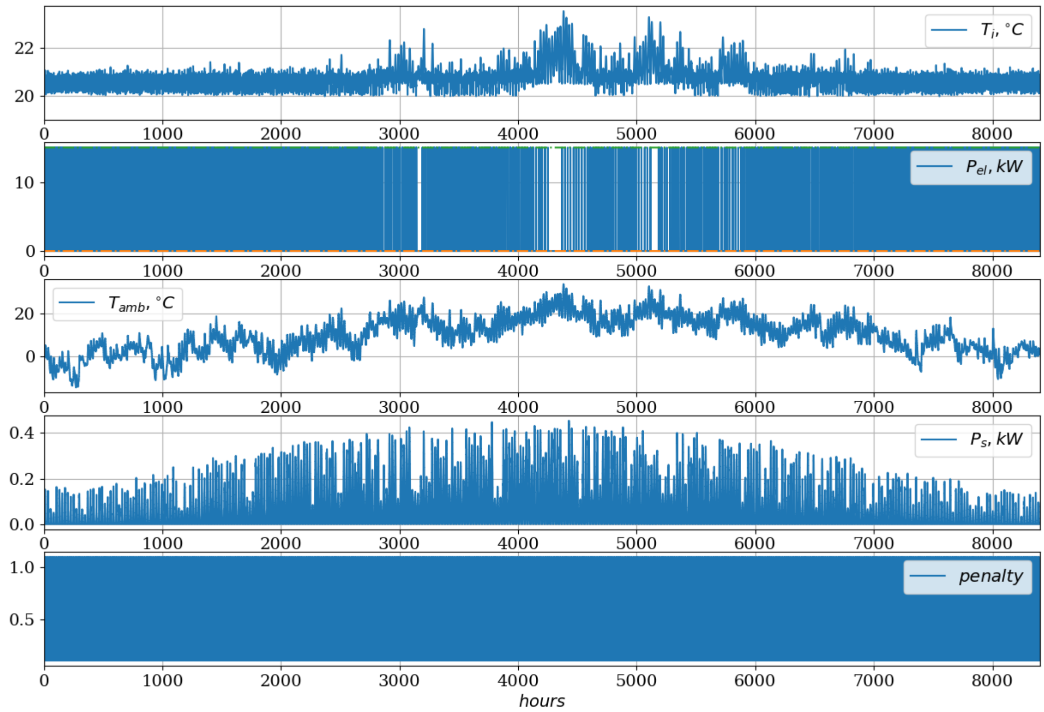

Figure 39 Annual simulation results of MPC using time-varying penalty signal. Top panel shows the indoor temperature. The second panel demonstrated the on/off control signal of the heat pump. The ambient temperature is provided in the third panel. The solar irradiation and the penalty signal are shown in the fourth and fifth panels, respectively.

6.4. Dutch demo

In the Dutch demo there are two levels of control. The Heat Pump Controller of ITHO takes care of all equipment sensor data measurement, control logic (turning pumps on/off, switching between boiler heating and floor heating, boiler temperature control) and operational constraints.

Multiple operational constraints have to be taken into account, such as a minimum switch-on time of the heat pump, minimum time intervals between subsequent activations of the heat pump, minimum switch-over time between boiler heating and floor heating.

The second level of control is formed by MPC. The MPC has two control signals (manipulated variables: MVs) it can send to the heat pump controller:

- Switching the heat pump on/off
- Switching the heat pump between floor heating and boiler heating

The behaviour of the apartment is influenced by manipulated inputs (MVs) (denoted as u(t)) and external boundary conditions (denoted as d(t)), such as outside temperature, wind, wind direction, solar radiation, ground temperature, neighbour temperatures).

Time is denoted as: t. Since the MPC controller operates with a discrete time step Δt, time may be replaced by a discrete value k, where $t = t0+k\ \Delta t$ (k=0,1,....)

The objective function J quantifies cost of energy import from the electrical grid over a prediction horizon P of order 1 day. In the current Dutch situation power exported to the grid is sold at the same price as imported power. Therefore the objective function can be written as

$$J = \sum_{k=t0}^{t0+P\Delta t} p(k)\left(Q_{e,HP}(k) + Q_{e,app}(k) - Q_{PV}(k)\right) \tag{21}$$

Where p(k) is the time-dependent predicted cost of electric power. $Q_{e,HP}$ is the electrical power required by the heat pump and associated fluid transport pumps. $Q_{e,app}$ is the required electrical power of appliances and Q_{PV} is the locally produced electrical power by PV panels. t0 is the current moment in time and Δt is a discrete time step of 20 minutes.

MPC minimizes the objective function J by using the two manipulated variables u(t) as a function of time over the control horizon C <= P :

$$min_{u(1..C)}\, J\left(u(1..C), T(t0), d(1..P)\right) \tag{22}$$

The objective function value is calculated by forward simulation of the heat equation over the prediction horizon from the current moment in time t0 onwards using:

$$C\frac{dT}{dt} = HT + \sum_i Q_i \tag{23}$$

To simulate the system predicted weather conditions (outside temperature, wind, solar radiation) are imported from a meteorologic prediction website.

The data-driven profile-based occupant model is used to predict occupant behaviour based on historical data on tap water use, room temperature setpoint, window use and appliance use.

The optimization problem is subject to a large number of constraints. These constraints include thermal comfort constraints (the apartment may not be too cold or too hot), operational constraints on boiler temperatures, heat pump operational constraints (e.g. minimum switch-over times).

The constraints may be formulated as a vector of inequality constraints:

$$g\left(u(k), T(k), d(k)\right) \leq 0 \tag{24}$$

Where g is generally a set of non-linear functions of the manipulated variables u, the external conditions d(k) and the temperature state T(k) of the apartment.

Because of the on/off binary control of heat pump operation the MPC optimization is a MINLP (mixed-integer non-linear programming) problem.

The Model Predictive Controller is implemented as a moving horizon controller. Each time step t(k) the following sequence of actions is performed:

1. The initial state at time t(k) of the apartment (room and surface temperatures, boiler temperatures) is determined using a state estimator balancing the one step ahead model prediction and real-time measured temperatures at sensor locations.
2. The weather forecast and other external conditions are loaded for t(k)…t(k+P) .
3. The MINLP optimizer minimizes the objective function using the control time sequence u(t(k)..t(k+C)) of manipulated variables as the degrees of freedom.
4. The values of the calculated optimal control sequence for only the next timestep t+Δt are pushed to the local heat pump controller.

5. The MPC controller waits for the next time step (t(k+1)=t(k)+Δt), sets k=k+1, and proceeds with step 1.

Figure 40 illustrates the anticipatory behaviour of the MPC controller. Starting with a cooled down apartment at 00:00h the optimal control sequence is determined using a time step of 20 minutes (minimum switch time interval of the heat pump) and a prediction horizon of 16 hours.

The preferred temperature setpoint sequence in the living room is predicted by MPC using an occupant model profile method based on historical occupant behaviour. MPC expects the occupant to raise the setpoint from 18 to 20 °C at 8:00h. Since the apartment is cold the heat pump is immediately turned on (control state 2) and remains active. The living room temperature cannot be met at 08:00h, but is only reached at 12:00h. To avoid overshoot the heat pump switches off (control state 0) and is turned on again at 15:00h to avoid discomfort.

The figure shows the anticipatory behaviour of MPC turning on the heat pump during the night to minimize discomfort in the morning.

The occupant model predicts no tap water use, so the boiler temperatures gradually drops due to cooling to the environment. The boiler controller does not switch on until the mid-layer temperature drops below 50 °C.

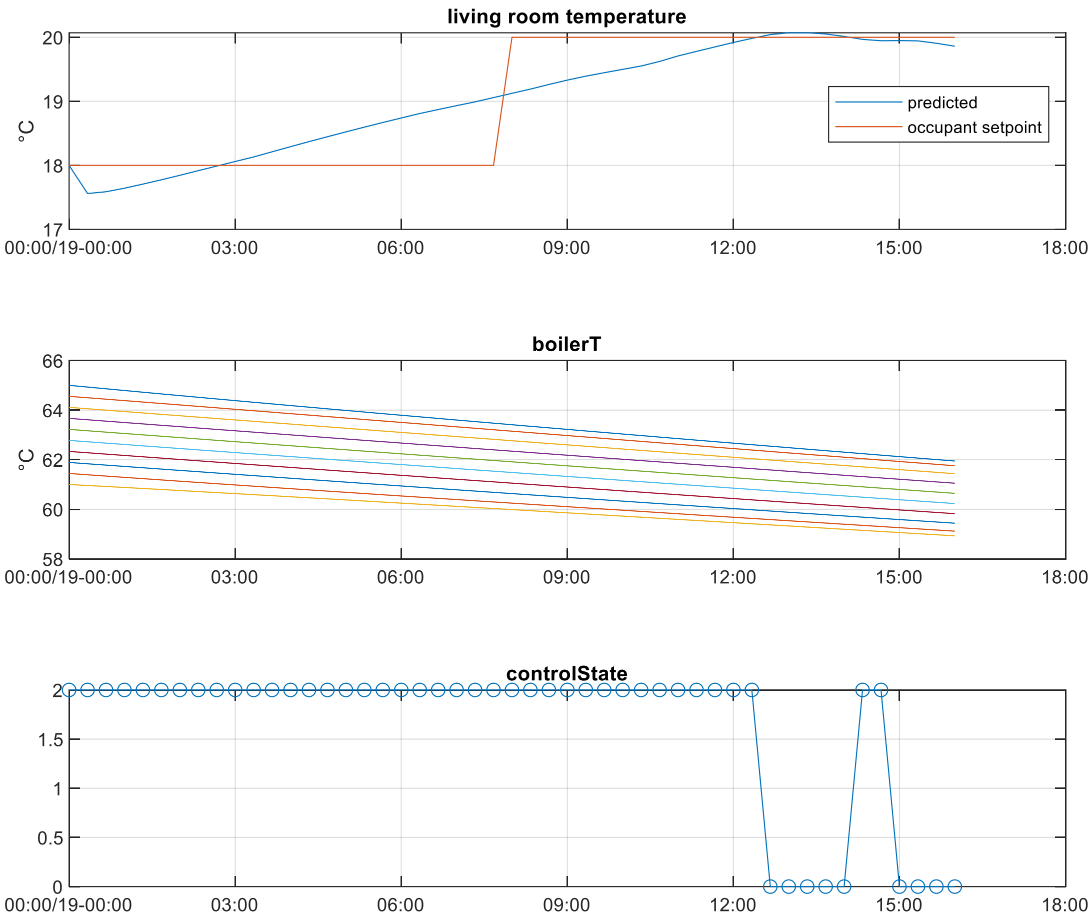

Figure 40 Calculated optimal control sequence at 0:00h with a prediction horizon of 18h.

7. Flexibility Index

Indices are used to indicate some characteristics of systems in such a way that it simplifies the interpretation of that characteristic for a wider audience, such as end users and legislative members. Flexibility index is an indicator of cost saving resulting from employing proper control algorithms capable of shifting loads [6].

7.1. Spanish demo

Indices are used to indicate some characteristics of systems in such a way that it simplifies the interpretation of that characteristic for a wider audience, such as end users and legislative members. Flexibility index is an indicator of cost saving resulting from employing proper control algorithms capable of shifting loads [6]

The accumulated energy and penalty with constant and variable penalty signals are provided in Figure 43. Using variable penalty, the accumulated energy is higher compared to the constant penalty. However, it is seen in the bottom panel that the accumulated penalty of using constant penalty is dramatically high compared to the variable penalty. This is due to the fact that MPC schedules the electricity consumption of HVAC system due to the electricity price.

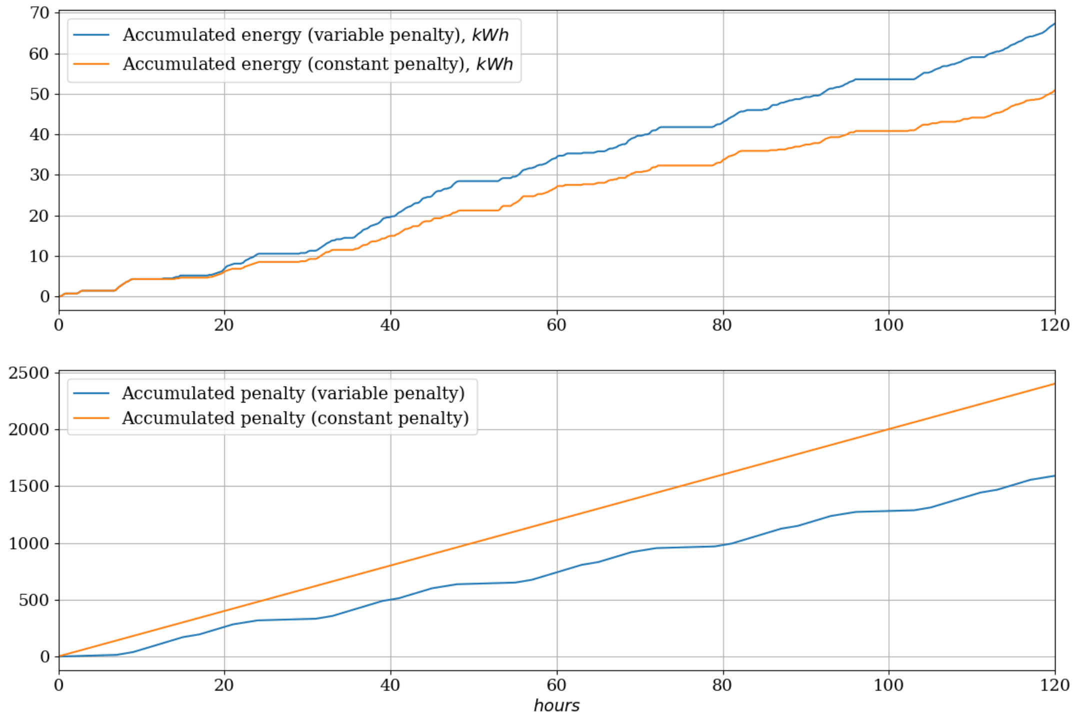

Figure 41 Accumulated energy and penalty with constant and variable penalty signals.

The flexibility index also shows that using MPC and variable penalty signal reduces the costs by 40.5%. The following formula calculates the flexibility index:

$$FI = 1 - \frac{\sum\big((variable\ penalty) \times (energy\ consumption\ with\ variable\ penalty)\big)}{\sum\big((variable\ penalty) \times (energy\ consumption\ with\ constant\ penalty)\big)} \qquad (25)$$

Simulating the system for a year, the accumulative energy and penalty is provided in Figure 42. The flexibility index (25) for the annual data provides a flexibility index of 48.18%.

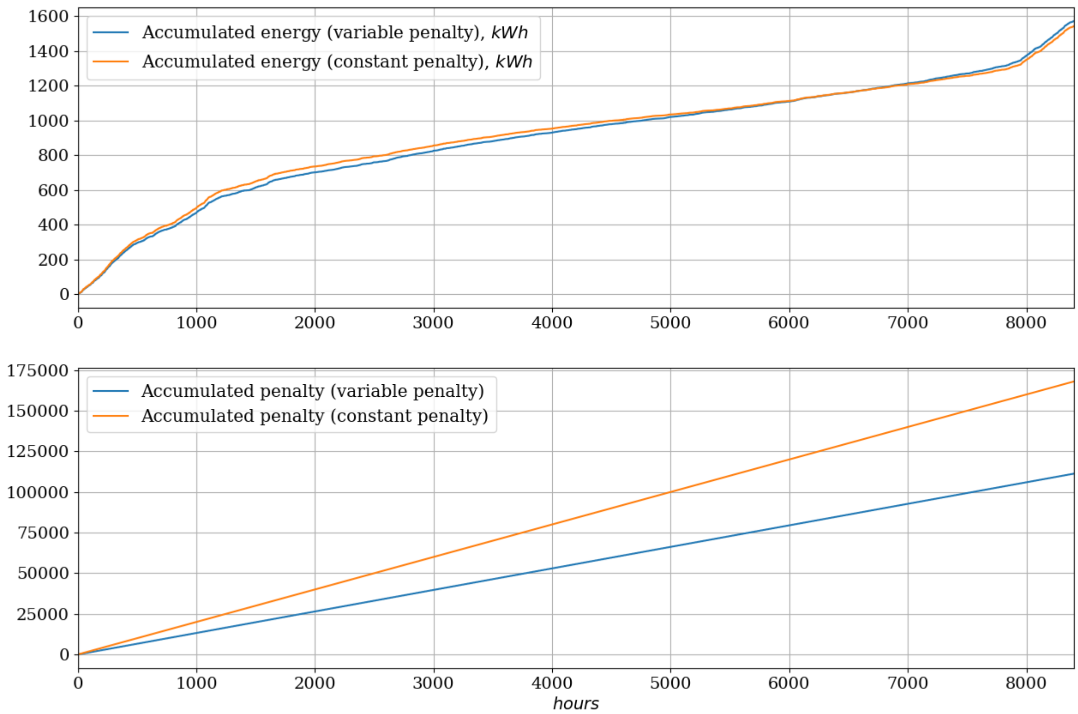

Figure 42 Accumulated energy and penalty with constant and variable penalty signals throughout a year.

7.2. Norwegian demo

Figure 43 demonstrates the accumulated energy and penalty with constant and variable penalty signals. It is observed in the top panel that using variable penalty, the accumulated energy is slightly higher compared to the constant penalty. However, it is seen in the bottom panel that the accumulated penalty of using constant penalty is dramatically high compared to the variable penalty. This is due to the fact that MPC schedules the electricity consumption of HVAC system due to the electricity price.

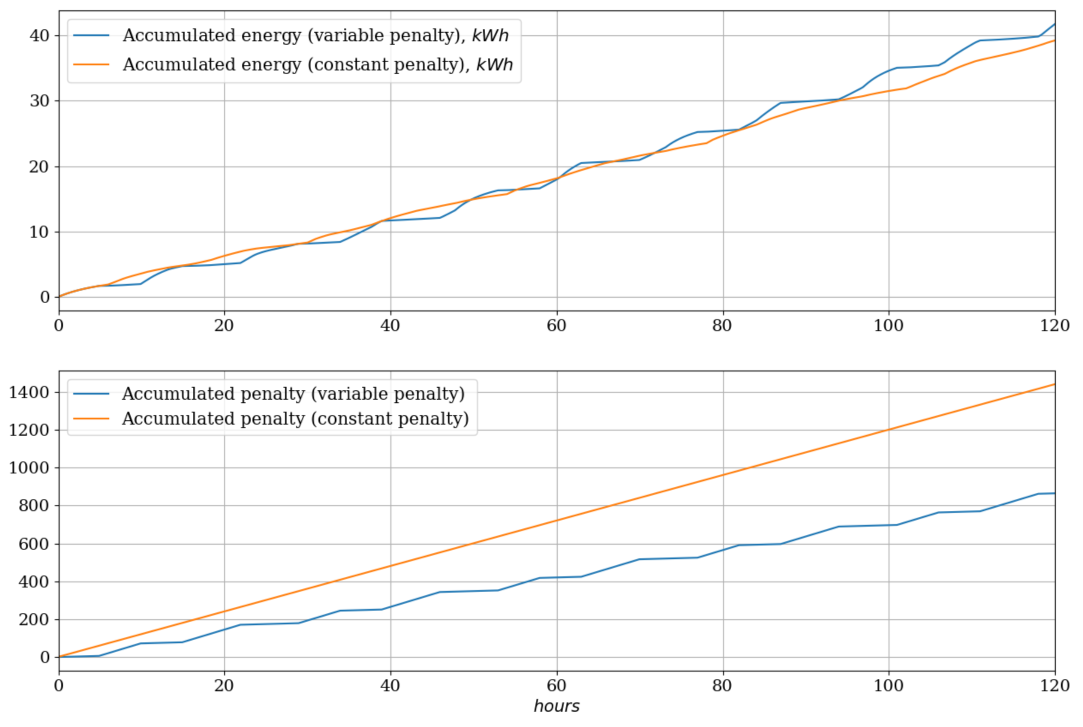

Figure 43 Accumulated energy and penalty with constant and variable penalty signals

The flexibility index (25) shows that using MPC and variable penalty signal reduces the costs by 66.44%.

Simulating the system for a year, the accumulative energy and penalty is provided in Figure 44.

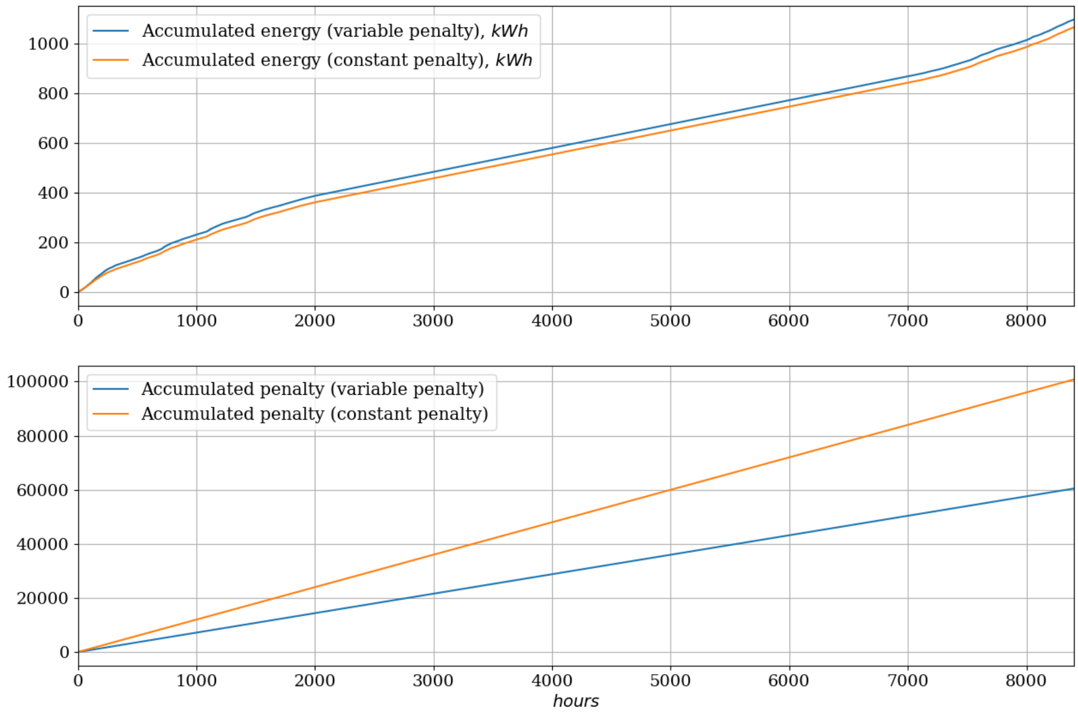

Figure 44 Accumulated energy and penalty with constant and variable penalty signals throughout a year.

The flexibility index (25) for the annual data provides a flexibility index of 67.7%.

7.3. Austrian demo

Figure 45 demonstrates the accumulated energy and penalty with constant and variable penalty signals. This figure shows that using time varying penalty signal, the accumulated energy is slightly higher compared to using constant penalty signal. However, the bottom panel demonstrates that the accumulated penalty is dramatically higher once constant penalty signal is employed. This implies that MPC can handle energy consumption while reducing the electricity costs.

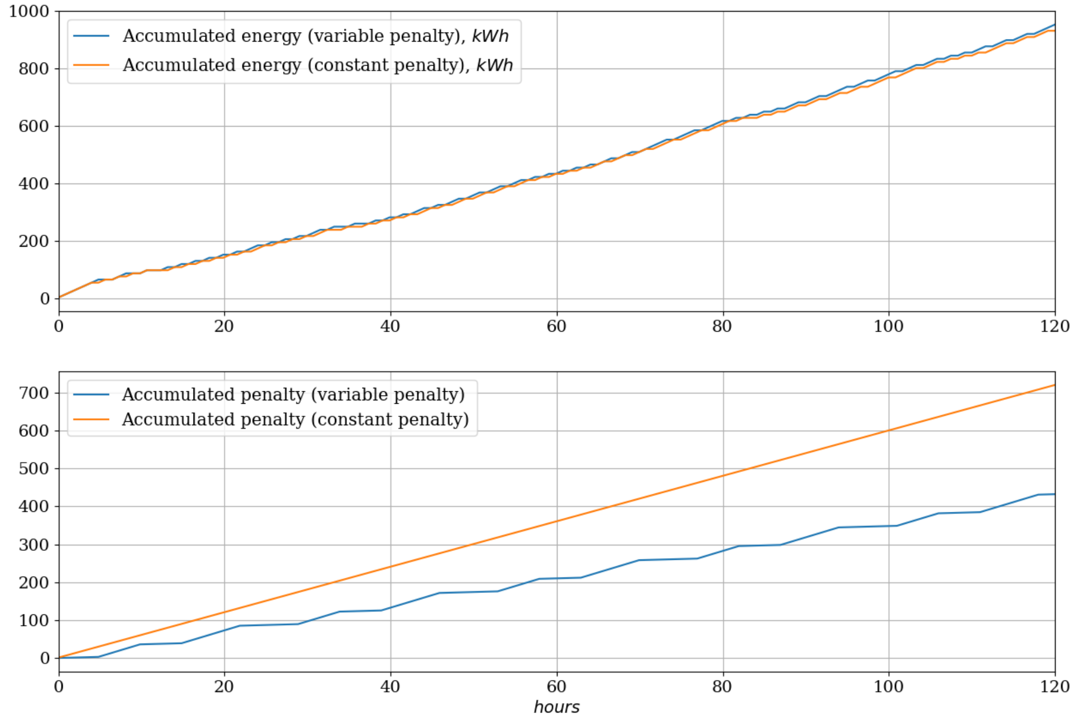

Figure 45 Accumulated energy and penalty.

The flexibility index (25) shows that using MPC and variable penalty signal reduces the costs by 2.9%.

It can be seen in Figure 46 that the obtained flexibility is not at the expense of missing thermal comfort. The figure demonstrates that the controllers, with constant and time-varying penalty signals, are able to preserve the indoor temperature around 20 ℃. Also, it can be observed that the distribution of indoor temperature using time-varying signal is slightly shifted towards right. This is due to the fact that the controller with time-varying penalty signal tries to heat up the indoor at the periods of low electricity price to compensate the indoor temperature at the periods of high electricity price.

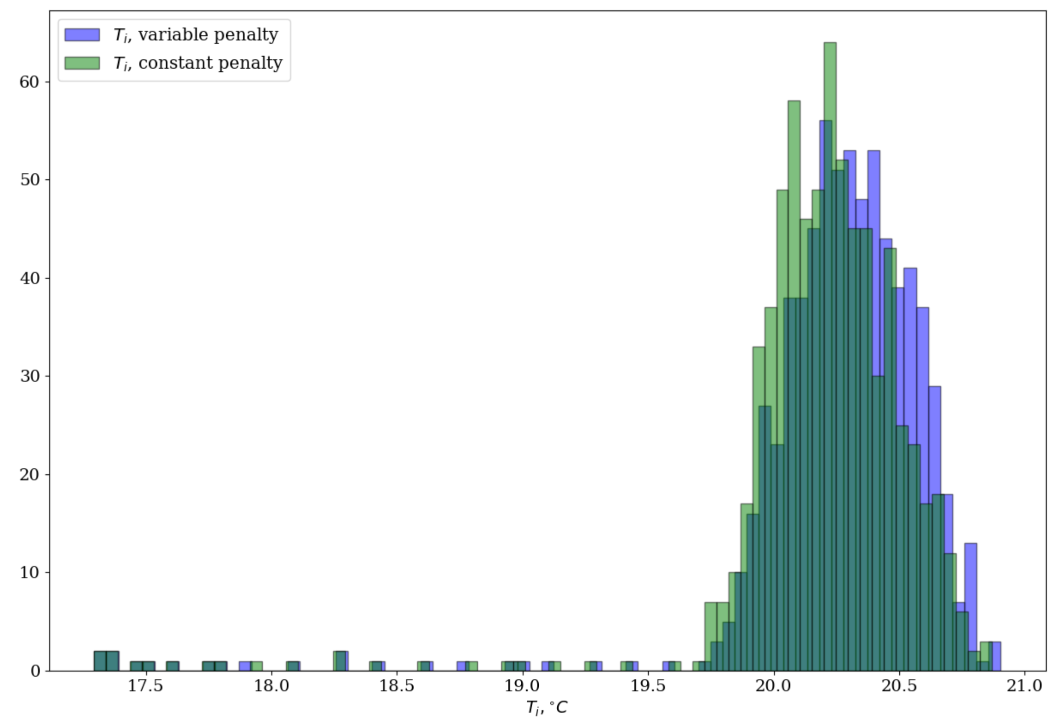

Figure 46 Distribution of indoor temperature.

Simulating the system for a year, the accumulative energy and penalty is provided in.

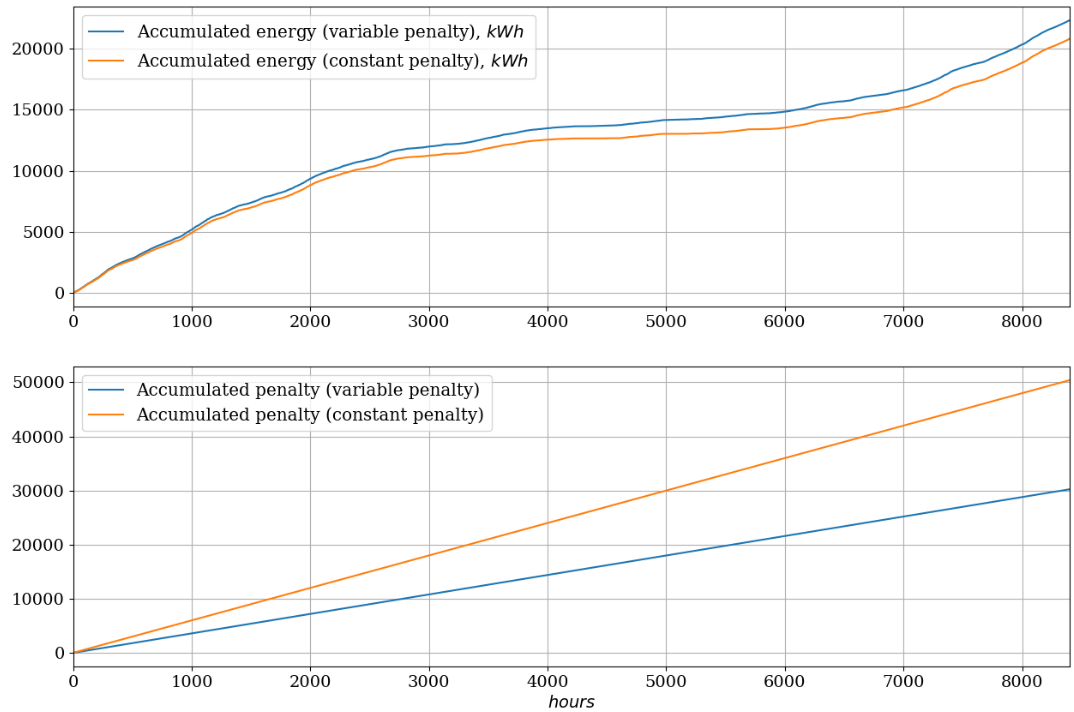

Figure 47 Accumulated energy and penalty.

The flexibility index (25) for the annual data provides a flexibility index of 14.5%. The distribution of the indoor temperature using the annual simulation data with constant and time-varying penalty signal are provided in Figure 48.

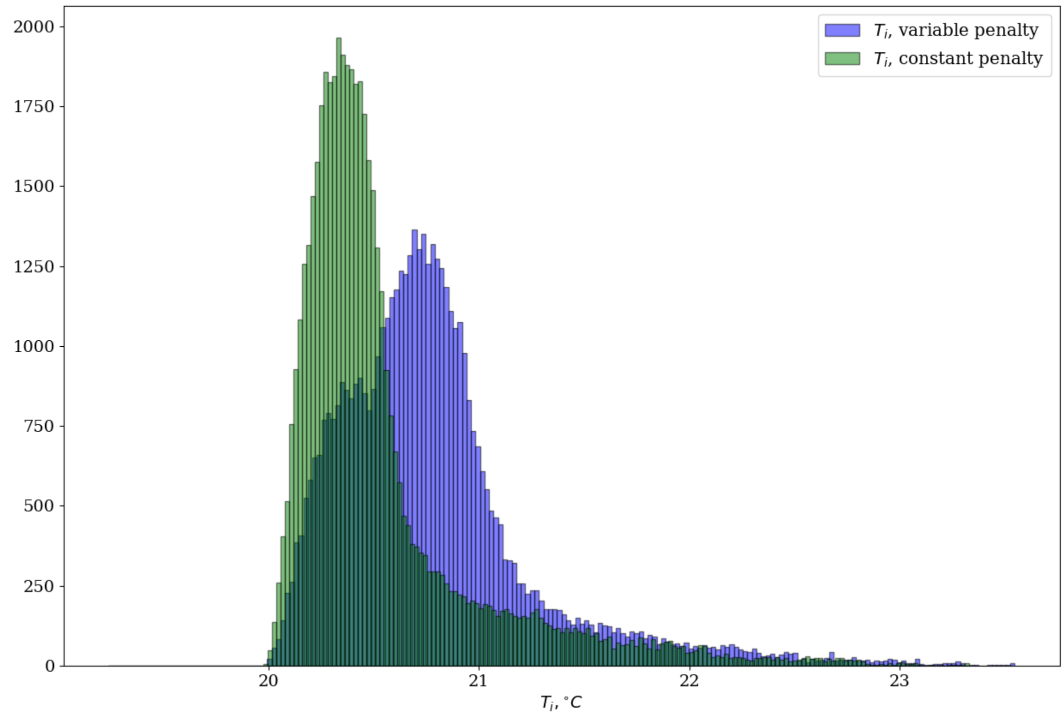

Figure 48 Distribution of indoor temperature based on annual simulation.

7.4. Dutch demo

Definition

Flexibility index symbolizes the fractional savings, that is possible to achieve when applying the flexibility control strategy. Flexibility index 0 symbolises zero improvement in the flexibility scenario, meaning that both the base and flexible case had equally many penalties. Flexibility index 1 indicates that flexible case accumulated penalty is close to 0.

Calculation:

$$FI = 1 - \frac{C1}{C0} \tag{26}$$

$$Cn = E * \lambda \tag{27}$$

Where:

FI – Flexibility index

$C1$ – Accumulated penalty of flexible case, penalty unit

$C0$ – Accumulated penalty of base case, penalty unit

Cn – Accumulated penalty, penalty unit

E – Energy consumption, kWh
λ – Penalty signal, penalty unit/kWh

Upward Flexibility: penalty function and flexibility index

Based on the optimal upward strategy that was found in the earlier research (see D3.4: Guidelines for realizing energy flexibility), a penalty function can be constructed to promote the use of generated solar energy. It is assumed that the penalty function is zero between 9 a.m. and 1 p.m. and one everywhere else (Figure).

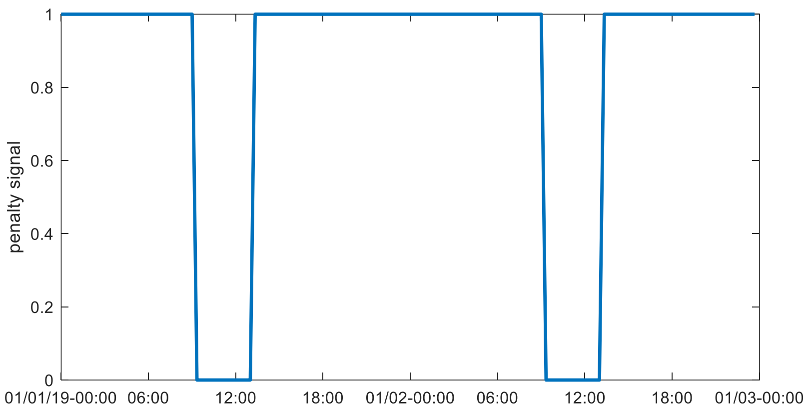

Figure 49: Penalty function constructed from the optimal upward strategy for 2 consecutive days.

Based on the penalty function in Figure the flexibility index can be calculated. Figure 50 shows the flexibility index calculated over the successive weeks. It can be seen that the flexibility index remains positive during the entire heating season. Day-to-day variations are evident, which are caused by not only the magnitude of the rebound effect, but also by the accumulated penalty in the reference scenario. This is why the points with high flexibility index do not necessarily correspond to the points with highest capacity or efficiency. When calculated over the whole year, the optimal strategy has a flexibility index of about 0.27.

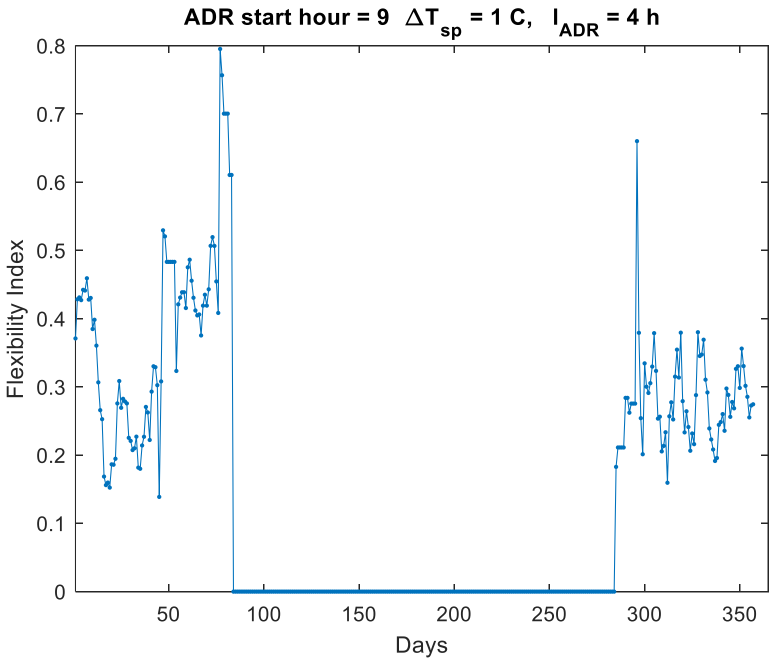

Figure 50: Flexibility index for the optimal upward strategy calculated over successive periods of one week, where the starting day of the week is changed throughout the year.

8. General discussion on the results from the different models

This report presents the simulation results of using economic model predictive controller to control the HVAC systems of each demonstration case. Each designed model predictive controller is equipped with a simplified low-dimensional model specific to the conditions and limitations of each demo. This model, also called grey-box model, is identified using white-box models, specific for each demo, and is responsible to provide reliable prediction for the controller. The simulation results of employing economic model predictive controllers with grey-box models demonstrate the efficiency of the designed controllers to shift the load to low-cost periods of the day.

The grey-box model identification is a prominent part of design procedure. Finding a reliable grey-box model is dependent on the provided data and physical knowledge about the model. The parameters of the model cannot be estimated properly unless the provided data has some properties. High-resolution data generally lead to more accurate models. In additions, persistently exciting data is the other requirement resulting in convergence of parameters in the process of identification. It is also seen that a more realistic white-box model leads to a reliable model for the model predictive controller and, consequently, improves the load shifting performance.

Although the grey-box models are simplified and low-dimensional models compared to the complicated white-box models, they represent the dynamic behaviours properly. This makes them an appropriate choice for optimization and prediction purposes. Also, some thermodynamic properties of apartments can be identified from them. Among them are time constant, settling time, total thermal resistance, total heat capacity, and heat loss coefficient. The identified values are in accordance with the reported values. The observed errors are due to simplification, model reduction, unmodelled dynamics or local convergence of optimization algorithms.

Moreover, reviewing the simulation results reveals that the model predictive controller is able to keep the indoor and tank temperatures in a prespecified boundary during the day for a whole year, considering the electricity price. Regulating the indoor temperatures in a certain boundary enhances the thermal comfort as well. It is observed that the load shifting capability of the model predictive controller is not at the expense of missing thermal comfort.

Calculating flexibility index is another part of this report, indicating the cost saving possibility resulting from employing a proper control algorithm. Flexibility index based on the five-day results are calculated for each demo. To be more precise, an annual simulation is conducted, and flexibility index is recalculated based on them.

9. Summary and Future Works

This report introduces the modelling and control methodologies required for load shifting leading to cost effective designs. A description of HVAC system including information about setpoints, controllable parameters, and constraints are provided for each demonstration case. A low-dimensional model, representing the dynamical behaviours of the white-box model at the apartment level, is identified. It is also shown that the error between the identified model and the data resembles the properties of white noise. This validates the accuracy of the identified grey-box models. Also, thermodynamic properties, calculated from the grey-box model, are aligned with the real properties. This simplified model is then employed to provide predictions for the model predictive controller.

Economic model predictive controllers are designed for each demo to minimize the electricity consumption of HVAC system during high-price periods of time, while considering constraints and thermal comfort in each demo. Simulation results demonstrate the capability of model predictive controllers in shifting loads to some certain periods without sacrificing the indoor thermal comfort. Furthermore, flexibility index is calculated using short-term and long-term simulation results to indicate the possibility of decreasing costs by applying advanced control strategies.

Future control designs rely on more realistic data from demonstration cases. This requires a better understanding of all aspects of the system including control parameters and setpoints. Then, a modified version of the model needs to be identified and MPC have to be revised and retuned based on that. This leads to an improved prediction and robustness. In addition, the control strategy should be enhanced by considering CO_2 emission information, on-site PV and/or economic compensation of exported energy, and more realistically validated constraints and tariffs.

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11. Appendix A – Glossary of Terms

COP	Coefficient Of Performance
CTSM-R	Continuous Time Stochastic Modelling in R
DHW	Domestic Hot Water
EMPC	Economic Model Predictive Control
EV	Electric Vehicle
FF	Flexibility Function
FI	Flexibility Index
GB	Grey Box
gbXML	Green Building eXtensible Markup Language
HP	Heat Pump
HLC	Heat Loss Coefficient
HTC	Heat Transfer Coefficient
HVAC	Heating, ventilation, and Air Conditioning
MINLP	Mixed-Integer Non-Linear Programming
MPC	Model Predictive Control
MV	Manipulated Variable
PV	PhotoVoltaic
SDE	Stochastic Differential Equation

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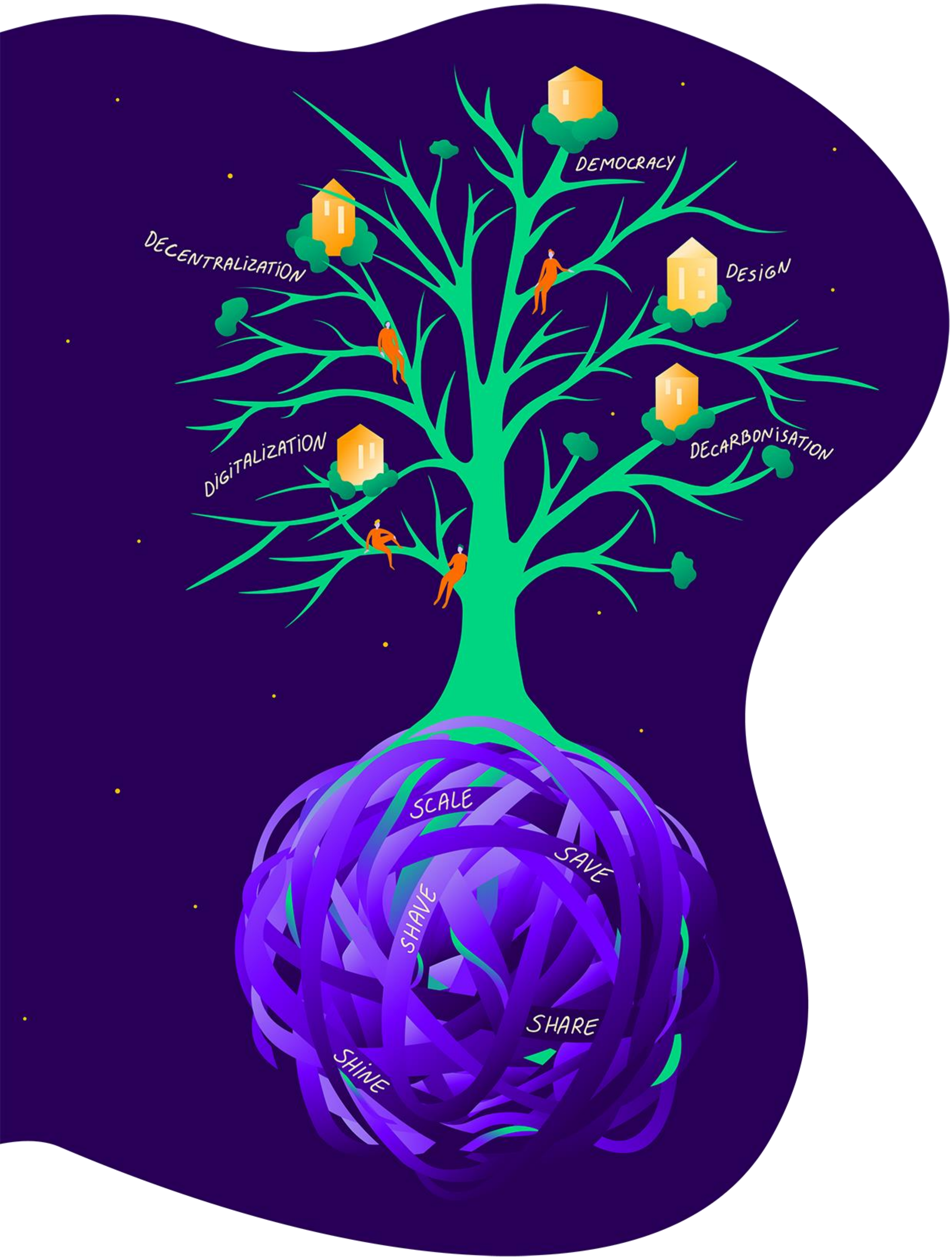
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