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Model complexity of heat pump systems to investigate the building energy flexibility and guidelines for model implementation

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HIGHLIGHTS

- Comparison of a modulating and an on-off air-source heat pump as well as direct electric heating.
- Implementation of a detailed heat pump system model into a building performance simulation tool.
- In-depth analysis of the controller for heat pump units.
- Model complexity of the heat pump controller influences short-time behavior of the heat pump.
- Domestic hot water prioritization of the heat pump can influence auxiliary heater operation during demand response.

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ABSTRACT

Building performance simulation (BPS) is a powerful tool for engineers working in building design and heating, ventilation and air-conditioning. Many case studies using BPS investigate the potential of demand response (DR) measures with heat pumps. However, the models are often simplified for the components of the heat pump system (i.e. heat pump, electric auxiliary heater and storage tank) and for their interactions. These simplifications may lead to significant differences in terms of DR performance so that more comprehensive models for a heat pump system may be necessary. The contribution of this work is twofold. Firstly, this work investigates the influence of the modeling complexity of the heat pump control on different key performance indicators for the energy efficiency, the DR potential and the heat pump operation. To this end, the performance of six different heat pump controls is compared. Secondly, it describes the implementation of a comprehensive control for a heat pump system in BPS tools. This control is not often documented in the BPS literature and is error-prone. Generic pseudo-codes are provided, whereas IDA ICE is taken as an example in the case study. A predictive rule-based control is implemented to study price-based DR of residential heating. It is shown that a realistic operation of the heat pump system can be achieved using the proposed modeling approach. The results prove that the modeling complexity of the system control has a significant impact on the performance indicators, meaning that this aspect should not be overlooked. For some performance indicators, e.g. the annual energy use for heating and average water tank temperature, it is shown that a proportional (P-) and proportional-integral (PI-) control can lead to similar results. If the heat pump operation is investigated in detail and a short-time resolution is required, the difference between P- and PI-controls and their tuning is important. As long as the heat pump operation and electrical power at short timescales are not of importance, the choice of controller (P or PI) is not crucial. However, the use of P-control significantly simplifies the modeling work compared to PI-control. If DR is performed for domestic hot water, it is also demonstrated that the prioritization of domestic hot water heating can indirectly influence the operation of auxiliary heaters for space-heating, significantly increasing the use of electricity. However, the electricity use is only slightly increased if DR control is only used for space heating.

1. Introduction

Demand response (DR) measures can be applied to building energy systems to achieve load shifting and peak power reductions, according to reviews on demand side flexibility [1] and demand response [2,3]. DR measures can deploy building energy flexibility by making use of available thermal energy storages [4], such as the thermal mass of a building [5] or hot water storage tanks [6]. Several studies consider the

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Nomenclature

ASHP	air-source heat pump
BAU	business as usual
BPS	building performance simulation
COP	coefficient of performance
CP	circulation pump
CSP	control strategy price
DE	direct electric
DHW	domestic hot water
DOT	design outdoor temperature
DR	demand response
HP	heat pump
HPT	high-price threshold
HTSP	high temperature set-point
k	gain parameter
LPT	low-price threshold
LTSP	low temperature set-point
max	maximum
MHP	modulating heat pump
min	minimum
MPC	model-predictive control
OHP	on-off heat pump
OTCC	outdoor temperature compensation curve
P	proportional
PI	proportional integral
PMV	predicted mean vote
PPD	predicted percentage dissatisfied
PRBC	predictive rule-based control
PV	photovoltaic
RTSP	reference temperature set-point
SH	space heating
SCOP	seasonal coefficient of performance
SP	spot price
T_i	integral time
TM	temperature measurement
TSP	temperature set-point
τ_c	tuning parameter for PI-controller tuning
ZEB	zero emission building

activation of the building energy flexibility using (predictive) rule-based control ((P)RBC), e.g. [7,8]. These controls are frequently implemented into building performance simulation (BPS) tools. Heat pump systems can be used to perform DR measures to deploy the demand side flexibility of buildings. A *heat pump system* refers to a heat pump unit combined with auxiliary heaters and (potentially) thermal storage as well as the system control. Typically, a heat pump is connected to a water tank to store domestic hot water (DHW) or provide space heating (SH).

1.1. Model complexity and simplifications

An overview of simulation-based studies of DR using heat pumps and applying RBC is presented in Table 1, focusing especially on the model simplifications applied to the respective heating systems. From this overview in Table 1, it appears that there is a lack of detailed

Table 1
Typical model simplifications for heat pump systems to perform demand response using rule-based controls.

Reference	Control aim	Heat pump	Water tank	Software tool
De Coninck et al. [12]	– Reducing non-renewable energy use	– Air-to-water – Based on performance maps – No minimum run time	– For DHW only – Calibrated and validated DHW tank model	Modelica
Dar et al. [13]	– Increasing PV self-consumption	– Air-to-water – Based on performance maps – No minimum run time	– For SH and DHW – 20 stratification layers	MATLAB
Esfehani et al. [14]	– Using surplus electricity generation from wind power	– Ground-source – On-off heat pump – Monovalent operation – No minimum run time	– For SH and DHW – 4 stratification layers	TRNSYS
Alimohamma-disagvand et al. [15]	– Reducing operational costs	– Ground-source – Perfect modulation (0–100%) – DHW prioritized over SH – No minimum run time	– For SH and DHW – 10 stratification layers – Model validated with measurement data	IDA ICE
Masy et al. [16]	– Reducing operational costs	– Air-to-water – Simplified empirical model – Calibrated on manufacturer data – No minimum run time	– Fully mixed	–
Georges et al. [17]	– Reducing operational costs	– Air-to-water – Based on performance maps – DHW prioritized over SH – On-off and modulating heat pump – No minimum run time	– Two separate tanks used for SH and DH – DHW tank: two-node model with homogeneous temperature in each zone – SH tank: fully mixed	–
Salpakari and Lund [18]	– Increasing PV self-consumption	– Ground-source – Perfect modulation (0–100%) – No minimum run time	– Fully mixed	–
Psimopoulos et al. [19]	– Increasing PV self-consumption	– Exhaust air heat pump – Based on performance maps – Modulating heat pump	– Two separate tanks used for SH and DH – DHW tank (180 L): 5 stratification layers – SH tank (25 L): fully mixed	TRNSYS
Lizana et al. [9]	– Reducing operational costs – Reducing environmental footprint	– Air-to-water – Based on performance maps (use of correction functions to correct rated operation data to nominal conditions)	– For DHW only (200 L) – 3 stratification layers	TRNSYS

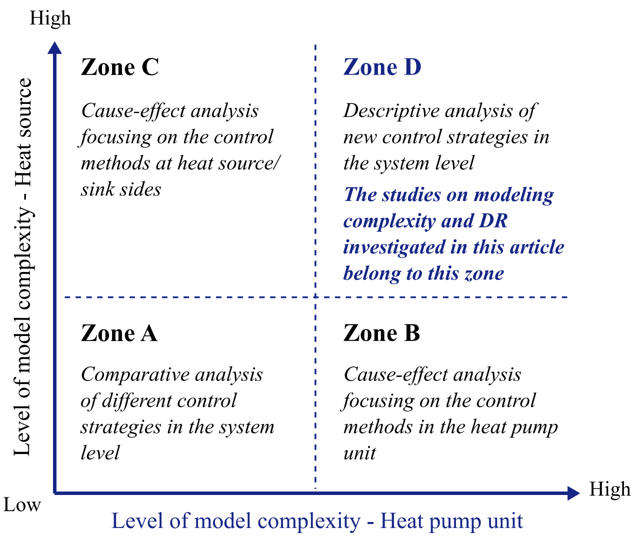

Fig. 1. Roadmap for required model complexity depending on the type of study (adapted from [11]): the work carried out in the current paper is in Zone D.

information of the heat pump system and that modeling simplifications are introduced. These studies typically combine one or several of the following simplifications for the modeling of the heat pump system:

(1) *The heat pump modulates perfectly between 0% and 100%, or is on/off*. These assumptions make the operation of the heat pump continuous or discrete which considerably simplifies the modeling when considered separately. Obviously, with a perfect modulation, the number of heat pump cycles throughout the year cannot be studied.
(2) *Minimum duration and pause times in the heat pump cycle are not considered*. Without these constraints, frequent on-off cycling could occur.
(3) *The water storage tank is simplified.*
  (a) *Thermal stratification is neglected.* Thermal stratification in a water tank results from complex heat transfer phenomena. The use of stratification is part of the working principle in many heat pump systems. To model the stratification, detailed information about the tank construction is required such as the location of the connections to the tank. Regarding control, the location of the temperature sensors inside the tank is also important.
  (b) On the contrary*, the tank may be idealized in order to maximize stratification.* In this idealized framework, the physical heights of the tank connections vary continuously depending on the temperature to be supplied. The height of the connections to the tank do not need to be known.

  A *realistic tank model* should be used for detailed analysis of DR measures. Here, a *realistic tank model* means that the tank connections are at fixed heights, where the exact height of connections has to be defined in the model. In addition, a reasonable number of horizontal layers in the tank should be chosen to account for stratification inside the tank. Furthermore, the location of temperature sensors inside the tank for controlling the heat pump operation also has to be defined. Manufacturers of water tanks usually provide a detailed technical description of their products.
(4) *DHW prioritization over SH is not considered.* Heat pumps usually prioritize DHW production. Detailed knowledge of this control is required for realistic modeling of the operation of the heat pump and auxiliary heaters. DHW prioritization has been considered in some studies, e.g. [9] and [10].
(5) *There is no temperature limit for the condenser and evaporator temperatures.* Heat pumps have a maximum supply temperature which should be considered as well as a minimum temperature at the evaporator side. In addition, *defrosting cycles* of air-source heat pumps are usually not taken into account in a consistent way.
(6) The *control strategy of the auxiliary heater(s) is idealized*. It is sometimes assumed that auxiliary heaters exactly compensate for the lack of power from the base load to meet the heating needs. In reality, the control of auxiliary heaters is not perfect. In addition, the heating required for the legionella protection may involve the auxiliary heater (due to the maximum temperature limit of the heat pump).
(7) The *heat pump model only considers steady-state operation at full load measured during standard rating conditions according to EN 14511*. The influence of cycling losses (meaning transient losses) or the change of the coefficient of performance (COP) at part load are not considered even though these are key phenomena as explained in Section 2. In general, performance data during part load operation are often not communicated by heat pump manufacturers [3].

Ideally, knowledge about the short-time dynamics of heat pump systems is required when DR measures for heating are performed to study the energy flexibility potential of these systems. These short-time dynamics depend to a great extent on the tuning of the heat pump controller, which usually is a proportional-integral (PI) controller. The controller tuning is often overlooked in studies regarding DR and energy flexibility using BPS and cannot be captured in detail by strongly simplified models for heat pump systems. Regarding these DR applications, the specific level of modeling complexity of the heat pump (system) control has not yet been addressed in the literature. In this paper, *modeling complexity* of the heat pump system refers to the models for the water storage tank, the heat pump control, the auxiliary heater control and the heat pump system control. The required modeling complexity of a heat pump system depends on the objectives of the respective study. For example, simplified models may be sufficient to analyze the annual energy use whereas a more detailed model of the heat pump system is required if the detailed operating conditions of the heat pump system are of interest. Madani et al. [11] address the question of the required model complexity for complex heat pump systems. Their aim is to find the minimum level of detail to capture the behavior of the heat pump system with satisfactory accuracy. As shown in Fig. 1, they suggest a roadmap to select the necessary level of model complexity for a given type of analysis considering both the heat pump unit and the heat sources or sinks. The current work focuses on Zone D in Fig. 1 where both a detailed modeling of the heat pump system and the heat sinks are required. As a detailed building model is needed, BPS packages, such as IDA ICE or TRNSYS, are assumed to be used as simulation environment.

1.2. Physical characteristics of heat pumps

The responsiveness of the heat pump to an external penalty signal for DR influences the short-time behavior of the heat pump system. Therefore, it is essential to carefully consider the heat pump characteristics when developing the respective component models of the heat pump system and its control. The heat pump characteristics that are also of interest for studies of DR are described in the remainder of this section.

A vast number of studies focus on the design and operation of heat pump systems in residential buildings. Specifically, many studies compare the energy performance of on-off heat pumps (OHP) and modulating/inverter-driven heat pumps (MHP), e.g. [11,20,21]. The run-time performance of heat pump systems depends on several conditions, such as the choice of heat pump system sizing (monovalent vs. bivalent), the heat distribution system, the thermal mass of the building and insulation level, ambient climate conditions, the occupant behavior, the choice and integration of thermal energy storages as well as the control to operate all the components of the heat pump system [11,22].

The importance of heat pump sizing is addressed by several studies, e.g. [11,21,23]. Using a monovalent heat pump system, the heat pump is sized to fully cover the heating needs of the building, even for its nominal heating power evaluated for the design outdoor temperature (DOT). As cold outdoor temperatures similar to DOT do not occur frequently during a heating season, the heat pump behavior in part load should be considered carefully. In particular, the use of inverter-driven heat pumps offers the possibility to modulate the heat pump capacity to meet the heating loads of the building [21] during periods with higher outdoor temperatures (and thus lower SH demands in the building). As pointed out by Dongellini et al. [23] and Bettanini et al. [24], the seasonal performance of heat pumps depends strongly on their COP during part load operation. On the contrary, using a bivalent heat pump system, the heat pump covers the heating load above the so-called bivalent temperature. Below this temperature, auxiliary heaters support SH or DHW demands. Therefore, the heat pump is sized to only cover a fraction of the nominal heating power of the building. For on-off heat pumps that are sized to meet a high fraction of the nominal building power, this will eventually lead to shorter cycles so that the impact of losses due to frequent on-off cycling would be increased.

Cycling losses occur during the start-up of each cycle because the compressor has to re-establish the pressure difference between the evaporator and the condenser. The heating capacity of the heat pump unit is lower until steady-state conditions are reached [22]. Dongellini et al. [22,23], Bagarella et al. [20] and Uhlmann and Bertsch [25] investigate energy losses due to on-off cycling. Based on experimental data provided by a heat pump manufacturer, Dongellini et al. [22] reported that the steady-state condition for a small residential heat pump is reached after approximately 150 s and that the heating capacity of the heat pump unit is 42% lower during transient periods compared to steady-state conditions. Bagarella et al. [26] also found that steady-state condition was reached after 100–200 s and that the average COP during the start-up period was about 50% lower than during steady-state operation. They also found that cycling losses should not be neglected if an on-off heat pump is sized to cover a high fraction of the building nominal demand as this would lead to a high number of cycles throughout the year [20]. Uhlmann and Bertsch [25] performed field and laboratory measurements of the start-up and shut-down behavior of residential heat pumps. They concluded that the loss of efficiency is less than 2%, if a minimum heat pump run time of 15 min can be ensured.

Several studies found that the performance is improved for modulating heat pumps compared to on-off heat pumps [20,22,27]. For example, Madani et al. [28] investigate the operation of an on-off heat pump and a modulating heat pump system for a single-family residential building in Sweden. They found that there is no significant difference between the performance of the two heat pumps, if the on-off heat pump is sized to cover more than 65% of the peak heating demand of the building and if an electric auxiliary heater was used as a peak load system. In addition to cycling losses, this is due a second physical effect. Many modulating heat pumps have a higher COP at part load compared to nominal load. In Dongellini et al. [22], the COP is ~20% higher between 40 Hz and 60 Hz compared the nominal frequency of 120 Hz. For a same nominal frequency of 120 Hz, the minimum capacity is limited to 20–30 Hz according to Bagarella et al. [20]. Below this minimum frequency, the volumetric efficiency of the compressor decreases significantly as the lubrication cannot ensure a sufficient tightness against the return of the refrigerant to the suction.

Furthermore, a modulating heat pump is typically controlled by PI-control. The tuning of the two control parameters (i.e. the gain parameter k and integral time T_i) is important for the time response of the controller. A very reactive controller usually oscillates until it reaches the required compressor frequency that satisfies the heat load. If the heating load is too low and the amplitude of the oscillations is too high, the compressor frequency may drop below the minimum compressor frequency set by the manufacturer and thus the heat pump may be switched off to protect the compressor. Oscillations usually occur for high (proportional) gains k and low integral times T_i. If the controller is less reactive, it has less or even no oscillations and is thus more stable, but it takes more time for the heat pump to match the required heating load [20]. As an example, Dongellini et al. [22] use a PI-controller to modulate an inverter-driven heat pump where the parameters of the PI-controller are chosen according to manufacturer data: the values of the proportional gain k_p and the integral time T_i have been set equal to 10 and 300 s. If manufacturer data are not available, commonly used tuning rules for PID-controllers are Ziegler-Nichols [29] or Skogestad tuning rules (SIMC) [30]. On top of the PI-controller tuning, an anti-windup control should be established.

1.3. Main contribution of the study

This paper addresses two questions. Firstly, it investigates the model complexity of the heat pump system control required to study the behavior of heat pump systems in detail, with a special focus on DR.

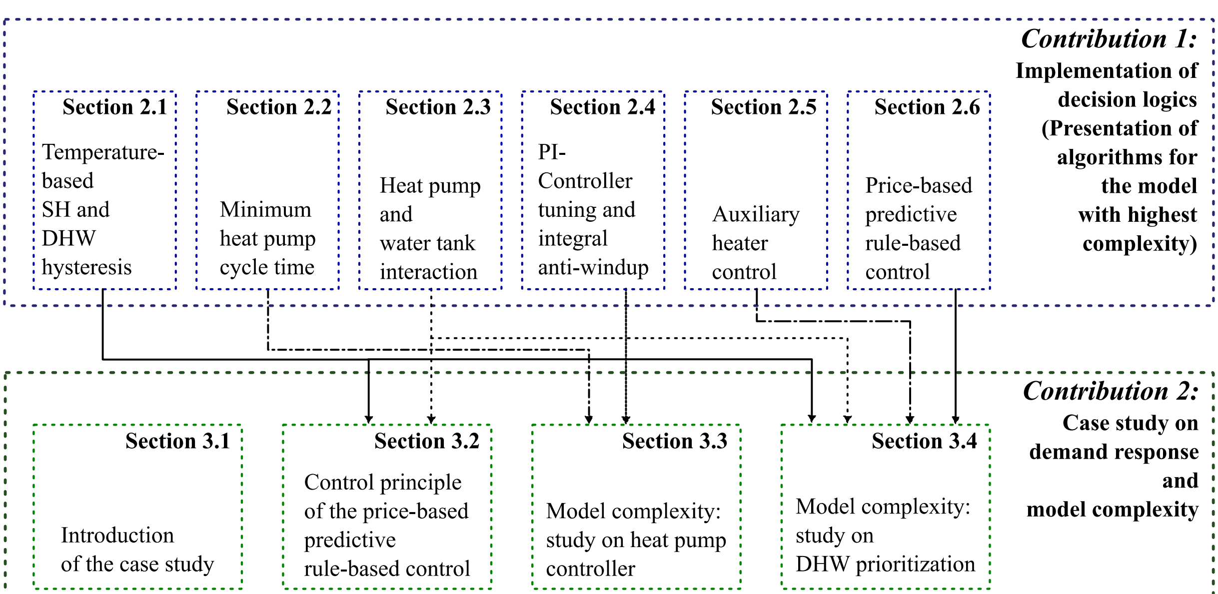

Fig. 2. Overview and coherence of the main contributions.

Secondly, the paper documents generically how to implement temperature-based control of heat pump systems into a BPS tool in order to investigate DR. An overview of the main contributions of this paper is given in Fig. 2.

As this paper deals with detailed modeling, different model complexities should be compared using a specific case study where the technical specifications of all the components and their interconnections are known in detail. As a case study, the heating of a detached house using an air-to-water heat pump (ASHP) is simulated in IDA ICE. Although the layout of an HVAC system can differ from building to building, the presented approach and conclusions remain generic. In this work, the heat pump modulates continuously between 30% and 100% of its nominal compressor capacity using a PI control. A minimum modulation of 30% is chosen as it is a typical lower modulation capability of heat pump compressors, e.g for the Hoval Belaria SRM 4 heat pump [31]. Below 30%, the heat pump cycles on-off. Minimum run and pause times have been implemented to prevent too frequent heat pump cycles. In addition, a realistic prioritization of DHW heating over SH is implemented so that the heat pump cannot support SH when producing DHW. All these three actions require supplementing an anti-windup to the PI control (to prevent the saturation of the integral action). To the authors' knowledge, the proposed level of modeling complexity with detailed models for the building and the heat pump system is hardly found in other studies of DR. The models taken for the different components of the heat pump system are not always the most sophisticated. For instance, the model for the heat pump unit is steady-state. However, the interaction between these components is comprehensive.

It is worth mentioning that most of the commercial BPS tools do not propose this level of modeling complexity in their default library of heating systems. In other words, the modeling complexity can be investigated using these tools but this requires the user to create the system based on the available library of components, including the control. This implementation is time-consuming and error-prone. However, comprehensive descriptions of detailed models for heat pump systems and their control are not often available in the literature. Therefore, this paper documents the implementation of a heat pump system in BPS tools. In addition, this description makes the interpretation of our simulation results transparent. In order to be generic and not specific to IDA ICE, the control logic (or algorithm) is defined as pseudo-codes.

Using the proposed comprehensive model of a heat pump system, the influence of the modeling complexity is investigated for two key components that are overlooked in the literature regarding building energy flexibility. Firstly, the controller for the heat pump unit is analyzed. Secondly, the influence of the DHW prioritization on the auxiliary heater operation is analyzed when DR measures are applied. This paper demonstrates that the model complexity affects the short-time behavior of a heat pump system when performing DR. Furthermore, it is recommended to consider controller tuning for studies of heat pump systems with focus on DR regardless of the applied control strategies, e.g. PRBC or model-predictive control.

The heat pump controller model is progressively simplified to evaluate the influence of the modeling assumptions on some main key performance indicators (KPIs). Typically, these KPIs are the energy use of the heat pump, the yearly-averaged tank temperatures, seasonal performance factor (SCOP), the number of heat pump cycles per year, average heat pump run time, and the short-time dynamics of the compressor (i.e. with a 3-minute time step). To investigate the influence of the controller complexity, six different cases are compared: (1) an

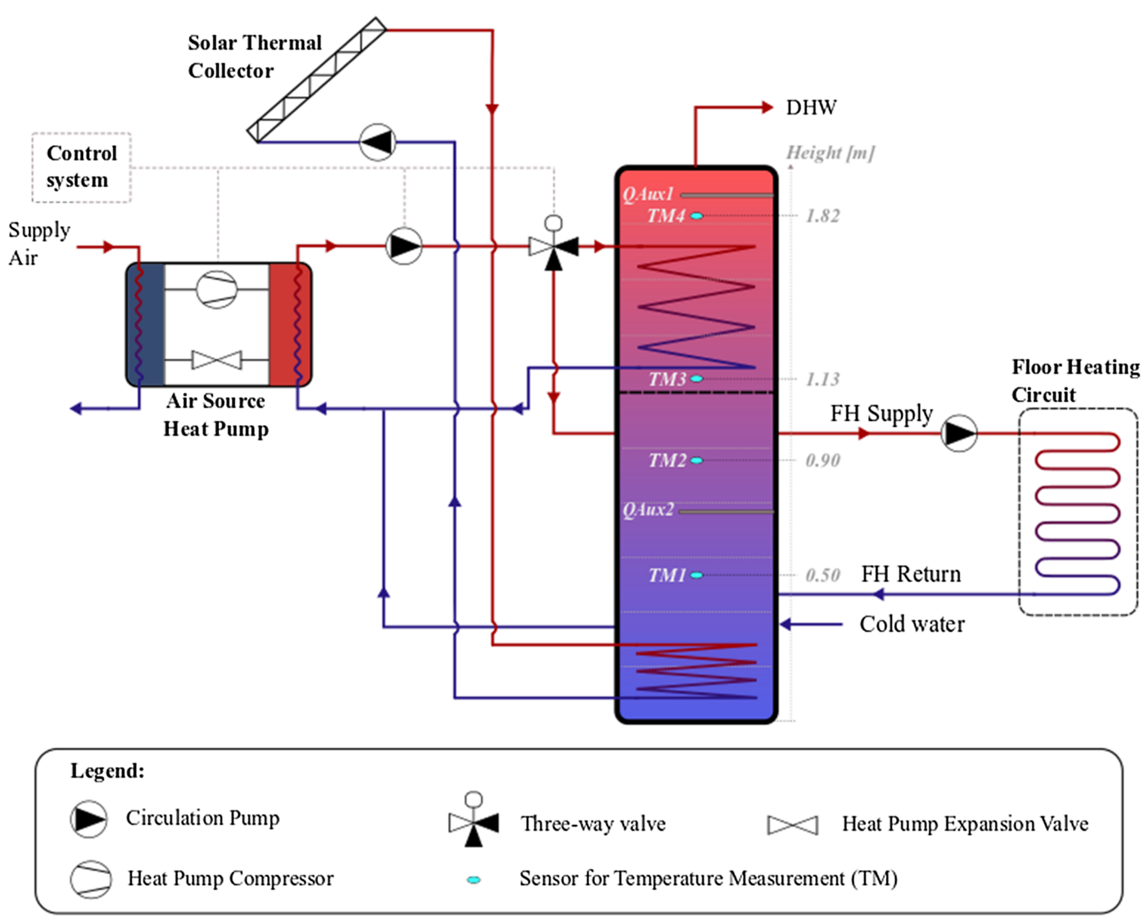

Fig. 3. Configuration of the energy system in a residential building (adapted from [34]).

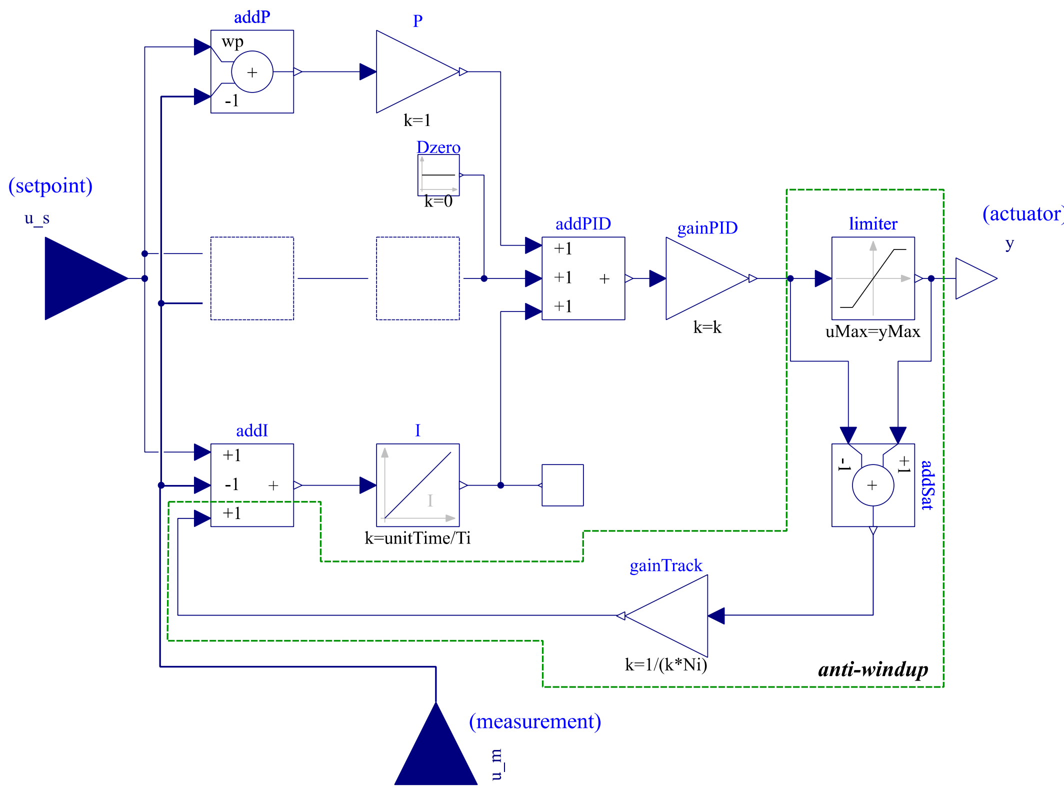

Fig. 4. Flow chart of the PI-controller with integral anti-windup control (which is marked in the green box) [35].

MHP with a tuned PI-controller, (2) an MHP with a PI-controller with a higher integral time (relative to the tuned integral time), (3) an MHP with a proportional (P-) controller, (4) an OHP, (5) an MHP without a minimum run time and (6) an MHP modulating continuously from 0% and 100%. The main reason to specifically focus on the heat pump controller is that these six investigated controls lead to very different levels of modeling complexity, and thus model development time and tuning. In addition, these scenarios are common approximations in existing studies on DR and building energy flexibility.

The remainder of the paper is structured as followed. Section 2 documents the detailed implementation of the temperature-controlled heat pump system into BPS tools. It also presents how price-based DR control using PRBC can be implemented. Section 3 presents the results and shows the influence of the heat pump controller and its modeling complexity on different KPIs. Furthermore, it illustrates how the influence of the DHW prioritization becomes critical when DR controls are introduced. The implementation of the control logics in Section 2 and the presented study in Section 3 are coupled (see also Fig. 2). The conclusions are presented in Section 4.

2. Implementation of a detailed heat pump system model

This section provides a detailed description of a temperature-based control of a heat pump system. The presented control logic is generic and can be implemented in other BPS software tools. However, in the case of this paper the BPS software IDA ICE is used. The overall control logic is divided into modules that are presented in form of pseudo-codes in the different sections. The combination of all the algorithms that creates the overall control is illustrated in Fig. 6.

The parameters of the realistic tank model are based on the EPTRC 400 water tank [32]. The tank is divided into ten horizontal layers, where the lower six layers represent the SH tank, and the upper four layers the DHW tank respectively. Even though the tank is modeled as one unit, it behaves like two physically-separated tanks. Four temperature sensors, two in the DHW tank and two in the SH tank, control the tank charging. Different possibilities for the integration of a water tank into a system exist, such as four-pipe, two-pipe, serial and parallel connections [33], but not all of these are considered in this paper. The configuration of the energy system is illustrated in Fig. 3, where it can be seen that the SH tank has a four-pipe connection.

In general, two different strategies can be applied to a heat pump in order to load a storage tank. The circulation pump (CP) that circulates water between the generator and the tank can have a constant mass flow. The compressor power of the heat pump is then controlled according to the needs of the tank. This is typically done using a PI-control for a modulating heat pump. Alternatively, the compressor power of the heat pump can be kept at full load while the mass flow of the CP is controlled according to the needs of the tank. In our case study, the compressor power is controlled using a PI in SH mode while the CP mass flow is controlled using P-control in DHW mode. The mass flow is controlled so that the heat pump heats up water at the DHW temperature.

To investigate DR measures, temperature-based controls for the heat pump as well as the auxiliary heaters are implemented. Both the thermal storage in the thermal mass of the building and the hot water storage tank are used for DR.

2.1. Tank: detecting DHW heating and SH requirements

As a starting point, the control should check whether the DHW and SH tanks require heating. In principle, the hysteresis for DHW heating and SH works as follows:

- As soon as the temperature in the upper layer of the respective tank part (DHW or SH) drops below a certain temperature set-point (TSP), the tank heating is started.
- The tank heating keeps working until the TSP of the sensor in the lower part of the respective tank is reached.

Algorithm 1 shows the pseudo-code to detect the need for DHW heating. This is based on an hysteresis function using the start and stop temperatures, $T_{start,DHW}$ and $T_{stop,DHW}$. The $T_{start,DHW}$ and $T_{stop,DHW}$ can be varied by the DR control, see Algorithm 7 in Section 2.6. However, unlike a standard hysteresis, the control is based on two measured temperatures. Therefore, the measurements from the temperature sensors in the water tank, TM3 and TM4, are compared to their respective set-points using a *Comparator* to determine if start or stop conditions have been reached. This signal then enters the hysteresis component. If the heat pump is in the DHW heating mode and the hysteresis input is a stop, the DHW heating should stop. If the heat pump is not in DHW heating and the hysteresis input is a start, the DHW heating should start. Otherwise, the DHW mode signal is unchanged.

Algorithm 1. Pseudo-code for the implementation of a DHW hysteresis.

Algorithm 1: Detect the need for DHW heating

```
% Comparator lower part of DHW tank
Input Hysteresis = 1
if (TM3 > T_stop, DHW)
  Input Hysteresis = 0
end
% Comparator upper part of DHW tank
if (TM4 < T_start, DHW)
  Input Hysteresis = 2
end
 % Hysteresis component with DHW Signal in memory and output:
 if (DHW Signal = true) & (Input Hysteresis < =0)
   DHW Signal = false % DHW mode off
 end
 if (DHW Signal = false) & (Input Hysteresis > = 2)
   DHW Signal = true % DHW mode on
 end
 % Algorithm output is DHW Signal
```

The pseudo-code for the SH hysteresis is illustrated in Algorithm 2. The logic of the SH hysteresis is similar to the DHW hysteresis. Here, the measured temperatures TM1 and TM2, are compared to the set-points $T_{stop,SH}$ and $T_{start,SH}$. These two set-points depend on the outdoor temperature compensation curve (OTCC) of the heat distribution system. To provide enough heat storage even during milder outdoor temperatures, $T_{start,SH}$ is set to OTCC while $T_{stop,SH}$ is set to OTCC+ a differential ΔT, here taken at 8 K. This last measure prevents too frequent cycling of the heat pump but this large temperature differential generates a loss of energy efficiency. Again, $T_{start,SH}$ and $T_{stop,SH}$ can depend on price signals because of DR measures. The *SH Signal* is the output from Algorithm 2.

Algorithm 2. Pseudo-code for the implementation of a SH hysteresis.

Algorithm 2: Detect the need for SH

```
% Comparator lower part of SH tank
Input Hysteresis = 1
if (TM1 > T_stop,SH)
  Input Hysteresis = 0
end
% Comparator upper part of SH tank
if (TM2 < T_start,SH)
  Input Hysteresis = 2
end
 % Hysteresis component with SH Signal in memory and output:
 if (SH Signal = true) & (Input Hysteresis < =0)
   SH Signal = false % SH mode off
 end
 if (SH Signal = false) & (Input Hysteresis > = 2)
   SH Signal = true % SH mode on
 end
 % Algorithm output is SH Signal
```

2.2. Heat pump: Minimum heat pump cycle time

The pseudo-code for the determination of the minimum heat pump run and pause time is presented in Algorithm 3. The *minimum HP cycle time* is implemented via a timer component.

If the duration of a heat pump cycle is above the minimum run time, the SH and DHW signals of Algorithms 1 and 2 are left unchanged. If the minimum run time has not been reached and no more heating is required according to Algorithms 1 and 2, the heating is forced to continue by changing the SH signal from 0 to 1. The temperature in the SH tank will then exceed the stop temperature, $T_{stop,SH,}$ and keep increasing until the minimum run time is reached. As it will be explained in Section 2.4, the minimum modulation capability of the heat pump is modeled by a saturation of the PI-control output (here taken at 0.3). During this period where the heat pump is forced to continue, the heat pump will therefore be operated at this minimum modulation capability.

Algorithm 3. Considering the requirement of a minimum heat pump run and pause time.

Algorithm 3: Minimum heat pump run and pause time

```
% Timer component integrates the run/stop time
Input Timer = (DHW signal or SH signal)
% Heat pump run time requirement considered in Output Timer
% SH Signal overridden if run time too short
if HP run time < minimum HP cycle time
  if (DHW Signal = 0) or (SH Signal = 0)
    SH Signal = 1
  end
End
% Algorithm output is SH and DHW Signal
```

A minimum run time could also be achieved by sizing the heat pump system considering the volume of water in the tank that has to be heated as well as the choice of the differential between the start and stop temperatures for both SH and DHW hysteresis. For some heat pumps, the start and stop temperatures are replaced by a control based on degrees-minutes. The control error for the temperature is integrated over time and the heat pump is started or stopped if this integral exceeds some thresholds.

2.3. Heat pump and tank interaction

Once the need for SH or DHW heating has been detected (see Section 2.1), the control should prioritize these two needs and control the heat pump accordingly. In this work, a realistic prioritization of DHW heating over SH is implemented so that the heat pump cannot support SH when producing DHW.

Regarding the charging of the tank, if the heat pump is in DHW mode, the mass flow through the condenser is adapted by a proportional control (P-control) to control the condenser outlet temperature to a given TSP. The heat pump compressor is then operated at full load. This TSP is set to a slightly higher temperature than the $T_{stop,DHW}$ of the DHW tank (here taken 5 K higher). This ensures that the heat pump supply temperature is always sufficient for DHW heating. If the heat pump is in SH mode, the mass flow through the condenser is kept constant and the compressor power is adapted using a PI-control and the SH temperature set-point from the tank, $T_{start,SH}$. The pseudo-code is shown in Algorithm 4.

Algorithm 4. Pseudo-code of the heat pump and tank interaction.

Algorithm 4: Heat pump and tank interaction

% DHW prioritization and charging the tank
if *DHW Signal* = 1 (prioritization)
  % heat pump in DHW mode
  TSP = $T_{stop,DHW}$ + 5K
  CP_{DHW} = P-control of mass flow comparing HP outlet temperature to TSP
  CP_{SH} = 0.0
  HP control = 1.0
else
  if *SH Signal* = 1
    % heat pump in SH mode
    TSP = T_{start_SH}
    CP_{SH} = 1.0
    CP_{DHW} = 0.0
    HP control = *PI-control* comparing TSP to TM2
  else *% no heating mode*
    CP_{SH} = 0
    CP_{DHW} = 0
    HP control = 0.0
  end
end

2.4. Heat pump: PI modulation and anti-windup control

The PI-control is implemented here using a PID where the derivative action is set to zero. This does not limit the scope of these explanations. A flow chart of a typical PID-controller is presented in Fig. 4. A heat pump modulation between 30% and 100% is implemented by a limiter component placed right after the output of the PI-control and with a lower limit of 0.3 and an upper limit of 1.0. The implementations of (1) a heat pump modulation limited between 30% and 100%, (2) a prioritization of DHW over SH (Algorithm 4) as well as (3) a minimum run time (Algorithm 3) require supplementing an anti-windup to the PI control. These actions can lead to the tank temperature TM2 deviating from its TSP over a relatively long period of time which can saturate the integral action.

The integral anti-windup ensures that the control error (i.e. temperature difference between TM2 and the TSP) is not integrated when one of the three above actions prevents the TSP from being continuously tracked by the PI-controller. Firstly, a standard anti-windup is directly embedded inside the PI-control to take the effect of the saturation into account, see the dotted green box in Fig. 4. In our implementation in IDA ICE, this is done using the ***LimPID*** component from the IDA ICE component library, combining a PID-controller with limited output and an anti-windup compensation. The ***LimPID*** component works similar to the PI-controller presented in Fig. 4. The default PI-controller in the IDA ICE thermal plant does not have integral anti-windup. The ***LimPID*** should therefore replace the default PI-controller. The ***LimPID*** component is not adapted here but the input should be adjusted to account for the “reset”. The ***LimPID*** compares the PI output signal before and after the saturation (i.e. the ***limiter*** in Fig. 4). The difference between both signals is used to adapt the control error at the input of the integral action and thus limit its saturation. Secondly, the PI-controller should be reset every time the controller is not used. The reset aims to keep the PI-controller input close to 0. In other words, if not reset, the PI-controller would try to take action to keep the measurement signal (here TM2) close to the TSP even though the PI-controller output is not used anymore. This happens if the heat pump is either heating DHW (i.e. *DHW Signal* is 1) or if no SH is required according to Algorithm 2 (i.e. *SH Signal* is 0). Algorithm 5 shows the pseudo-code for the logic of a PI-controller reset.

As mentioned in Section 1.2, the gain parameter k and integral time T_i are usually not given by heat pump manufacturers. Among existing PI tuning rules, Skogestad’s method [30] can be applied to adjust the gain parameter k and the integral time T_i. SIMC tuning rules rely on one tuning parameter, τ_c. A small τ_c leads to a fast response (more oscillations) and a large τ_c leads to a slower response (less or no oscillations). The tuning is case-dependent and thus k and T_i differ for each system.

Algorithm 5. Pseudo-code for the reset of the PI-controller.

Algorithm 5: PI-controller anti-windup and reset

if *SH Signal is* 1
  Standard use of the limited PI-control with embedded anti-windup
else
  % SH Signal is 0 *or DHW Signal* is 1
  Control error at the input of the PI control forced to 0
end

2.5. Tank: control of the auxiliary heaters

The pseudo-code for the control of the auxiliary heater in the SH tank is presented in Algorithm 6. The auxiliary heater is controlled by a thermostat, which has a differential of 4 K in this study. The start temperature of this thermostat, $T_{start,aux}$, is related to the $T_{start,SH}$ of the heat pump, which can change if DR measures are applied. Generally, $T_{start,aux}$ is taken slightly lower than the $T_{start,SH}$ (here 3 K lower) so that the auxiliary heater only starts to operate if the heat pump cannot cover the SH demand. However, using this control strategy, the auxiliary heater may start when the heat pump is heating DHW (and thus cannot heat the SH tank).

Regarding DR measures, the $T_{start,aux}$ is kept at its reference set-point even though the heat pump set-point $T_{start,SH}$ might be increased. The $T_{start,aux}$ is decreased if the $T_{start,SH}$ is decreased.

Algorithm 6. Pseudo-code for the implementation of the control for the electric auxiliary heater in the SH tank.

Algorithm 6: Auxiliary heater control

```
% TM2 as measurement input to thermostat of auxiliary heater
if (SH Signal = 1)
  if (DHW Signal = 1)
    % SH Signal is 1 and DHW Signal is 1
    T_start,aux = T_start,SH
  else
    % SH Signal is 1 and DHW Signal is 0
    if (no DR)
    T_start,aux = T_start,SH − ΔT % here, ΔT = 3 K (in the case of no DR)
     if (DR)
     T_start,aux = T_start,SH − ΔT % here, ΔT = 3 K (for reference and low TSPs (see
  Section 3.6))
    end
  end
```

2.6. Price-based demand response measures

Thermal energy can be stored in the building using time-variable TSPs for heating. For indirect DR measures, these TSPs are adapted as a function of a penalty signal such as a time-varying electricity price or the dynamic $CO_{2eq.}$ intensity of the electricity mix [36,37]. For the sake of the clarity, this paper only reports a price-based control using the day-ahead electricity spot price (SP). However, the conclusions of this paper remain valid using other types of penalty signal or even using direct controls.

With PRBC, a typical way to create a control signal to perform DR is to divide the spot price time profile into three price segments as shown in Fig. 5. A similar approach has been reported in [17] and [9]. In this work, the PRBC makes use of a 24 h sliding horizon to determine a low-price threshold (LPT) and a high-price threshold (HPT) which are used to define the three price segments of low, moderate and high prices. The LPT has been selected to $SP_{min} + 0.3\ (SP_{max} - SP_{min})$ and the HPT to $SP_{min} + 0.75\ (SP_{max} - SP_{min})$, where SP_{max} and SP_{min} are taken as the maximum and minimum spot prices for the next 24 h. 30% and 75% have been chosen for the thresholds based on a sensitivity analysis evaluating the influence of the LPTs and HPTs on the control signal in terms of the number of hours per set-point segment [34]. The PRBC compares the spot price to the HPT and LPT at each hour of the day and adjusts the TSPs for both DHW and SH accordingly.

The following control rules and the choice of thresholds are not trivial and based on the user experience. This tuning of a PRBC may be time consuming as reported in [7]. Algorithm 7 illustrates the pseudo-code for the PRBC logic of a price-based TSP variation. The same logic is applied for DHW heating and SH. Fig. 5 illustrates this principle of

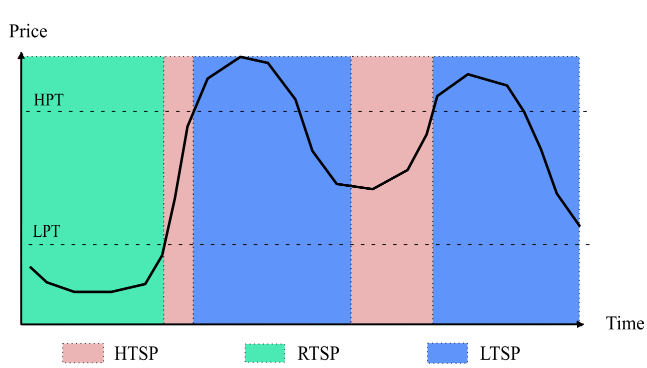

Fig. 5. Principle of the determination of the price-based control signal (HTSP is high temperature set-point, RTSP is reference temperature set-point, LTSP is low temperature set-point).

the determination of the price-based control signal. TSPs are increased to a higher temperature set-point (HTSP) for pre-loading before periods of high prices. Therefore, the HTSP is used if the current spot price is between the LPT and HPT and if it will increase during the next 2 h. On the contrary, the TSPs are decreased to a lower temperature set-point (LTSP) if the current spot price is above the LPT and is decreasing or, alternatively, during period of high prices, meaning if the spot price is above the HPT. The reference temperature set-point (RTSP) is kept for low-price periods, i.e. spot prices below the LPT.

TSP for SH can be applied to the SH storage tank ($T_{start,SH}$) and the room temperature ($T_{room,SH}$). This set-point for the room temperature is typically chosen based on the predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) method. According to EN15251:2007 [38], a LTSP of 20 °C and HTSP of 24 °C for $T_{room,SH}$ corresponds to a PMV between −0.5 and + 0.5 or a PPD lower than 10%, assuming a residential building, a clothing factor of 1.0 clo and an activity level of 1.2 MET.

Algorithm 7. Pseudo-code for the implementation of a price-based temperature set-point variation.

Algorithm 7: Price-based temperature set-point variation (same routine for SH and DHW)

```
% RTSP:
  for DHW: RTSP = 50 °C
  for SH tank: RTSP = OTCC
  For SH room: RTSP = 21 °C
% LTSP:
  for DHW: LTSP = RTSP – 5 °C
  for SH tank: LTSP = RTSP – 1 °C
  for SH room: LTSP = 20 °C
% HTSP:
   for DHW: HTSP = RTSP + 10 °C
   for SH tank: HTSP = RTSP + 3 °C
   for SH room: HTSP = 24 °C
 % Price-based temperature set-point variation:
   if (LPT < SP < HPT) & (SP increases during the next 2 h)
     T_start,SH, T_room,SH and T_start,DHW = HTSP
   else
     if (SP > HPT) or ((SP > LPT) & SP decreases during next 2 h)
       T_start,SH, T_room,SH and T_start,DHW = LTSP
     else
       if (SP < LPT)
         T_start,SH, T_room,SH and T_start,DHW = RTSP
     end
   end
 % Algorithm output is TSP
```

As shown in the principle sketch in Fig. 6, the algorithms are combined together to form the overall control of the heat pump system. The algorithms have been presented in a generic form that does not depend on a specific heat pump system or BPS software. However, the combination of these algorithms will always be case-specific. For instance, the combination of algorithms here follows the system layout of Fig. 3.

3. Case study on demand response and model complexity

A case study of a building heated by either an MHP, an OHP or direct electric (DE) heating is simulated in IDA ICE using the previously described algorithms. To illustrate the control principle of the price-based PRBC, the results for the case with an MHP are shown in Section 3.2. The influence of the modeling complexity of the heat pump control on chosen KPIs is presented in Section 3.3, while Section 3.4 focuses on the DHW prioritization of the heat pump.

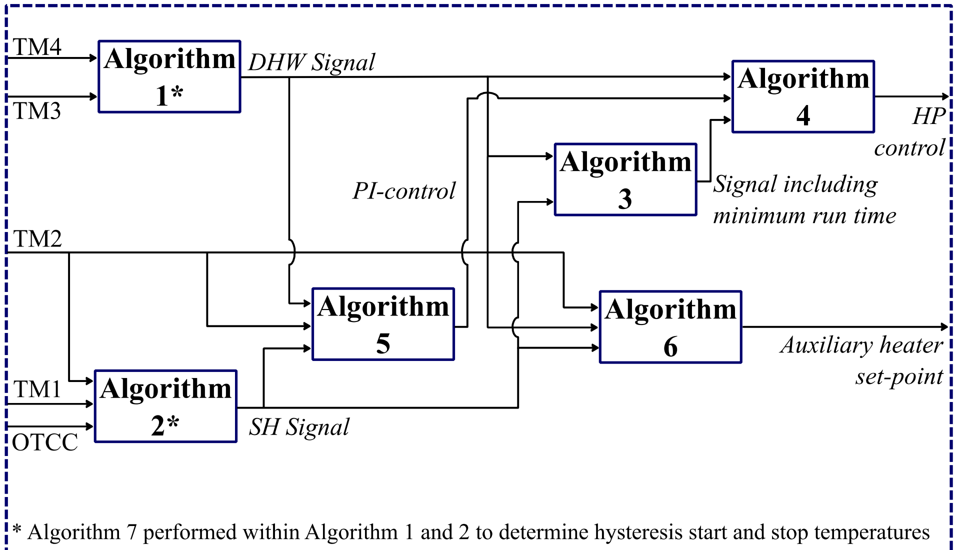

Fig. 6. Simplified sketch of the algorithm combination for the heat pump system control.

3.1. Description of the case study

DR measures have been investigated for the case of a Norwegian detached single-family house with a heated floor area of 105 m^2. The building is located in Trondheim, Norway. As shown in Fig. 7, it has two bedrooms, one bathroom and two living rooms [39]. It is a zero-emission residential building (ZEB) with a lightweight timber construction. The electricity generation from on-site photovoltaic (PV) is designed to compensate for embodied emissions as well as emissions from the operational phase during the lifetime of the building [39]. The IDA ICE model of the building envelope, which is used in this paper, has been calibrated using dedicated experiments. During these experiments, the building was excited using a specified pre-defined heating sequence with sub-hourly resolution and the air temperatures and operative temperatures were measured as a response to this excitation [40]. The short-term dynamics of the building were predicted correctly by the model.

Internal heat gains from occupants, electrical appliances and lighting are chosen according to the Norwegian technical standard SN/TS 3031:2016 [41]. Schedules for lighting and occupancy are based on prEN16798-1 and ISO/FDIS 17772-1 standards whereas the schedule for electrical appliances is taken from SN/TS 3031:2016. Also the DHW consumption profile is based on SN/TS 3031:2016. All schedules have hourly resolution. Additional information is provided in [34].

The modeled heat pump is based on the Hoval Belaria SRM 4 [31] which has a nominal capacity (with standard test conditions A7/W35) of 5.1 kW and a COP of 4.57 using EN 14511. The parameters of the heat pump model are calibrated with the manufacturer data based on the calibration procedure explained in [42]. The heat pump is dimensioned as a bivalent/mono-energetic system with a bivalence outdoor temperature of −9 °C. The heat pump is able to operate continuously using power modulation for outdoor temperatures of up to 5 °C. This temperature range (i.e. −9 °C to 5 °C) represents most of the SH season in Trondheim. Furthermore, a heat pump supply temperature of 65 °C can be achieved with this kind of state-of-the-art heat pump technology, e.g. [43]. In accordance with common concepts of Norwegian ZEBs, a solar thermal collector (4 m^2) assists the heat pump to provide DHW heating and SH [44].

It should be mentioned that IDA ICE has a steady-state grey-box heat pump model which is explained in detail in [42]. In this

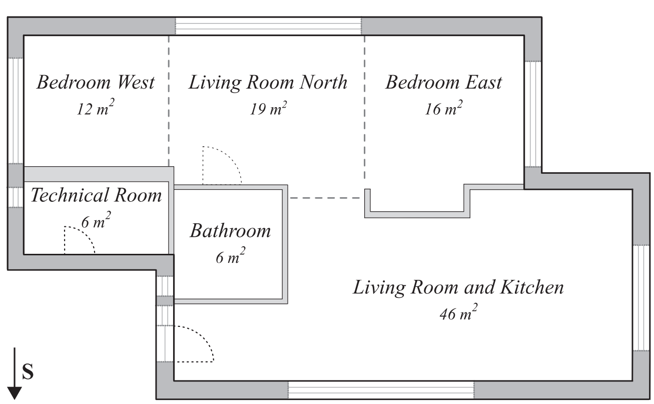

Fig. 7. Floor plan of the case study building [34].

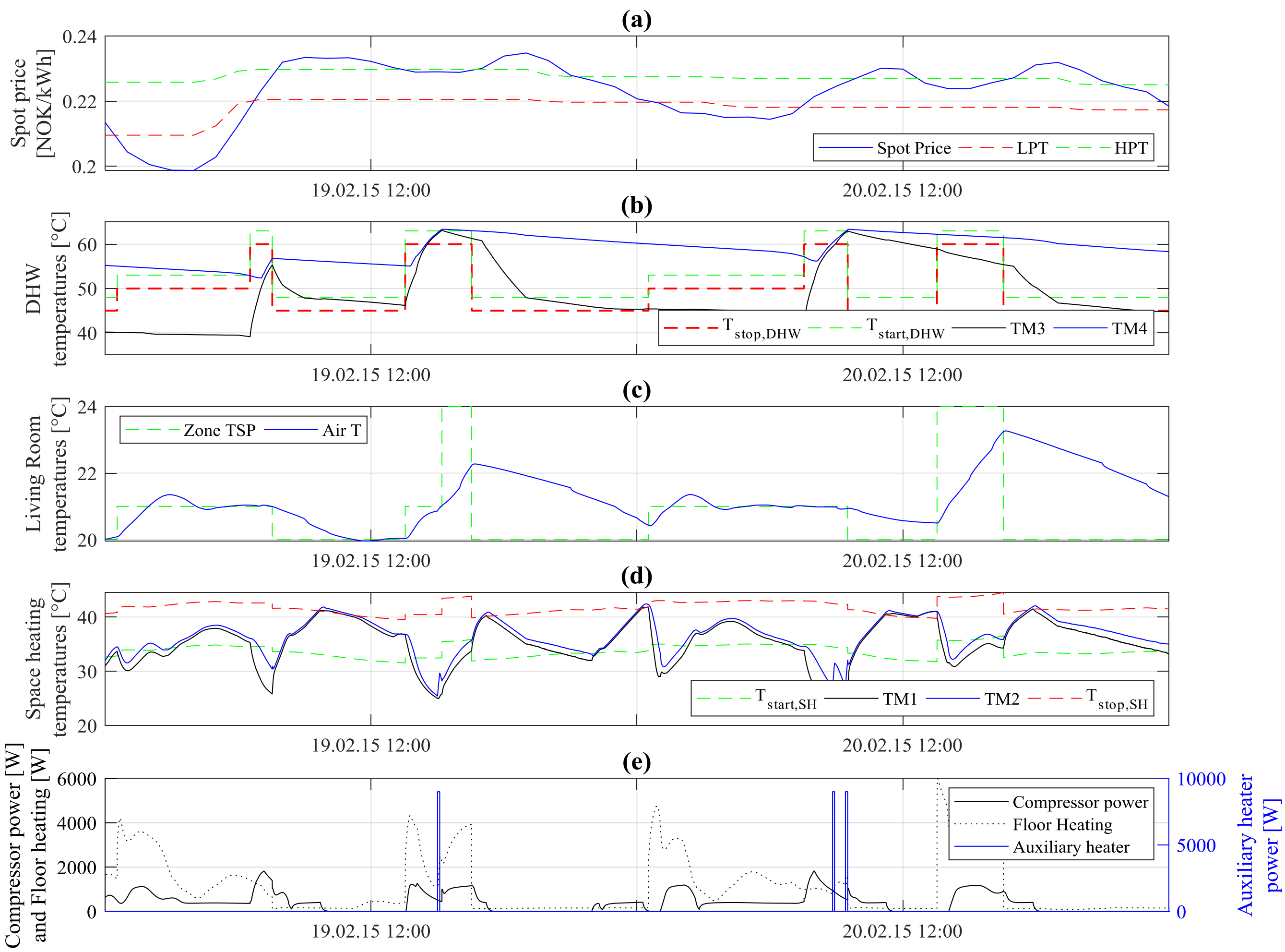

Fig. 8. Control principle of a price-based control for the MHP during an exemplified period of two days [34].

framework, it is impossible to take cycling losses into account, and neither the increase of the COP at part load for the modulating heat pump. Our investigations of the OHP and MHP exclude these phenomena even though they would be important if the objective of the paper was to compare both technologies. However, this does not impact the conclusions of this work about the modeling complexity of the heat pump controller. In addition, these cycling losses and variations of COP at part load can be integrated in other BPS tools, such as TRNSYS [22] while these properties are currently not available in the current IDA ICE heat pump model.

Regarding load shifting, peak periods are defined to be between 7 a.m. and 10 a.m. as well as between 5 p.m. and 8 p.m. based on a typical hourly profile for the electricity use in Norwegian households [45]. Pre-peak and after-peak hours are defined as the three hours before and two hours after a peak period, respectively. The analysis is performed using the historical measurements of 2015 for electricity prices and weather data so that their correlation is taken into account. Weather data are taken from [46] and spot prices are available at [47].

3.2. Control principle of a price-based PRBC for demand response

Simulations show that a realistic operation of the MHP system can be reached. Results presented in Fig. 8 illustrate the working principle of the control. It is evident from Fig. 8 that DHW heating is prioritized over SH because the TSPs for DHW heating are increased as soon as the spot price signal allows it (Fig. 8(b)). The SH-related TSPs are increased after the DHW tank has been charged (Fig. 8(c)), for example, as in the early afternoon of 19 February.

In general, the heat pump modulates to keep TM2 close to the $T_{start,SH}$. This principle can be seen in Fig. 8(d) and (e) from midnight to

Table 2
Definition of the heat pump controls including their parameters as well as their influence on the chosen KPIs for an evaluation period of one year.

Case	Controller parameters		E_{Use} [kWh]		Average tank temperature [°C]		No. of HP cycles [–]	Average HP run time [min]	SCOP
	k [–]	T_i [s]	HP	Q_{Aux}	SH	DHW			
MHP-PI-tuned	0.1	300	2025	8	36.7	52.5	983	260	3.72
MHP-P	1	–	2028	9	36.8	52.6	808	322	3.73
MHP-PI-highTi	0.1	3300	2035	9	36.8	52.5	1059	239	3.69
OHP	–	–	2197	2	38.2	53.0	1988	59	3.41
MHP-noCT	0.1	300	2033	8	36.8	52.6	870	297	3.71
MHP-PM	0.1	300	1891	17	33.7	51.9	438	767	4.43

10 a.m. on 19 February. The heat pump modulates down to 30% of the nominal compressor capacity if the heating demand in the rooms is low and the temperatures in the SH tank are sufficiently high. When no more SH is required in the rooms, the compressor continues to operate until the stop criteria of the SH hysteresis, $T_{stop,SH}$, is reached. In this way, the SH tank is charged as well. Regarding the operation of the electric auxiliary heaters, Fig. 8(b), (d) and (e) show that the SH tank cools down when DHW heating is prioritized as warm water is continuously supplied to the floor heating system. This temperature decrease eventually leads the electric back-up heater in the SH tank to start operating. This happens in the morning of 20 February.

3.3. Modeling complexity: The heat pump control

This section investigates the control of the heat pump unit and how its modeling complexity influences some important KPIs: (1) energy-related KPIs, such as energy use for heating and the average tank temperature during the heating season and (2) KPIs related to the heat pump unit, such as the seasonal coefficient of performance (SCOP), the number of heat pump cycles per year and the average heat pump run time.

Six different cases are investigated: (1) an MHP with a tuned PI-controller (called MHP-PI-tuned), (2) an MHP with a PI-controller with a high integral time compared to the tuned integral time (called MHP-PI-highTi), (3) an MHP with a P-controller (called MHP-P), (4) an OHP, (5) an MHP as defined in case (1) but without a minimum run time (called MHP-noCT, with noCT meaning no cycling time) and (6) an MHP modulating between 0% and 100% (called MHP-PM, with PM meaning perfect modulation). If not mentioned, the cases include a minimum heat pump run time and a heat pump that is able to modulate between 30% and 100%. Table 2 presents the influence of these different heat pump controls on the chosen KPIs.

The electricity use for heating is rather similar for all studied cases, except for the perfect modulation (MHP-PM). The heat pump with a perfect modulation (MHP-PM) performs best whereas the OHP has the highest electricity use for heating. The MHPs with different P- or PI-controls have very similar electricity use for heating. Therefore, it can be concluded that the perfectly modulating heat pump idealizes the performance of the system and thus overestimates the potential for cost or emissions savings.

The tank temperatures for the SH and the DHW tanks are the average temperature of the uppermost two layers of each tank. These temperatures are averaged over the SH season which is assumed to be from 1 September to 15 May. Indeed, during summer time, only DHW heating is required so that all the investigated heat pumps behave in the same way, namely like an OHP. Regarding the DHW tank, the

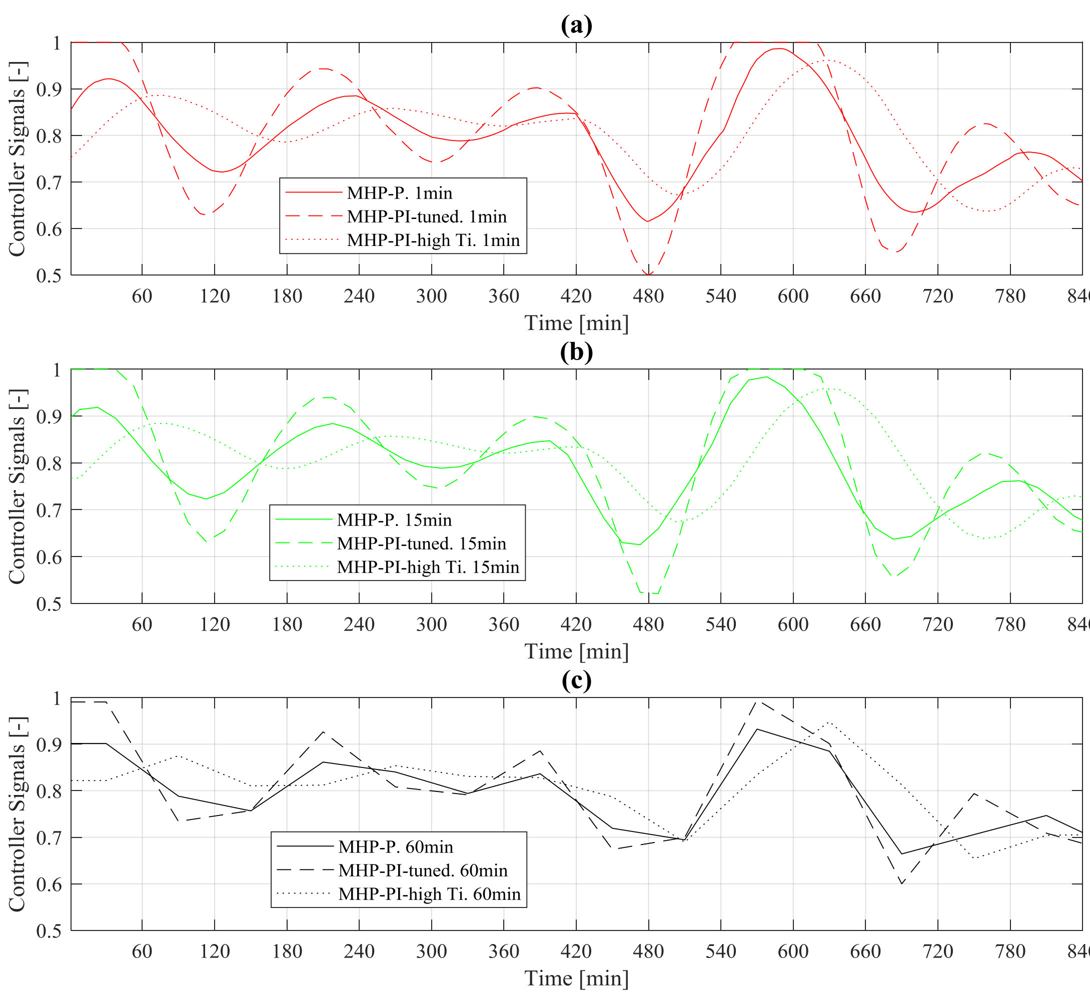

Fig. 9. Comparison of P-controller and two PI-controller output signals to the heat pump for (a) time resolution of 1 min, (b) 15 min and (c) 60 min during an exemplified period of 14 h.

temperature differences in all the cases are within 1.1 K. The differences are small because DHW heating is always controlled by a hysteresis.

Regarding the SH tank, the maximum temperature difference between the studied cases is 4.5 K. The OHP has the highest average temperature in the SH tank because it charges the tank to higher temperatures for each cycle based on the hysteresis. For the MHP cases, the compressor speed is controlled to keep the temperature in the tank close to the $T_{start,SH}$. On average, this leads to a lower tank temperature during the heating season and thus to lower heat losses from the tank. Due to higher condenser temperatures and thermal losses from the tank, the OHP has the lowest SCOP. On the contrary, the MHP-PM the highest SCOP.

Even though the electricity use and average tank temperatures are relatively similar for all cases, there are significant differences for the number of cycles and the average run time of the heat pump. The OHP has approximately twice the number of cycles compared to the MHP with a tuned PI-controller. The average run time is lowest for the OHP while it increases with a decreasing number of heat pump cycles. This confirms the advantage of MHPs over OHPs. The number of cycles is influenced by the choice of control (i.e. P- or PI-control) and the tuning of the control parameters.

Fig. 9 compares the output control signal to the heat pump for the P-control (MHP-P) and two PI-controls (MHP-PI-tuned and MHP-PI-highTi) for different time resolutions. The resolutions of 15 and 60 min are evaluated by averaging the original time series with a time step of 1 min over the last 15 and 60 min, respectively. Generally, the output of the PI-controls is smoother than the P-control which can have sudden variations in the signal. If the aim is to achieve a smooth operation of the heat pump, a PI-controller should be preferred to a P-controller. As it can be seen in Fig. 9(a) between minutes 420 and 545, the tuned PI-control leads to larger oscillations. The PI-controller with a higher integral time has weaker oscillations. These differences are directly related to the PI tuning rules applied in this work. Regarding the SIMC tuning parameter, a τ_c could be chosen so that a P-controller and a PI-controller would give a very similar behavior. The large difference in output signals between the three controllers will lead to different electricity use in the short-term. These differences would be even larger if transient effects (such as cycling losses) were accounted for in the heat pump model. These differences between controllers almost disappear for a resolution time of 60 min. Actually, Fig. 9 shows that the control signals for the P- and PI-controls are under-resolved above an averaging time of 15 min. Therefore, a time resolution lower than 15 min should be chosen if the aim is to investigate the dynamics of the heat pump in detail. The choice of controller is also important when power is investigated. The maximum power required during a year is very similar for a P- and a PI-controller as a controller output signal of 1 leads to the heat pump operating at full load. However, for time intervals lower than 15 min, the controllers will lead to different electrical powers.

In summary, the most appropriate modeling complexity depends on the type of investigation. Is the focus solely on energy and operational costs or is the detailed behavior of the heat pump or power of interest? The KPIs in Table 2 show that a P-controller and a PI-controller can lead to similar results as long as the heat pump operation and power are not investigated for short time scales. A P-controller has the advantage of significantly simplifying the modeling setup. Its tuning is easier and the problem of integral windup avoided. On the contrary, if the heat pump operation is investigated for short time scales, the heat pump control and tuning cannot be simplified. To conclude, it is worth mentioning that the conclusions regarding the controller modeling and tuning are not only valid for PRBC. For instance, model predictive control (MPC) would also adapt the TSPs and not directly control the compressor power.

3.4. Modeling complexity: Influence of DHW prioritization

As it will be shown, the DHW prioritization can strongly influence the auxiliary heater operation. This influence is more pronounced for the periods when DR events are performed and significantly impact the system performance such as the energy use for heating and energy costs. Therefore, this aspect should not be overlooked for bivalent heat pump systems. To demonstrate this, the price-based DR scenario (CSP), introduced in Section 2.6, is compared to a reference case (called BAU for business-as-usual) where all the set-points are constantly at RTSP. However, it is distinguished whether the CSP is applied to both SH and DHW, to DHW only (then termed CSP-DHW) or to SH only (then termed CSP-SH).

3.4.1. Influence on energy use

The performance of the different control scenarios is compared in terms of annual electricity use for heating, see Fig. 10(b). The share of the heat pump and the auxiliary heaters in the electricity use is shown

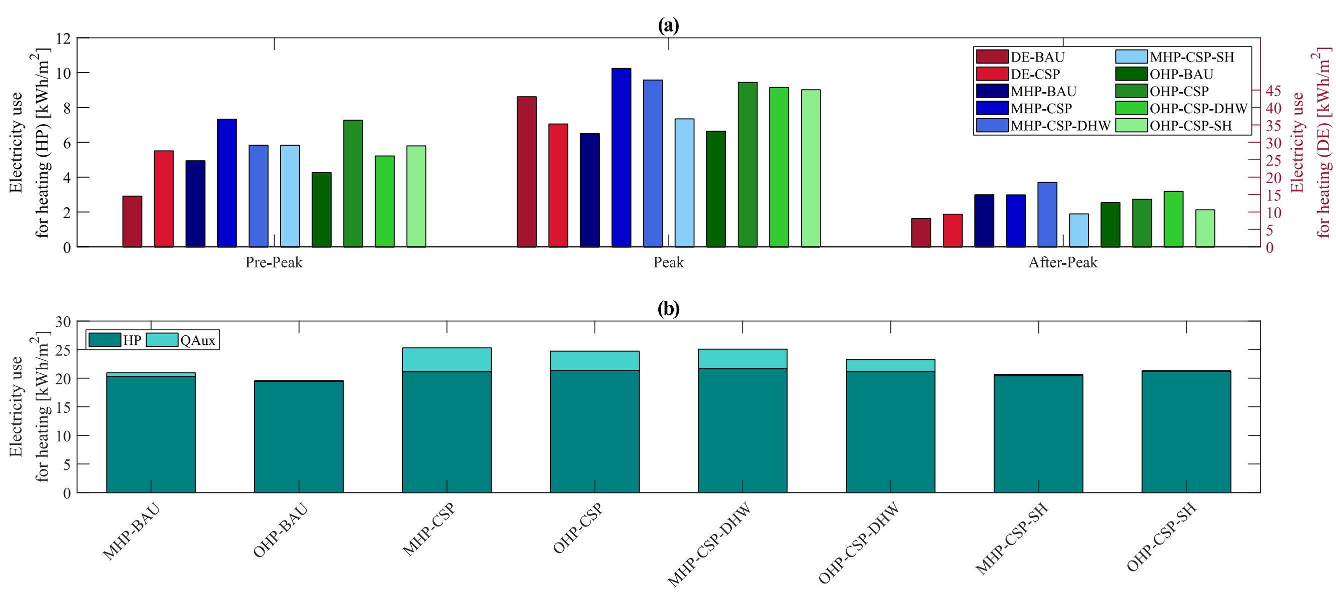

Fig. 10. (a) Electricity use for heating using direct electric heating (DE) (right axis), a modulating heat pump (MHP) and an on-off heat pump (OHP) (both left axis) and (b) annual electricity use for heating for the MHP and OHP for the different DR scenarios.

in order to emphasize the operation of auxiliary heaters. In addition, it is also worth comparing the CSP if applied to direct electric heating (DE). In this case, SH and DHW have two distinct systems so that no DHW prioritization is required. Finally, it is instructive to present results at shorter timescales, especially during periods where the price-based control applies sudden variations of the TSPs. In Norway, prices are higher during peak hours and a price-based control should adapt TSPs accordingly. Therefore, the electricity use for heating is analyzed for pre-peak, peak and after-peak periods, see Fig. 10(a).

Regarding DE heating, it can be seen in Fig. 10(a) that the CSP leads to reduced electricity use during peak periods, whereas the electricity use increases during pre-peak and after-peak periods. This conclusion does not hold for the MHP and OHP systems. Unlike DE, the electricity use for heating increases for all HP cases during peak hours. Given the DHW draw-off profiles, DHW heating is required during peak hours for all test cases. During the SH season, SH needs are usually present when DHW is produced by the heat pump. This leads to a temperature decrease in the SH tank that ultimately triggers the operation of the auxiliary heater. As the duration of DHW mode is prolonged by DR compared to BAU, the resulting increase in electricity use is larger when DR is applied to DHW. This confirms that the primary cause of increased electricity use for heating is the prioritization of DHW. This is especially true for the MHP but significantly less pronounced for the OHP. Unlike MHP, the OHP control is exclusively based on a hysteresis and thus, somehow, on a charging of the SH tank. Therefore, with OHP, the SH tank has a larger autonomy when the HP is in DHW mode before the SH auxiliary heater has to be triggered. The auxiliary heater is then used less frequently by the OHP compared to the MHP.

To further confirm these conclusions, Fig. 10(b) illustrates the annual electricity use for heating. When the CSP is applied, it leads to increased annual electricity use for heating compared to BAU. This is due to the energy storage in the water tanks or the building thermal mass at a temperature higher than in the BAU scenario. All these storages have thermal losses which may eventually lead to a decrease of the energy efficiency compared to the reference scenario. Nonetheless, a decrease in energy use is possible if the TSP for SH (here with a LTSP of 20 °C) is often below the RTSP (here 21 °C) using the DR scenarios. These conclusions will be further discussed in the next section but were needed here to explain the order of magnitude in Fig. 10(b). The share of electricity use from the auxiliary heater is most significant for CSP when DR is applied to both DHW and SH. If only applied to DHW, the auxiliary heater is still operated frequently. Even though DHW is prioritized in the CSP-SH case, the auxiliary heater does not contribute significantly to the electricity use for heating.

This case study is used to demonstrate the importance of the DHW prioritization in relation with the auxiliary heater control. However, the specific values for the energy use are case-dependent and should not be considered universal (unless further research proves that they are). For instance, the power sizing of the heat pump and the choice of system design (monovalent or bivalent) are essential. If the heat pump was oversized, the DHW tank would be charged faster thus reducing the risk of using the auxiliary heater for SH. Furthermore, it was possible to use additional set-points for DHW heating along lower electricity spot prices to operate the heat pump more frequently and to avoid a too frequent operation of the electric auxiliary heater.

3.4.2. Annual heating costs for the heat pump systems

Table 3 presents a comparison of the annual heating costs for both DHW heating and SH. Heating costs are calculated by multiplying the hourly electricity use with the current spot price for each hour of the year. The electricity fee for the grid connection of the building is not considered in the cost calculation.

As energy costs are directly related to the energy use, the annual energy use for heating is analyzed first. If the CSP is only applied to SH, the annual energy use for heating is slightly decreased for the MHP and slightly increased for the OHP. If CSP is applied to DHW, this annual energy use is significantly increased due to the auxiliary heater operation. Even though the CSP operates the heating system during periods with favorable electricity prices, energy costs are not decreased if the energy use has increased considerably. This explains that the annual heating costs using the MHP are increased up to 21% when CSP is applied to DHW whereas costs are slightly decreased if CSP is applied to SH only. Regarding the OHP, annual heating costs are increased by up to 27%. Even for the DR scenario which only considers SH, costs are still increased by almost 10%.

It should not be concluded that the CSP control introduced in Section 2.6 always fails at reducing costs. In this case study, the daily fluctuations in the Norwegian spot prices are too small to counterbalance the increase of energy use generated by the CSP and to eventually obtain reasonable costs savings. For example, the use of model predictive control (MPC) instead of PRBC may give different conclusions as this optimal control is in a better position to limit this increase in energy use and to benefit from price fluctuations.

4. Conclusions

This paper investigates the influence of the modeling complexity of the heat pump control in the context of demand response (DR) and building energy flexibility. Based on a summary of typical modeling simplifications for heat pump systems, the paper analyses two key components: the heat pump controller and the DHW prioritization of the heat pump.

To investigate the model complexity of the heat pump controller, the performance of six different controls are compared: on-off control, power modulation using a P-control or different PI-controls, perfect power modulation between 0% and 100% of the compressor power, and the inclusion of a minimum heat pump cycle time. The case of a detached single-family house heated using an air-source heat pump is analyzed with a price-based predictive rule-based control (PRBC).

The results demonstrate that the modeling complexity of the system control has a significant impact on the key performance indicators, proving that this aspect should not be overlooked:

– (1) The model complexity affects the short-time behavior of a heat pump system when performing DR. It is recommended to consider controller tuning for studies on heat pump systems with focus on DR regardless of the applied control strategies, e.g. PRBC or model-predictive control (MPC).

Table 3
Annual heating costs for the two heat pump systems.

		MHP				OHP			
		BAU	CSP	CSP-DHW	CSP-SH	BAU	CSP	CSP-DHW	CSP-SH
Heating energy use	kWh/m^2	20.94	25.30	25.08	20.67	19.57	24.74	23.26	21.27
	%	–	+21	+20	−1	–	+26	+19	+9
Costs w/o el. fee	NOK	484	585	583	470	451	571	541	490
	%	–	+21	+20	−3	–	+27	+20	+9

– (2) The annual electricity use for heating is rather similar for all cases, expect for the perfect modulation. In fact, the perfectly modulating and on-off heat pumps lead to the lowest and highest average tank temperatures, respectively. The on-off heat pump charges the tank using a hysteresis with a temperature differential, whereas modulating heat pumps (MHP) modulate to keep the temperature in the tank close to a set-point (corresponding to the starting temperature of the hysteresis). Hence, average tank temperatures and heat losses are lower for MHPs leading to higher SCOPs compared to on-off heat pumps. Therefore, it can be concluded that the perfectly modulating heat pump idealizes the performance of the system and thus overestimates the potential for cost or emissions savings.
– (3) The MHP using P- and PI-controls have a similar number of heat pump cycles while these numbers are significantly different for on-off and perfectly modulating heat pumps. The average run time per cycle is therefore different.
– (4) The controller type (i.e. P- or PI-control) and tuning are important when heat pump operation is investigated at short time scales. In practice, a PI-controller would be preferred to achieve a smoother operation of the heat pump. The controller tuning is often overlooked in studies on DR and energy flexibility using building performance simulation (BPS) and cannot be captured in detail by strongly simplified models for heat pump systems.

For short time scales, the modeling of the heat pump controller and the transient effects of the heat pump, such as cycling losses during start-up, are important. The difference between P- and PI-controllers and their parameter tuning should be considered in a realistic way if the heat pump operation is investigated at short time scales. Besides PRBC, these conclusions are also valid for other controls, such as MPC, where typically temperature set-points are controlled and not the compressor power directly. The choice of MHP controller (i.e. P- or PI-control) and its tuning is not crucial if the heat pump operation and electric power are not investigated at short time scales. A P-controller can be advantageous as it significantly simplifies the modeling setup. Its tuning is easier and the problem of integral windup is avoided.

Regarding the DHW prioritization, the results demonstrate a strong influence of this prioritization on the control of the electric auxiliary heaters. Electricity use increases significantly when the DR is applied to DHW as this increases the use of the auxiliary heater for space-heating. With price-based control applied to DHW, the annual heating costs increase because the advantage of consuming during lower electricity prices is outweighed by the large increase in electricity use. The use of additional set-points for DHW heating along lower electricity spot prices to operate the heat pump more frequently should be considered in future studies to avoid a too frequent operation of the electric auxiliary heater.

Furthermore, this paper describes the control for a detailed model of a heat pump system in a BPS tool. The system is equipped with an MHP and applies PRBC to perform DR. The approach is presented in a generic way using pseudo-codes, whereas the BPS tool IDA ICE is taken as an example. Results show that the presented modeling approach leads to a realistic operation of the heat pump system.

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