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The energy efficiency potential of intelligent heating control approaches in the residential sector

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Abstract

Space heating control in residential buildings has been subject of various research efforts over the past years, accompanied by discussions on improving energy efficiency in building. The focus of prior research has been on technology-specific analysis of heating control systems, not allowing for a comprehensive comparison across demand-side heating control approaches. Therefore, the objective of this thesis is to provide further insight into the efficiency and effectiveness of currently prevailing and potential future demand-side heating control approaches for end users in residential buildings.

The research question has been addressed by a performance comparison of archetypical heating control approaches. Therefore, a categorization of heating control approaches has been derived on literature and existing products, characterized by the controller-type, temperature set point variation and disturbance prediction. This includes constant temperature set point approaches, manual set point variation approaches like programmable thermostats as well as automatic temperature set point approaches with further intelligent control features like occupancy-state prediction or weather prediction. Subsequently, the categorized heating control approaches have been evaluated and compared based on energy consumption and occupants' comfort. For this purpose, a comprehensive simulation environment has been developed and combined with long-term empirical building and occupancy data of ten households. The performance comparison is complemented by a variation of the building unit, such as the insulation type, and a sensitivity analysis on individual variables, including the occupancy characteristics, weather exposure and heating system configuration.

The results indicate that net energy required for space heating can be reduced by over 25% without significant reduction of tenant comfort. The performance of the intelligent heating control approaches is higher compared to programmable thermostats in both energy savings and achievable comfort level. The results are promising for a potential diffusion of technologies of intelligent heating control approaches, as they do not face typical drawbacks of programmable thermostats, like low comfort levels or user-interaction issues. This in turn can significantly increase building energy efficiency in the residential sector. Future research is recommended to enhance the findings for further climate regions within the European Union, include air conditioning systems as well as provide insights from a customer point-of-view.

Keywords

Space heating, heating control technologies, residential sector, energy efficiency, HVAC

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Abbreviations

AGEB	Arbeitsgemeinschaft Energiebilanzen
ASHRAE	American Society of Heating, Refrigerating and Air Conditioning Engineers
CABSE	Control Approach and Building Simulation Environment
CO_2	Carbon Dioxide
EnEV	Energieeinsparverordnung (German regulation for energy saving in buildings)
ETH	Eidgenössische Technische Hochschule
EU	Europäische Union
HVAC	Heating, ventilation and air conditioning
IEA	International Energy Agency
IWU	Institut für Wohnen und Umwelt
kWh	Kilowattstunde
PID	Proportional-integral-derivative
RC	Resistance-capacitance
SIA	Schweizerischer Ingenieur- und Architektenverein (Swiss Society of Engineers and Architects)
SusTec	Chair of Sustainability and Technology
WSVO	Wärmeschutzverordnung (thermal insulation standard)

1 Introduction

1.1 Energy for space heating and potential of intelligent control technologies

Given the accelerating climate change as well as emerging countries demanding for amenities prior exclusively available to industrial countries, the topic of energy consumption gains in importance. The currently high share of fossil fuels deployed to satisfy energy demands is causing tremendous CO_2 emissions and is diminishing the energy reserves of the world to a minimum within decades. The formulation of implementable strategies that significantly contribute its share for a sustainable future of energy consumption should therefore be in everyone's interest.

In the following investigation, household space heating is presented as a field of application, in which significant improvements in energy efficiency is potentially possible through innovative technologies. The significance of this field of application on total energy consumption and CO_2 emission is first demonstrated (1.1.1) and then the therefore promising means to improve energy efficiency, i.e. intelligent heating control technologies, are introduced (1.1.2).

1.1.1 Energy for household space heating

Household space heating can be identified as a significant contributor to overall energy consumption and CO_2 emissions. This becomes apparent when conducting a sectoral breakdown of energy consumption and CO_2 emissions. This is followed by a further segmentation in its application areas to highlight the substantial share of space heating energy.

There are four sectors that significantly contribute to final energy consumption. These are transport, service, industry/manufacturing and household sector (s. Figure 1). At a global level, households are the second largest contributor to final energy consumption with a share of 29% to the total final energy consumption. At a national level, this number is almost identical in the case of Germany[1]; however, households thereby constitute the largest sector for final energy consumption in Germany in the year 2010.

[1] The research focuses on Germany for the reason that an in-depth analysis requires thorough data and analysis methods that have been available only for the country of Germany.

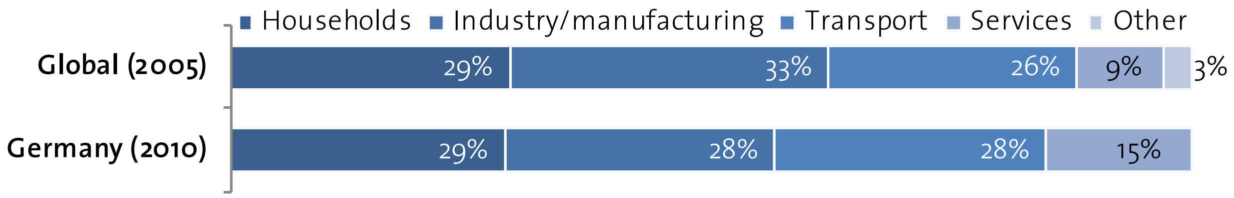

Figure 1: Final energy consumption by sectors in percent. Households account for almost one third of the total energy consumption [Arbeitsgemeinschaft Energiebilanzen e.V., 2011a; International Energy Agency, 2012]

The impact of the energy consumption of each sector on the environment in terms of the greenhouse effect and exploitation of natural resources can be estimated when examining their CO_2 emissions. For the mentioned sectors, households amount to close to one fifth of the overall CO_2 emissions (s. Figure 2).

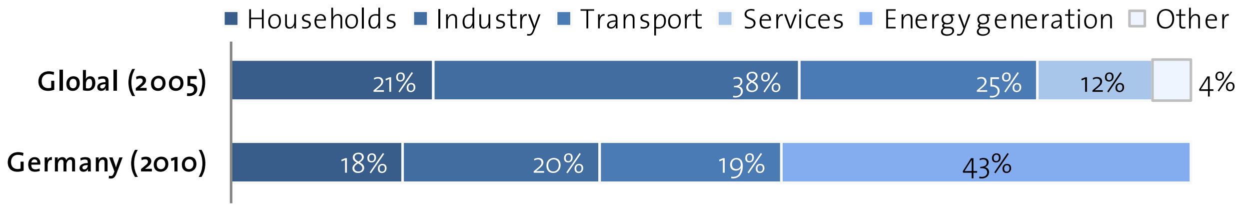

Figure 2: Total CO_2 emissions by sectors in percent for Germany[2] and global. Households account for about 1/5th of the total CO_2 emissions [Bundesministerium für Wirtschaft und Technologie, 2012; International Energy Agency, 2012]

Thus, household energy consumption poses a significant share of the overall energy consumption as well as CO_2 emissions. Therefore, it is insightful to investigate the various application types of household energy (s. Figure 3). These are categorized under space heating, appliances, hot water, lighting and space cooling. For the 19 IEA countries, the major part of the household energy consumption, i.e. 53%, is caused by space heating. Singling out Germany, almost 3/4 of the final energy consumption in household is related to space heating. The remaining areas, especially space cooling, contribute with substantially lower shares to the total energy consumption. Combining these numbers with the above-mentioned sectoral analysis, it becomes apparent that 20% of the total final energy in Germany is used for household space heating.

[2] Statistics on Germany state the sector energy generation, which is not available for statistics on the global energy consumption.

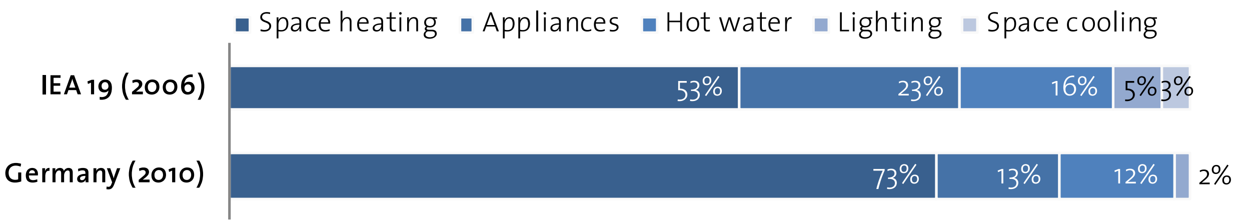

Figure 3: Household final energy consumption structure for selected regions: Space heating accounts for the majority of energy consumption in households [Arbeitsgemeinschaft Energiebilanzen e.V., 2011b][International Energy Agency, 2012]

While the household space-heating sector has been identified as a major contributor to the overall energy consumption, it needs to be investigated, to which extend it actually impacts the environment. The heating structures for Germany address this question by stating the share of final energy for each source of energy used for space heating.

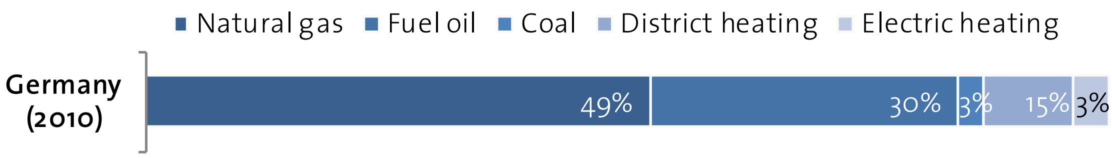

Figure 4: Household heating structure for Germany, 2010 [% of final energy used for space heating in German households][Arbeitsgemeinschaft Energiebilanzen e.V., 2011c]

Space heating energy is to the greatest part contributed by fossil fuels (s. Figure 4), which make up a share of close to 3/4[3]. This figure is even greater considering the additional amount of fossil fuels used for district heating as well as electric heating.

From the above considerations, it can be summarized that

1. The household sector is one of the major contributors to both energy consumption and CO_2 emissions on global scale as well as singled out for Germany.
2. Space heating is by far the greatest contributor to household final energy consumption.
3. Space heating is to the largest part realized through the usage of fossil fuels. Natural resources are depleted and the greenhouse effect is enhanced.

Thus, reduced energy consumption for household space heating with concomitant CO_2 reductions would significantly impact the total global energy consumption and CO_2 emission balance and therefore contribute to a more sustainable use of energy.

1.1.2 Potential of intelligent heating control technologies

The above findings should be a great motivation for improving energy efficiency in the household space-heating sector. Stated in the EU's 2020 Energy strategy, the goal is to achieve 20% of energy savings in 2020. Within a report on this topic, it is stated that buildings pose substantial energy-savings potential [Berliner Energie Agentur GmbH, 2011].

[3] This figure is calculated as a summation of fuel oil, natural gas and coal.

Searching for effective and implementable ways for the reduction of household space heating energy consumption, heating control technologies can be identified as promising means for this purpose. This becomes apparent when investigating the process for the provision of space heating in households (s. Figure 5). For each process stage, a measure of energy efficiency is presented and evaluated for its potential improvement. The overall energy-efficiency for space heating is described in terms of the amount of energy used to provide the occupant a specific level of comfort (s. 2.5.4 for more on comfort evaluation). The process steps are presented from supply- to demand-side.

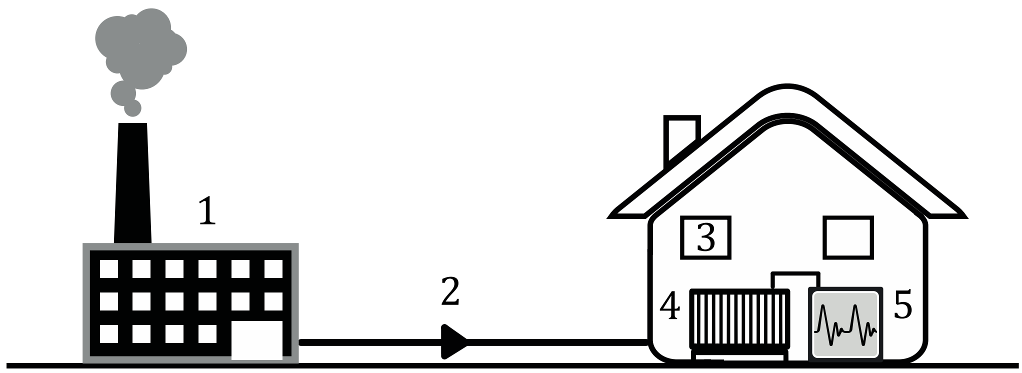

Figure 5: Process for the provision of space heating: Energy losses occur along multiple process steps

1: Primary to secondary energy (supply-side)

In the first stage, the raw energy sources are converted into energy carriers, i.e. secondary energy, e.g. by power plants or designated heating plants. This can be the transformation of crude oil into fuel oil, biomass into enthalpy or electricity or natural uranium into electricity. A major influencing factor on the energy efficiency in this stage is the power plant efficiency. As heating plants are drafted for a lifespan of several decades, only very slow adaptions of energy efficiency improvements can be achieved.

2: Secondary energy to final energy (supply-side)

In the second stage, the transportation process, secondary energy is transformed to final energy which is available to the end-user. Final energy is for instance electricity at the power outlet, fuel oil in the tank or briquettes. It therefore accounts for further conversion and transport losses. Taking into account the high fix costs of infrastructure such as gas pipelines, the implementable improvements for energy-efficiency remains costly as well as inappropriate in the short-term.

The conclusions made for process stage 1 and 2 are backed by the primary energy factors, which are indicators for energy losses. This factor is the ratio of the total employed energy to the final energy available to the household. These are e.g. 1.1 in the case of fuel oil and 3.0 in the case of electricity [Schweizerischer Ingenieur und Architektenverein, 2011]. For fossil fuels, which have been explained to be the major source of energy in household space heating, these are comparably low. It is therefrom concluded, that the energy efficiency in process stage 1 and 2 for the purpose of household space heating is already high, thus leaving only little potential for improvement.

3 and 4: final energy to useful energy (demand-side)

The energy that is available to the consumer for the respective use is called useful energy. In the case of space heating, the useful energy provides for an increase in room temperature. To generate useful energy, the final energy has to be first converted into its purpose (process stage 3), i.e. heat, and further distributed in the building (process stage 4) to be available as useful energy to the occupants.

3: Final energy conversion

Except of a few cases such as district or electric heating, the natural resources have to be converted to heat by a furnace. The efficiency of this process stage is measured by the annual efficiency of the heating system. It is the quotient of the useful heating energy to the total final energy consumption over one year and depends on the type and age of the heating system (s. Table 1).

Table 1: Annual efficiency of selected heating types: Modern systems greatly reduce energy losses [Minergie, 2010][4]

Heating type	Annual efficiency in %	
	Old type	New type
Fuel oil heating	75-80	85-95
Natural gas heating	80-85	85-95
Electric heating (direct)	93	97

With the application of modern furnaces, a significant reduction of energy losses can be achieved. As the investment decision for a furnace is made by the landlord or the occupants, it has been observed that renovation of furnaces occur on lengthy cycles. The heating system refurbishment rate in Germany is approximately 3.5% [Neitzel et al., 2012]. Improvements in energy efficiency in this process stage therefore remain rather difficult for the actual implementation.

4: Final energy distribution

In the next step, the generated heat needs to reach the inside of the building and actually heat the room to serve as useful energy. Thermal losses on this stage can occur by a poor insulation of the building or heating pipes.

Thus, thermal losses can be reduced by an improved building insulation. The requirements for insulations have been greatly increased over the past years. As these improvements are enforced by law, they are reliably finding their way into new buildings. These new buildings remain in the minority though with less than 5% of the number of total buildings built since 2001 [Statistisches Bundesamt, 2010]. Therefore, the climate targets cannot be met without retrofit of existing building stock [Girod et al., 2013; International Energy Agency, 2011]. A major drawback for existing buildings is the low refurbishment rate with approximately 1.6% per year [Schimschar et al., 2011]. The energy efficiency goals for 2020 are therefore very ambitious considering the actual refurbishment rate [Schimschar et al., 2011].

[4] Based on a study for the Swiss country.

Summarizing process stage 3 and 4, a significant potential for energy efficiency improvements is apparent. However, the incentive for a short-term implementation for energy efficiency improvements is low due to the high investment costs and lengthy building renovation cycles.

5: Useful energy - a superset of "comfort-serving" energy (demand-side)

In the final process stage, a crucial point in the assessment of energy efficiency in household space heating is included. Useful energy incorporates the total heat that effectively raises the room temperature. It is not possible though to make a conclusion, whether the employed heat actually provided a benefit in terms of an increased occupants' comfort level. This leads to an important assumption used throughout the research: **Any energy input in household space heating, which is not serving for a benefit of the occupants' comfort level, is considered a waste of energy[5].** Therefore, the so called comfort-serving energy can be considered as the lowest possible useful energy input to achieve a specified comfort level. Thus, a heated unoccupied house over a longer time might be energy-efficient in process stage 1-4, but performs poorly in terms of process stage 5, since it does not provide occupant comfort with the lowest energy input. The energy-efficiency on this process stage is determined by the heating control technology. This describes the technology that is responsible for controlling the provision of heat over time in the building. The energy-efficiency on this stage can be easily improved by manually turning down the heating system for unoccupied times or by employing programmable thermostats. However, studies have shown that occupants are not programming the heating systems accordingly [Meier et al., 2010].

Intelligent heating control technologies address this issue and can significantly improve energy efficiency by lowering energy consumption at times, when heating is not increasing the occupants' comfort. "Intelligent" is thereby related to a control principle, which automatically modifies its settings over time without the interaction of a user. In [20], up to 50% of savings are reported through the tracking of occupancy patterns by wireless sensors. In [16], the use of weather predictions leads to energy savings of up to 40%.

The recent focus and research on these more complex, high tech opportunities can be further explained from a technology-push perspective. Hardware costs are falling within short time frames [Mack, 2011] and innovations in pervasive computing such as smartphones and cloud computing [Fox et al., 2009] have enabled new ways to control appliances and heating and cooling at home. The year 2012 was the first year, in which the majority of the population in the EU was using a smartphone [Comscore, 2012]. This makes building heating control technologies very attractive, since it enables low-priced control systems with low user-interaction but full remote control opportunities and high energy saving potentials. The amortization time of high-tech automation tools has fallen below one year and is therefore outperforming lengthy and costly building renovation. For these reasons, intelligent heating control approaches[6] might be most promising for an implementable improvement of energy efficiency in the residential space heating sector. This is topic covered by the research presented in this thesis, which is introduced in the following.

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[5] One can argue that according to this assumption rooms would not have to be heated at all when occupants are away. This is only true to a certain extent, as boundaries for the minimum temperatures have to be defined in order to remain the functionalities of the systems and to keep heat-up times low.

[6] The term heating control approach is introduced to describe a general control function principle, that can be realized by various technologies (s. 2.2.3).

1.2 Research definition

As stated above, the research serves for the assessment of the energy-efficiency potential of intelligent heating control approaches in the residential sector. Therefore, an extensive literature review has been conducted (s. 2.2.2), which then revealed the research gap (s. 1.2.1) of this topic. Subsequently, the research question with core aspect to be investigated is defined (s. 1.2.2).

1.2.1 Research gap

As the detailed study of existing work in section 2.2.2 shows that there have been many research approaches, especially in the recent years covering intelligent heating control technologies [Gupta et al., 2009; Lu et al., 2010; Scott et al., 2010]. These highlight for the most part technology-specific analysis on heating control approaches. While these are revealing details on the implementation and operation as well as energy potentials for specific use cases, a general assessment and evaluation of the various heating control approaches, irrespective of the technical implementation, remains undiscovered. Furthermore, a realistic evaluation of control approaches under a range of real-world use cases[7] has not been found in literature. This is particularly important, since energy-efficiency potentials might greatly vary for individual use cases.

1.2.2 Research question

Derived from the research gap and the aim to assess the energy efficiency potential of intelligent heating control approaches in the residential sector, the research question has been defined[8].

Research question	How much reduction of energy usage do different heating control approaches allow for in households situated in temperate climate zones? • Achievable occupant comfort levels by the different heating control approaches • Sensitivity analysis of influencing factors for the energy-efficiency performance

The research focuses on an investigation on the energy-savings potential of heating control approaches on household level with location in temperate climate zones, i.e. Germany and Switzerland. The energy-savings potential of a heating control approach is assumed to be related to its achievable comfort level, which is therefore included in the research. To identify factors that drive energy-efficiency performance and test the robustness of the results, a sensitivity analysis for specified variables is conducted. The research question is addressed by the research approach (s. Chapter 2).

[7] A use case describes the sum of the settings, under which the heating control approach is employed, i.e. in terms of the building characteristics, interdependence to the environment type, the occupancy pattern and heating system.

[8] The research is conducted under the assumption, that users prefer higher comfort levels, which are determinants for successful technology diffusion. This is crucial, since the proposed intelligent control technologies might not be superior in sole energy-considerations when comparing e.g. to programmable thermostats.

1.2.3 Research scope

The research incorporates five characteristic elements (s. Figure 6) that are applied to answer the research question[9]. These elements are on the one side directly derived from the research gaps stated in (s. 1.2.1) on the other side defined as requirements to sufficiently cover the research question.

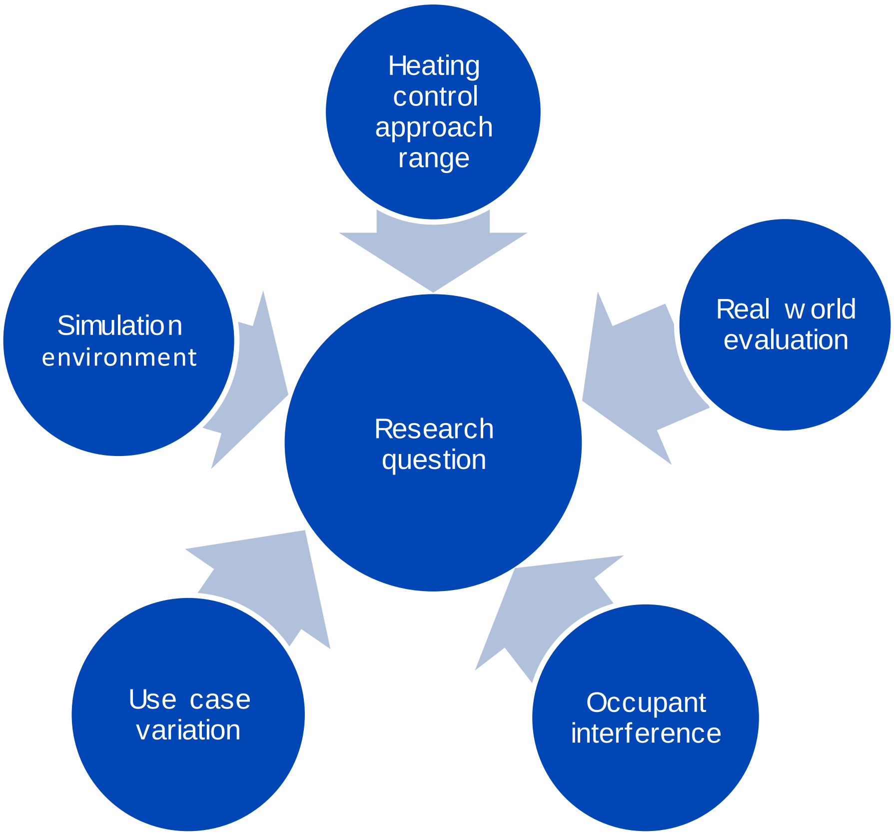

Figure 6: The research gap and research question is addressed by a research approach with five characteristic elements

1. <u>Heating control approach range (s. 2.2)</u>

   The focus is not on a single, technology specific inquiry, but a comparison of the most relevant heating control approaches in terms of their annual energy consumption. They are categorized under eight archetypical control approaches.

2. <u>Simulation environment (s. 2.3)</u>

   Within a complex simulation model, named CABSE, the major influencing factors are accounted for and their interdependences are considered on a micro level.

3. <u>Real world evaluation (s. 2.4)</u>

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[9] Excluded from the research is the interdependence of the heating control approach to the applied heating system as well as the type of energy source. Only the net energy consumption for space heating, excluding energy generation and distribution losses within the building, is considered. This is for the reason that the net performance of a heating control approach is not affected by the efficiency of the underlying fuel-to-heat process. Implementation topics are further described in the discussion chapter (s.4.1).

The research is based on detailed empirical data on the building and on occupants' behavior. The results are designed to be closely matching real world outcomes. For that reason, long-term empirical data of 10 households has been acquired.

4. Use case variation (s. 2.5)

   The impact of specific variables on the performance is highlighted, which is tested in a variation of use cases, meaning building characteristics, building environment and occupancy patterns. This investigation is carried out for the country of Germany.

5. Occupant interference (s. 2.5.4)

   This is studied in terms of the impact of the heating control approach on the comfort of the occupant. Therefore, a measure of occupants' comfort for space heating is introduced.

These elements are formulated in the research approach, which is described in its structure and execution in the following chapter.

2 Research approach and methodology

2.1 Overview

The research approach (s. Figure 7) is defined along the research question and applies a methodology for a performance comparison (s. 2.5) of the heating control approaches in realistic settings. Therefore, a categorization of heating control approaches is derived based on existing work (s. 2.2). The heating control approaches are then integrated in a simulation environment (s. 2.3) which provides accurate building models and includes various data sources (s. 2.4) including empirical data to ensure a close match to real-world behavior.

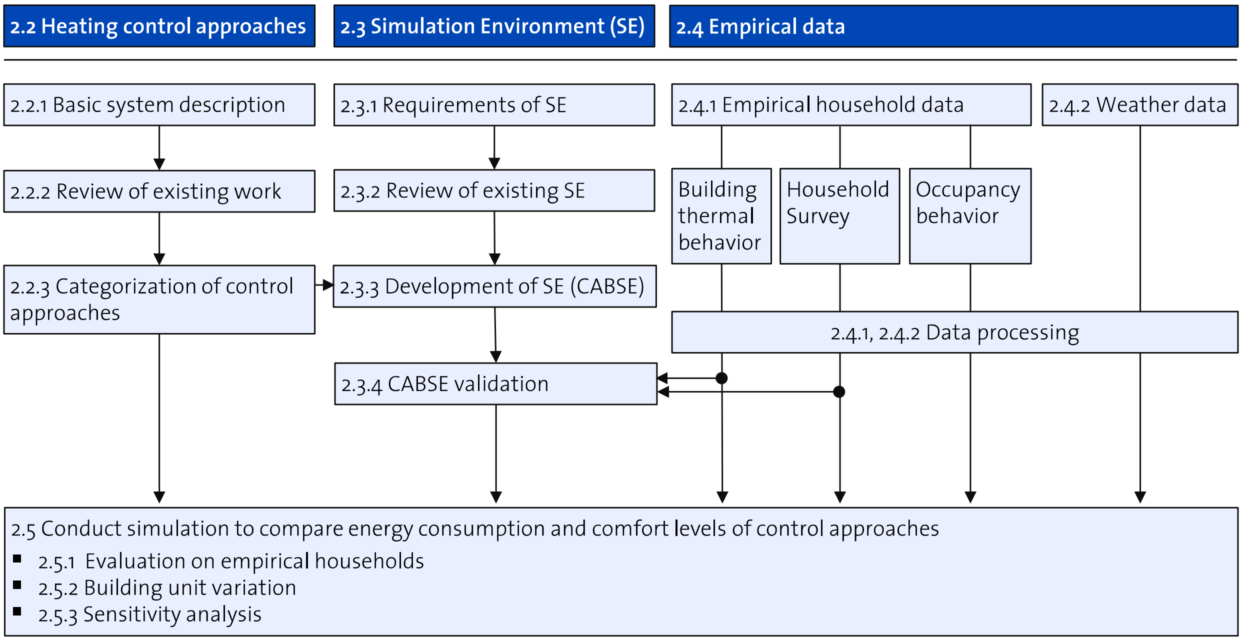


Figure 7: Overview on research approach with process steps to address research gap

The choice for the simulation environment and selection of the control approaches are crucial steps in the research process and are made after conducting a thorough literature review, expert interviews as well as defining the requirements to the output derived from the research question. After the development of the simulation environment and acquiring the empirical data, the validation process ensures that the building model is adapted to a household specified by a real-word instance. For every household, each of the selected control approaches is tested in its energy and comfort performance. The simulation process further includes a variation of the building characteristics to extrapolate the results on additional use cases and concluded by a sensitivity analysis on influencing variables.

2.2 Heating control approaches

The heating control approaches are required to be representative of the range of existing heating control technologies as well as be closely reproducing their features and behavior. Prior to the definition of heating control approaches, a basic overview on the functioning of heating control is presented (s. 2.2.1). Subsequently, a review of existing solutions and research projects provides an overview on the evolvement and current state-of-the-art heating control technologies (s. 2.2.2). Therefrom, the heating control approaches relevant for the performance comparison are derived and described in its technical specifications (s. 2.2.3).

2.2.1 Basic description of a heating control system

This section provides a short introduction into the topic of heating control system with a description of the functional principles of the components.

2.2.1.1 Schematic representation and principles of a heating control system

The heating control approaches and technologies are described along a basic control system representation shown in Figure 8.

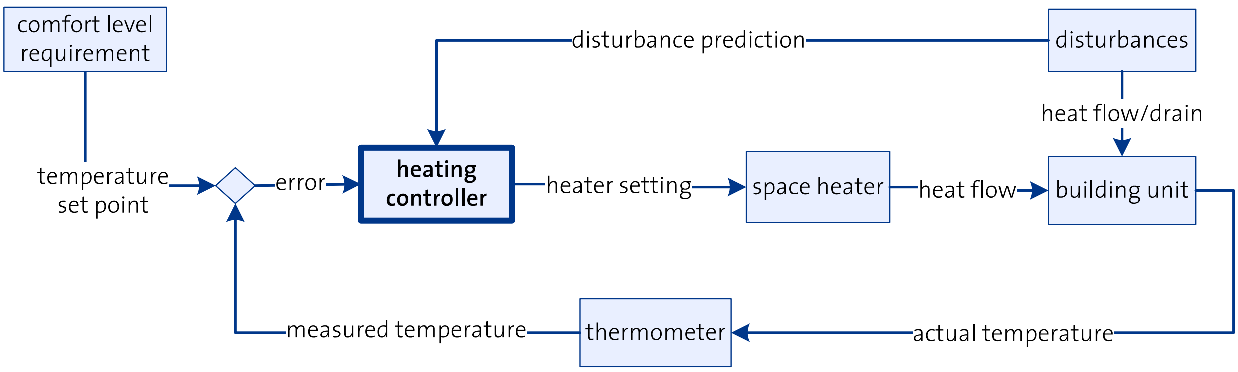


Figure 8: A representation of the heating control system shows the interdependence of the various control system elements

Within this control system, it is the purpose of a heating controller to reach a certain level of thermal comfort for the occupants of the building unit. The comfort level is attained by supplying occupants' desired room temperatures, called temperature set points, at every given point in time. The actual temperature in the building unit is measured by a temperature sensor[10]. The measured temperature is compared with the temperature set point; the deviation is the temperature error. The heating controller obtains the information on this error and undertakes actions to minimize it. Therefore, the heating controller signals the heating system, here represented by a space heater, a particular heating setting. This setting is for example the heating power or the supply temperature of the water. The space heater then supplies the house with a heat flow. Influences on the state of the system, i.e. the temperature of the house, can also occur by various

[10] For simplification, the measured temperature equals the actual indoor temperature of the building.

disturbances. These are for example the outside temperature, solar irradiation, occupancy of the house or appliances with an own heat flow[11].

2.2.1.2 *Varieties of the controller type*

As the controller adjusts the heater settings, it is determining the energy consumption. It controls when and how much energy is invested to achieve a change in room temperature. It is therefore a key element for the energy-efficiency of the heating system. There are various types of controllers that can be implemented within a heating system. Two of the most common are described in the following[12].

- The on-off controller, also called bang-bang controller, can only trigger two states of the space heater, on and off. This means that it turns the heating system to either 100% of its maximum power, or turns it off (s. Equation 1). It causes oscillating over- and undershoot of the indoor temperature around the temperature set point (s. Figure 9) as the heated room reacts with a time delay on the heat flow [Montgomery et al., 2008].

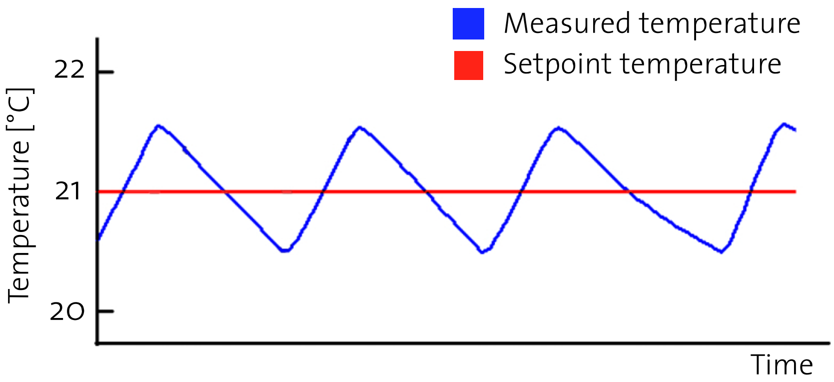


Figure 9: Typical oscillation of the indoor temperature around the temperature set point for an on-off controller

In this control system, an error differential around the set point, e.g. 0.5 °C, exists, for which no change of the output is possible. This is to prevent a rapid change of the heater settings within a short time frame, called short-cycling, which causes both a low energy-efficiency and a decreased life-span of the heater.

Equation 1: The output of an on-off controller is either 100% or 0% with no middle state. The error differential prevents short-cycling

$$\text{Controller output}(\text{error}) = \begin{cases} 0\%, & \text{error} > \text{error differential} \\ 100\%, & \text{error} < -\text{error differential} \end{cases}$$

[11] In contrast to the described systems that measure the room temperature, the outside temperature can be used in a rule-based control to determine the flow temperature. This system constitutes an open-loop control system which does not allow for the application of control algorithms. This is for the reason that no measurement of the indoor temperature is considered.

[12] Advanced control systems beyond temperature control, as e.g. used for HVAC systems are reviewed in [Dounis et al., 2009][12] .

- The second controller type is the continuous or modulating controller in the type of a proportional-integral-derivative (PID)-controller. It consists of three terms to act upon the temperature error (s. Equation 2).
    1. Proportional term: The greater the error, i.e. the further the deviation of the indoor temperature to the set point, the greater the action of the controller.
    2. Integral term: It is the product of the extent of the error to the time that the error existed. The longer the temperature error has existed, the stronger the action that is performed to decrease the error.
    3. Derivative term: It is the rate of change of the error. If the indoor temperature approaches the set point quickly, the controller backs-off the space heater in advance in order to prevent temperature over- and undershoot caused by the latency of the heating system.

Overall, the PID controller minimizes undesired ancillary effects such as temperature undershoot, overshoot, rise time, settling time and steady-state error (s. Figure 10). It is therefore much more refined than an on-off controller. It minimizes the energy output and is therefore suited to work in an intelligent heating control system.

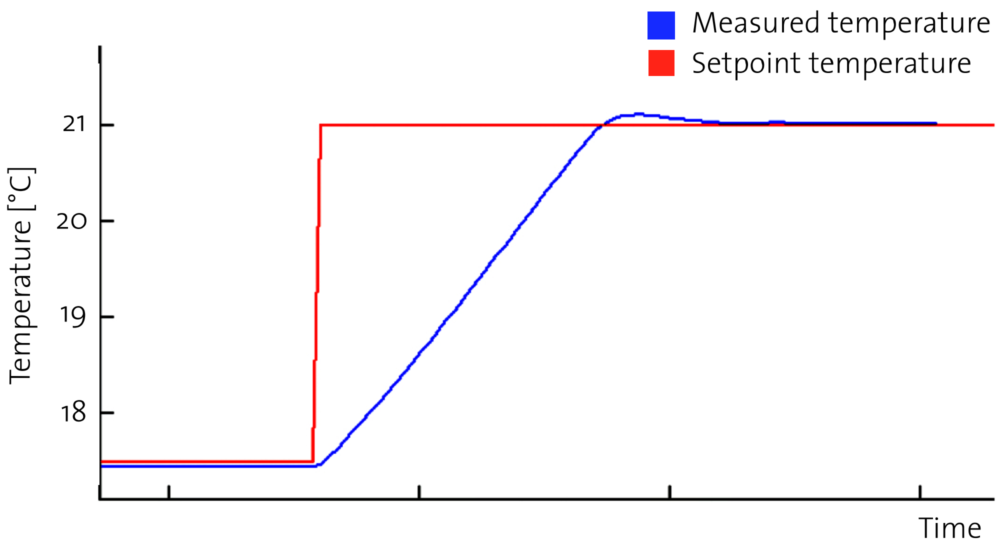


Figure 10: Example of an initial response of a PID controller: The overshoot is minimized and the oscillation is prevented

One disadvantage of the PID controller is that it needs to be tuned to the system [Montgomery et al., 2008], to optimize the stability and performance of the system. This requires more initial effort and knowledge of the system in terms of the response time of the heating systems. Within the research project, default parameterizations have been derived with tuning heuristics, which resulted in stable system behavior [J. Ziegler et al., 1942]. More on PID tuning is described in section 2.3.3.4.

Equation 2: The output of the PID controller is derived by three terms to avoid ancillary side-effects of the on-off controller

$$\text{Controller output (error)} = K_p e + K_i \int e\, dt + K_d \frac{de}{dt}$$

e	temperature error = set point - measured temperature
K_p	Proportional gain (tuning parameter)
K_i	Integral gain (tuning parameter)
K_d	Derivative gain (tuning parameter)

With the above description of a heating control system, the following presentation of existing theory and work can be understood and related to the mentioned control system elements.

2.2.2 Existing theory and work on heating control technologies

2.2.2.1 First thermostats in the 19th century

The first heating control technology was given by thermostats. A thermostat combines multiple elements of the control system: It measures the temperature, compares the measured temperature to a temperature set point and regulates the heater to achieve this temperature set point. The implementation is rather simple though, as it involves a bimetallic strip that flexes at temperature changes, thereby controlling the valve of a heat flow. Dr. Andrew Ure invented a mechanical device in 1830 and named it thermostat or "heat governor" [Ure, 1830]. It provides consistent comfort as it keeps the temperature around a given set point. The first commercial electric thermostat was developed by Johnson in 1883 [Johnson, 1883].

2.2.2.2 The evolution of programmable thermostats

Presumably one of the easiest ways to save energy is to take into account of a changing temperature level requirement over time. Usually, the occupants of a house do not require a high room temperature when being away or asleep. Therefore, a variable temperature set point over time can decrease the energy consumption while still maintaining the required comfort level at every time. In the following section, this is referred to as a set point variation feature. This feature can be performed manually, i.e. the occupants program time-events for set point changes, or automatically, i.e. the heating systems adapts for set point changes by itself. In 1906, the first commercially available programmable clock thermostats appeared [Peffer et al., 2011]. Since then, there has been great variety of improvements - see e.g. patents on modern thermostat interfaces [Donovan, 2010; Levine et al., 1986]. While programmable thermostats can lead to energy savings, they are very much influenced by the user behavior and how they utilize the programmable thermostat. Despite technological advancement, research showed that fewer than 50% of U.S. households actually own programmable thermostats and among households with programmable thermostats, over 30% are not setting up any programs. Over 89% never used a weekday or weekend program [Meier et al., 2010]. Uncertainty regarding actually realized savings potential remains high and as a result, the U.S. EnergyStar program for programmable thermostats has been canceled in 2009 [Energy Star, 2009].

2.2.2.3 *Intelligent heating control technologies as recent development*

The in the following used term "intelligent" control technology refers to a system, that includes either information on occupancy or additional system influences in an automatic manner. Intensified research on automated set point variation technologies has been conducted in recent years. This includes Lu et al. (2010), where low-cost motion sensors have been utilized to integrate occupancy and sleep patterns into dynamic HVAC settings, resulting in average energy savings of 28%. Gupta, Intille, and Larson (2009) describe a field experiment that reached average savings of 7% with the use of GPS-arrival prediction. A feasibility study conducted by Scott et al. in 2010 addresses the tradeoff between energy savings and thermal comfort with an occupancy-state prediction algorithm. Focusing on the fact that preheating is required to provide tenants with desired temperature levels upon arrival, combined occupant sensing and prediction has been addressed by Scott et al. (2011). In addition, the possibility of sleep detection or the use of location data from mobile phones is described. If the system is susceptible to influences from the environment, e.g. heat flows caused by solar irradiation or outside temperature changes, a disturbance prediction can help to lower energy consumption. For instance, if a space heater supplies the house with a certain heat flow to reach a given comfort level, but the solar irradiation or room occupancy would have sufficed to raise the room temperature to the set point, the energy efficiency is can be improved. Therefore, a prediction of disturbances can be integrated in the heating control system. Model Predictive Control (MPC) is one possible implementation of disturbance prediction. An MPC-based controller minimizes energy consumption using a constrained control function that integrates weather forecast and building specifics. Studies report an energy savings potential of 17-24% [Siroky et al., 2011] and 15-28% [Siroky et al., 2011]. However, the high costs of MPC implementation complicate usage in practice. An illustrative selection of commercially available intelligent thermostats is presented in the following.

- NEST: NEST features automatic set point variation and utilizes activity sensors as well as programmed schedules by the occupants. A weather forecasting is considered to improve energy efficiency[13]. The company states energy savings of up to 26% [Nest, 2013].
- eGain: eGain is a customized heating control system for business customers that integrates weather forecasts to reduce the operating costs by up to 15%. The company states an amortization time of less than one year [eGain, 2013].
- tado°: tado° offers a heating control technology that is enabled through smartphones to automatically adapt to the temperature set point according to the actual comfort requirements. Via a geo location tracking algorithm, it preheats the home prior to the arrival of the occupants. The company states energy savings of 27% on average [tado°, 2013].

2.2.3 Categorization of heating control approaches

Based on the review of existing research on heating control and discussion with experts in heating control technologies, eight archetypical control approaches have been derived that cover the range of investigated control technologies (s. Table 2). As mentioned above, the control

[13] This feature solely predicts the impact of the outdoor temperature changes and reaches its maximum potential for heat pumps [Nest customer support, March 07th, 2013]

approaches are representing features of heating control systems, but are irrespective of their actual technical implementation. The control approaches are characterized by controller-type, set point variation and disturbance prediction.

Starting point of the analysis is the simplest form of heating control, a standalone two-position or on-off controller. Their simple design and favorable economic properties have led to wide adoption in industrial and residential applications [Boyd Jr., 1959; Lu et al., 2010; Roots et al., 1969]. The second control approaches the technological evolution from discontinuous (on-off) to continuous control using a so-called proportional-integral-derivative (PID) controller for improved control loop effectiveness (s. 2.2.1.2).[14]

The third control approach includes nighttime temperature setback. With the advancement of electronic components, innovation around more intelligent ways to automatically control different temperature levels increased [Carlson, 1979; Thorsteinsson, 1967; R. N. Ziegler, 1976]. Nighttime setback is a basic yet common feature in today's building environment [Peffer et al., 2011]. The development of microprocessor technologies facilitated diffusion of more sophisticated means of setback and feedback systems. The desire to increase comfort as well as to reduce energy consumption and operating cost led to adoption of programmable thermostats (PT) (control approach 4). To overcome the burden of manual adjustments or deterministic, inaccurate schedules and with further development of sensor and later wireless communication technologies, the idea of occupancy-based, automatic set point variation arose (control approach 5). Integrating the actual occupancy-state of a building has been identified as an important aspect of building climate control [Oldewurtel et al., 2013]. To measure the theoretical potential of an occupancy-based set point variation control approach, it is valid to assume that occupancy information is available with sufficient level of accuracy, irrespective of the sensor technology (e.g. motion sensors, cameras, door sensors).

One aspect that is deficiently reflected in occupancy-state-based set point variation is the fact that most residential heating systems are inert [Chen, 2002; Oldewurtel et al., 2012]. Real time information about occupancy behavior alone does not allow to pre-heat homes to desired temperature levels before tenant arrival times. This has led to predictive, automated set point variation (control approach 6). Accurate prediction of real life occupancy-states (e.g. arrival, departure, sleep times) as well as heat-up times remains a significant challenge [Oldewurtel et al., 2010; Scott et al., 2010, 2011; Siroky et al., 2011]. However, for the theoretical evaluation in this thesis project, perfect prediction of occupancy-states was assumed. The effects of ambient air temperature, solar irradiation and wind on a buildings temperature gradient can be both, a blessing and a burden when intending to leverage a building's thermal storage capacity. It is a matter of control effectiveness that determines the amount of energy that can be saved and the comfort levels that can be realized when incorporating changing meteorological conditions (control approach 7 and 8). A frequent subject of academic inquiry[15], integration of weather forecasts into building climate control remains a challenging undertaking due to the inert and heterogeneous thermal behavior of buildings as well as the stochastic nature of atmospheric processes.

[14] The interested reader may refer to Bennett (1993) for an historical overview of the development of PID controllers.

[15] A comprehensive literature list on this topic can be found on the website of the OptiControl project [OptiControl, 2012].

Table 2: Detailed overview on reviewed control approaches

Control approach title	Control system features[16]			Technical specification
	Controller type	Set point variation	Disturbance prediction[17]	
1 On-off controller (standalone)	On-off	None	None	Standalone on-off (bang-bang) controller with a threshold value of 0.5°C, constant temperature over simulation period
2 PID controller (standalone)	PID	None	None	PID controller with K_p, K_i, K_d terms and anti-windup algorithm (integral limitation at 40% of positive controller boundary, integral reset at set point variation)
3 Nighttime temperature setback	PID	Manual[18]	None	PID controller as above; set point variation along two temperature set point positions for occupant states 'HOME' and 'SLEEP' on a week-long schedule with 30-min resolution
4 Programmable thermostat	PID	Manual	None	PID controller as above; set point variation along three temperature set point positions for occupant states 'HOME', 'SLEEP' and 'AWAY' on a week-long schedule with 30-min resolution
5 Occupancy-state detection	PID	Automated	None	PID controller as above; detection of occupant states[19] home, sleep and away on a 1 min resolution (e.g. motion sensors)
6 Occupancy-state prediction	PID	Automated and predictive	None	PID controller combined with occupancy detection as above with additional 1 hour occupancy-state prediction for preheating (e.g. GPS tracking)
7 Occupancy-state detection with weather prediction	PID	Automated	Weather influence	PID controller combined with occupancy detection; weather conditions prediction: 3 hour prediction of solar irradiation influence on heat balance through window transmission. Inclusion of predicted heat on control system and limitation of max. heat output to 50% during solar irradiation
8 Occupancy-state prediction with weather prediction	PID	Automated and pred.	Weather influence	PID controller combined with occupancy detection and weather conditions predictions (see above)

[16] Only feedback (closed-loop) control systems are considered, meaning that the controller reacts upon measured room temperatures.

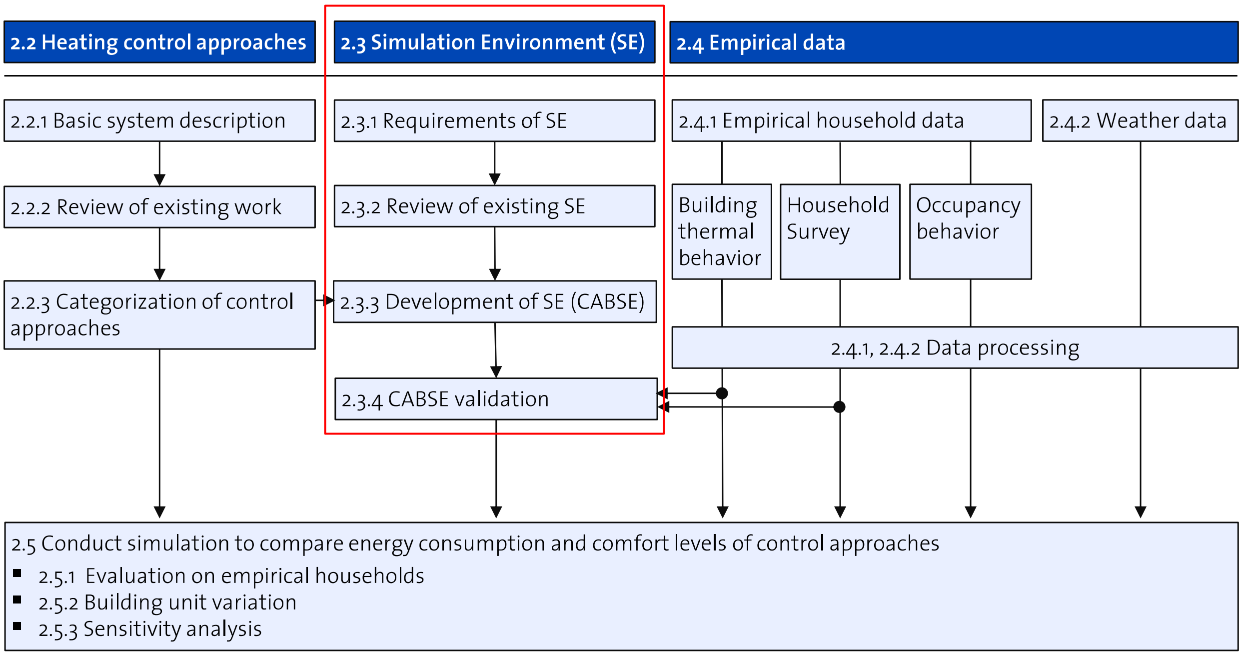
[17] This can be considered as a feed-forward on the control system. The predicted heat influence is considered before it has actually affected the system.

[18] Manual schedules are set once for the simulation period and are optimally adjusted to occupants' characteristic behavior and temperature requirements.

[19] Occupant states are irrespective of individual occupant behavior and describe representative system states for all occupants.

2.3 Simulation environment

The simulation environment is the key element from which the research results of the performance comparison of the heating control approaches are drawn from. Therefore, it needs to be set up thoroughly according to the defined requirements (s. 2.3.1). In the next step, existing simulation environments with respect to the defined requirements (s. 2.3.2). For the research topic, a customized simulation environment has been developed (s. 2.3.3). After the setup of the simulation environment, the building models are created and validated (s. 2.3.4) along the acquired data sources on households (s. 2.4).



2.3.1 Requirements of the simulation environment

As first and foremost step for the simulation process, the requirements of the simulation environment have been defined. As described above, the aim is to compare the heating control approaches in both energy and resulting occupants' comfort for a range of use cases. The results should be as close as possible to the real-world heating system behavior while utilizing the available data as well as be validated by it.

The following list summarizes the various requirements of the simulation environment.

a) Architectural complexity

The model needs to employ the basic characteristics of the architecture, meaning the area of roof, outer walls, floor areas and provide accurate heat flows among the various building elements. Internal heat flows within rooms have been assumed to be negligible for the results, since the required heat for a room results from the interface to the environment and not from within the building unit. Additionally, the research focus has been limited to heating control systems excluding air conditioning, for which air flows within rooms would be of greater importance[20]. Therefore, the architecture of the building is simplified to a few subsystems, in which each of these only one temperature is occurring (called ‘lumped-capacitance model’, [Incropera et al., 2007]). As described below in the simulation development (s. 2.3.3), this assumption has been partially loosened for improved accuracy in thermodynamics.

b) Thermodynamic accuracy

The requirements for thermodynamic accuracy are high, for the reason that the heat transfers directly impact the energy consumption and therefore the research results. Certain thermal building codes for buildings, like the so called Wärmeschutzverordnung in Germany, state heat transfer coefficient as a constant U-factors. This approach has been evaluated as deficient for the purpose of addressing the research question. For one reason, the thermal time-behavior would be overly simplified, because e.g. a sudden outside temperature change does not immediately impact the temperature of the building unit as the fixed U-factors imply, but with a certain latency. For another reason, the impact of the sun and wind, as well as the heat transfer of the indoor air temperature and the adjacent walls is reflected by time-depending variables. The weather impact gains importance with the implementation of control approaches with weather prediction, as weather influences affect the control system. Therefore, the simulation environment should incorporate a dynamic thermal behavior, as e.g. provided by a resistance-capacitance model (s. 2.3.3.2).

c) Control technology implementation

The simulation environment needs to be suitable for all defined control approaches. Besides the basic controller type on-off and PID, intelligent control approaches have to be employed. These are technically refined and act upon occupancy states as well as weather forecasts.

d) Adaption to empirical occupancy data

Since many heating control approaches are employing occupant behavior, an appropriate integration of the available occupant data needs to be chosen. The empirical occupancy data is at a resolution of 1 minute and differentiates between the occupancy states 'Home', 'Sleep' and 'Away'. The simulation environment should thus implement the occupancy data on the same base.[21]

e) Comfort evaluation

Besides the energy evaluation, the research question demands the measurement of occupants' comfort. The heating control approaches are by assumption only promising for future technology diffusion, if they are not imposing negative side effects on the occupants. This is represented by a comfort evaluation, which states how the heating control approaches are actually serving their purpose, i.e. providing a sufficiently heated building unit.

f) Integration of necessary external data sources, i.e. weather data

[20] Although some space heaters are only causing heat convection, which would negate the system difference to air conditioning, it is assumed that heating system are at least partially emitting heat radiation, therefore the study of temperature differences caused by air flows is less important.

[21] The occupancy state is an aggregation over all occupants and relates to the occupancy-state of the occupant with the highest temperature requirement among all occupants. Therefore, the temperature set point is only lowered if no occupant is in a state that demands a higher temperature.

The weather impact has been assumed as one of the major influencing factors for the resulting energy consumption. Therefore, weather data with high accuracy as well as high time-resolution has to be considered in the simulation environment. Additionally, the individual weather components such as air temperature, solar irradiation and wind speed are hypothetically impacting the performance of heating control approaches and should therefore be integrated individually.

g) Possible operation within the resources of the research project

The simulation model needs to be employable within simulation model development phase, timed to three months. Therefore, complex simulation tools that impose long adaption times for implementation are excluded. Also the investment costs as well as the computational costs have to be within the financial target values of the research project.

h) Adjustable simulation time-steps

The controllers in the real world are acting upon short time intervals, i.e. in the range of seconds. This demands small simulator time-steps to effectively compare controller types and their parameterization. Scott et al. recommends a simulator granularity of finer than five minutes)[22] [Scott et al., 2011]. There is an inherent trade-off between accuracy and computational complexity though, since finer simulator granularity is inversely related to computation time.

The requirements for the simulation environment have to be met either by employing an existing energy simulation performance tool or by a custom developed framework. This is evaluated in the following.

2.3.2 Existing building energy performance simulation programs

There is a wide range of available building energy performance tools. These are only briefly discussed since none of them could meet the requirements relevant for the research question. Two of the most common simulation tools are described in the following, a range of further tools can be found in [Drury B. Crawley et al., 2008].

- EnergyPlus: EnergyPlus [D B Crawley et al., 2004] has been developed by the U.S. Department of Energy and is considered as one of the baseline energy performance tools [Lu et al., 2010]. Its modular architecture integrates a detailed level of the physical structure of the building and provides an accurate calculation on heating and cooling systems and plant and electrical system response. EnergyPlus can apply detailed weather data from a range of weather stations around the world and operates on a default simulation time step of 15 minutes. Due to the accompanying engineering reference [EnergyPlus, 2012], the calculation methodology is transparent to the end-user. It has won several awards and is used extensively in research across disciplines [Lu et al., 2010].

- TRNSYS: TRNSYS is a transient systems simulation program developed by the University of Wisconsin [University of Wisconsin, 2013]. It is highly modular and features a range of

[22] Both 2-minute and 1-minute time steps have been tested. The occupancy data is acquired on a per minute basis, therefore the requirement for the simulation time-step has been set to 1 minute. As subsequent simulations revealed, the accuracy improvement from 2-minute to 1-minute time steps is approximately one percent while doubling calculation time. So this choice entails precise results but goes along with rather high computation costs.

technical components, such as solar collectors, batteries, heat exchangers. TRNSYS is especially applicable for multi-zone building model, e.g. to evaluate individual room heating. It is possible to integrate weather data and adjust the simulation time-steps. It is used in several research projects [Oldewurtel et al., 2013; Siroky et al., 2011].

The existing building energy performance simulation programs meet the requirements for architectural complexity and thermodynamics, as they are very detailed in the building's heat transfer and architecture. The integration of weather data is possible in each of the existing simulation tools and calculation accuracy in terms of time-resolution is controlled sufficiently within the tools. Although existing simulation tools fulfill many of the defined requirements, none of them has been employed within the research projects for the following reasons:

1. Control technology implementation

   In [Siroky et al., 2011] the problem of using existing energy performance tools for control purposes is mentioned. These tools cannot be readily used to implement the custom intelligent heating control features as intended. For example, implementation of the PID controller within EnergyPlus is not possible. This is a major drawback, since the main purpose of the research question is to compare the various heating control approaches.

2. Adaption to empirical occupancy data

   The empirical occupancy data is acquired on a per minute resolution, therefore the time steps of the simulation have been defined as 1 minute. For simulation tools without the possibility to adjust simulation time steps, information losses occur when employing the empirical data. The simulator granularity of existing simulation software is greater than this requirement, e.g. 15 minutes in the case of EnergyPlus [Pang et al., 2011] and are therefore not suitable to address the research question appropriately.

3. Possible operation within the resources of the research project

   Interviews with building model experts revealed that the utilization of the described energy performance tools result in complex models [Siroky et al., 2011]. This requires cropping to necessary elements as well as long adaption time to the software. Therefore, assumed time savings by employing existing tools compared to a custom development are indeterminate.

As a consequence, a customized control approach and building simulation environment, named CABSE, has been developed to meet each of the defined requirements. This is described in detail in the following.

2.3.3 A Control Approach and Building Simulation Environment (CABSE)

In this section, a customized framework to evaluate the performance of heating control approaches in buildings, named CABSE, is described in detail. This description is on the one hand to provide information about the functioning of the framework, on the other hand to serve as documentation for potential future research built upon this framework. It is closely based on the implementation code in MATLAB, but does not replace the additional programming code documentation. All developments and calculations have been conducted at the Chair of Sustainability and Technology (SusTec) at ETH Zurich. For further information on CABSE, please contact Dr. Bastien Girod or Dipl.-Wi.-Ing. Florian Nägele. The description contains the assumptions and mathematical description of the building model (s. 2.3.3.1, 2.3.3.2), the integration of heating control approach (s. 2.3.3.3), the parameterization (s. 2.3.3.4) as well as the program runtime and architecture (s. 2.3.3.5).

2.3.3.1 Assumption on the thermal influences

The thermodynamics of the building unit is simplified with regard to the requirements stated in section 2.3.1. The living area of the building unit is represented by one indoor area, inside which the temperature is homogenous, therefore called lumped capacitance model [Incropera et al., 2007]. Therefore, the sole controlled variable is the indoor air temperature. One space heater is coupled to the room, which can impose a heat flow on the room and adjust for the temperature set point. The controlled variable is further influenced by the heat flows from the environment as well as from the inside area (s. Figure 11):

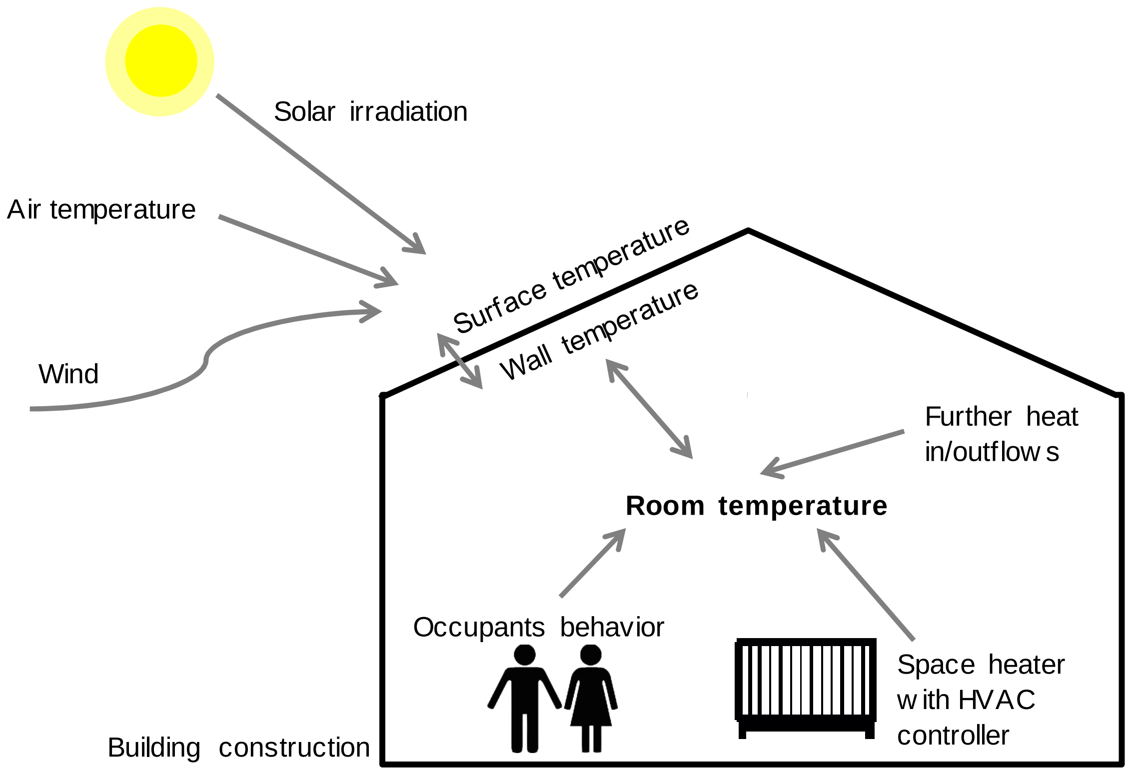


Figure 11: Representation of the major influences on the room temperature. The room temperature is affected by external and internal influences

a) External influences

The environment of the building unit affects the room temperature in terms of the weather impact as well as adjacent building structures. The weather influences are determined from the outside air temperature, solar irradiation and wind speed. For opaque building elements, i.e. walls, these are affecting the surface areas through convection (caused by wind), radiation (caused by solar irradiation) and conduction (caused by changes in outside air temperature). The windows transmit solar irradiation directly to the inside room and additionally allow for heat conduction of the outside air temperature. The convection at the windows is considered as air infiltration through the windows dependent on the window opening. Adjacent structures affect the building units through internal walls.

b) Internal influences

The primary internal heat source is the space heater. Besides, two major sources for heat inputs are considered: The heat emission of the persons and heat of appliances e.g. caused by television or lighting. These are dependent on the occupancy state, as e.g. absence results in lower heat emissions.

2.3.3.2 Description of the applied RC model

The thermodynamics of the system are described by a resistance-capacitance (RC)-model [Siroky et al., 2011]. This model is analog to an electric circuit, in which resistances and capacitances control the flow of power. Each building element, e.g. a wall, consists of capacitive and resistance elements. Elements with high heat capacities, for example insulation materials, react slow on heat inputs, whereas elements with low heat capacities such as air change their temperature fast when imposing heat on it. The resistance determines the intensity of the heat flow between the elements. To derive the RC elements, the building is simplified to a system consisting of one room and adjacent building structures, i.e. floor, foundation, windows, ceiling, roof, exterior walls and related surface layers. Each of the building's subsystem relates to a node that represents a temperature at each time step.

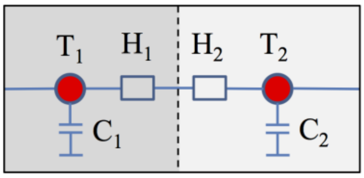


Figure 12: RC representation between two nodes 1 and 2 that are representing temperatures. C_1 denotes the thermal capacitance of node 1, H_{12} the heat transfer coefficient and T_i the temperature of node i

Figure 12 pictures the connection of two subsystems. The heat transfer of this system is described by a first-order equation (s. Equation 3). Heat sources, e.g. the heating system, appliances or persons are added on nodes as direct heat fluxes.

Equation 3: Heat transfer rate between two nodes 1 and 2. C1 denotes the thermal capacitance of node 1, H12 the heat transfer coefficient and T_i the temperature of node i

$$C_1 \frac{dT_1}{dt} = H_{12}(T_1 - T_2)$$

Figure 13 shows the employed RC model graph[23]. The building model is represented by a system of first-order equations and the building construction is configured through the parameterization of the RC values. The mathematical representation analog to Figure 12 is presented in Appendix C, I.

[23] Note that the assumption on a lumped-capacitance model has been loosened specifically in the walls facing the outside, i.e. the roof and outer walls. The reason for this is improved time-behavior accuracy on thermal heat transfers by increasing the numbers of sub-layers. This can be comprehensible when holding a metal stick against a heat source, e.g. a candle. The opposite side is heated with an increased latency; therefore the heat impact is not immediately noticeable. An indefinite amount of layers would provide the greatest accuracy.

Another reason for a sub-layering inside a building element is that some parts of the element are exposed to heat influences while others are not. This is the case for outer walls, where surface areas are exposed to solar irradiation and wind, whereas the inside part are not affected by it.

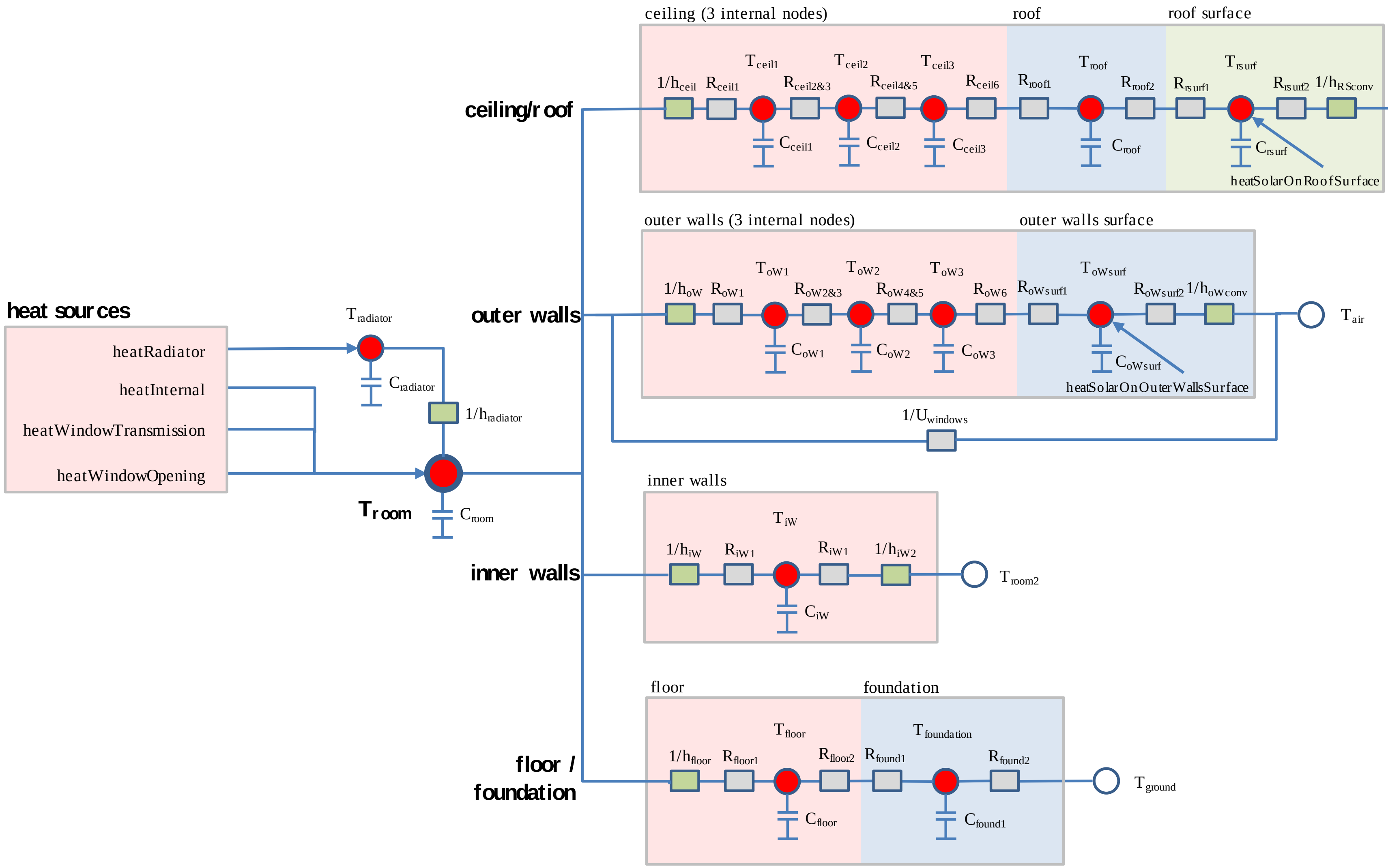


Figure 13: Representation of the thermal Resistance-Capacitance model for the simulation of heating control approaches. Red circles describe nodes which constitute a building element with its correlated temperature. The thermal characteristics are determined by the parameterization of resistances and capacitances

2.3.3.3 *Implementation of heating control approaches*

The heating control approaches are implemented inside an individual program module. The general calculation procedure as well as assumptions for the three control system elements controller, set points and disturbance prediction are described in the following. One may refer to section 2.2.3 for further information.

a) Controller[24]

- The on-off controller triggers the heater setting upon the occurring temperature error, but has to prevent short cycling due to fast-frequent setting changes. The error differential is assumed to 0.5°C with a reaction time of 1 minute. The space heater can only be set to operate at its maximum level or turned off.
- The PID controller, with proportional, integrative and derivative action on the temperature error can reduce temperature undershoot, overshoot, rise time, settling time and steady-state error. Besides the operation along the basic equation (s. Equation 2, 2.2.1.2) it additionally possesses anti-windup capabilities, i.e. the integral part is set to zero at set point changes [Montgomery et al., 2008].

b) Set points

The temperature set points for the indoor temperature are, dependent on the control approach, either constant throughout the simulation period, adjusted by a weekly, 30-min schedule, or triggered through occupant states in the modes 'Home', 'Away' and 'Sleep'. Programmable schedules are assumed to be unchanged over the simulation period[25] and derived from the actual programmed schedule of the household. For the preheating feature, it is assumed that a perfect one-hour prediction of the occupant states is possible. Therefore, the heater set point equals the maximum comfort temperature for the upcoming hour.

c) Disturbance prediction for solar impact

The disturbance prediction feature comprises a 3-hour forecast of the solar irradiation. It is assumed, that the weather forecast over this time period is accurate and that the forecast information is always available. Based on predefined parameters, i.e. the window size and average share of radiated window area to total window area, the simulation environment calculates the average expected heat impact for the following hours. The forecasted heat impact is fed forward to the control system and subtracted from the output of the space heater[26].

2.3.3.4 *Parameterization and initialization*

Up to this point, the structure of the simulation environment has been described. In a next step, the characteristics of the households are expressed in the parameterization of the simulation. These are partitioned into building, environment and occupancy specifications.

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[24] Refer to the controller output equations 2.2.1.2

[25] The assumption is based on research on this topic, which has found a range of issues and user-complaints about programmable thermostats, which leads to a rare usage of programmable thermostats [Meier, 2010].

[26] To avoid an overcompensation of the controller output, which would offset the effect of the disturbance prediction, the space heater is prevented from increasing the power at times of predicted solar irradiation.

Building thermal properties

The thermal properties are expressed in the parameterization of the RC variables. For each building element, the construction material (s. Appendix, Table 28) and thickness is defined. Windows are selected based on the solar energy transmittance of the glass (g-value) and the heat transfer coefficient (s. Table 29) In the case of surface layers, the coating material as well as the roughness is additionally set (s. Appendix, Table 30 and Table 31). These are relevant to calculate the solar absorptance as well as the convection. The equations for the thermal properties are described in Appendix C., II, Equation 5 - Equation 13. The total setup of thermal properties enables to allocate the building unit to a thermal building code. A thermal building code is a set of requirements on the thermal properties of the building construction, measured in the heat transfer coefficient, named U-factor. The U-factor is calculated by Equation 4. Table 32 in the Appendix shows the classifications for thermal building codes that have been applied. The building code is a known for each household.

Equation 4: The U-factor of a building element is calculated by its individual construction layers and the interior and exterior transition

$$U = \frac{1}{R_{si} + R_{layer1} + \ldots + R_{layer\ n} + R_{se}}$$

U	Heat transfer coefficient [W/(m²*K)]
R_{si}	Interior heat transfer coefficient [m²*K/W], see Table 33
R_{se}	Exterior heat transfer coefficient [m²*K/W], see Table 33
$R_{layer\ i}$	Resistance of layer i [m²*K/W]

Building dimension properties

The dimensions of the building are defined by the length, width and height of the building interior. The floor area is the product of length and width, the volume is the product of the floor area and the height. The area of the roof is assumed to be equal to the area of the floor, i.e. a flat roof. The wall measurements are likewise products of the indoor measurements. The window area is defined as percentage to the floor area and is subtracted to the total area of exterior walls. The volume of each of the building elements is calculated by the product of the area and thickness. This means that only rectangular cuboid shapes of building elements are possible.

Micro environment

The micro environment of the considered building unit comprises all adjacent building structures. Therefore, setups for the micro environment of the building unit can be created.

Table 3: The setup of the building unit in relation to the adjacent structure is determined in terms of the bottom and top adjacency as well the relation of the vertical walls to the adjacent building structures[27]

Relation to adjacent structures	Adjacent structure on top	Share of vertical walls adjacent to other building structures[28]	Adjacent structure on bottom
Detached house	No	0%	No
Semi-detached house	No	25%	No
Linked house (townhouse)	No	50%	No
Apartment on ground floor	Yes	50%	No
Apartment on intermediate floor	Yes	50%	Yes
Apartment on upper floor	No	50%	Yes

Macro Environment

The macro environment defines the location of the building and weather exposure. The location is mapped to hourly, location-specific weather data (s. 2.4.2). Furthermore, the weather exposure of the building is described by four variables: The average radiated share of total roof area, the average radiated share of total outer wall area, the average radiated share of windows area, and the percentage of wind speed that affects the building. For instance, if the average radiated share of total roof area is set to 20%, this means that on average 20% of the roof is impacted by the present solar irradiation. The percentage of wind speed that affects the building expresses, to what extend the wind is decelerated before it affects the building.

Occupancy

The occupancy is defined by the number of occupants in the building unit and the occupancy pattern. The occupancy pattern represents the occupants' behavior over the year and is derived from household empirical data (s. 2.4.1). This data contains desired comfort temperatures, occupants' states on a per minute basis.

Heating System

The setup of the heating system is given by the heat capacity of the entire space heating system and is impacting the latency of the thermal response of the controlled system. Its components are the furnace, the pipes and the radiator (s. Figure 14). The heat capacity of the space heater is the sum of the heat capacity of the water in the pipes and the radiator and the heat capacity of the radiator structure (s. Appendix C., III, Equation 14). Thus, the more water in the system and the more massive the radiator structure, the greater the heat capacity. The dimensioning of the heating system is given with the maximum power of the space heating system, i.e. the maximum heat output (s. Appendix C., III, Equation 15). The heating load is dependent on the building type

[27] Adjacent building structures are assumed to be heated at 20°C according to DIN 12831

[28] The vertical walls of apartments and linked houses are assumed to be to a share of 50% adjacent to other building structures. In the case of semi-detached houses only one of four sides of the vertical walls is assumed to be adjacent to another building structure.

and determined according to [Pistohl, 2009][29]. The heating load is derived from the sum of the transmission heat losses (s. Appendix C., III, Equation 16) and infiltration heat losses (s. Appendix C., III, Equation 17).

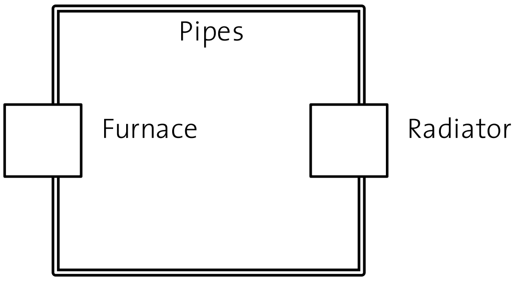


Figure 14: The heating system is simplified to one radiator inside the room with a heat capacity drawn from the entire system, including water volumes in pipes, furnace and radiator

PID-Tuning

The parameterization of the PID controller needs to be conducted for each of the households individually to provide optimal control performance. Therefore, the PID-tuning parameters K_p, K_i, K_d have been adjusted in an initial response test to optimize undershoot, overshoot, rise time, settling time and steady-state error. The Ziegler-Nichols algorithm [J. Ziegler et al., 1942] provided practicable parameterizations that have been further adjusted manually until validation with empirical data showed robust goodness-of-fit results.

2.3.3.5 Program architecture and runtime environment

The simulation environment CABSE is designed analog to the calculation steps stated in section 2.3.3. It consists of three modules, responsible for data input, simulation and data output (s. Figure 15). The input module is comprised of test setup specifications, including building and household characteristics, as well as the control approach specifications and simulation settings. These are read by the graphical user interface or derived from the underlying building physics database (s. Appendix D).

[29] The maximum power that can enter the controlled system is assumed to be equal to the maximum heat power of the boiler, which is a simplification on the power losses on the pipes. This is not affecting the resulting energy consumption, since the model calibration compensates for all influencing factors on the actual power output.

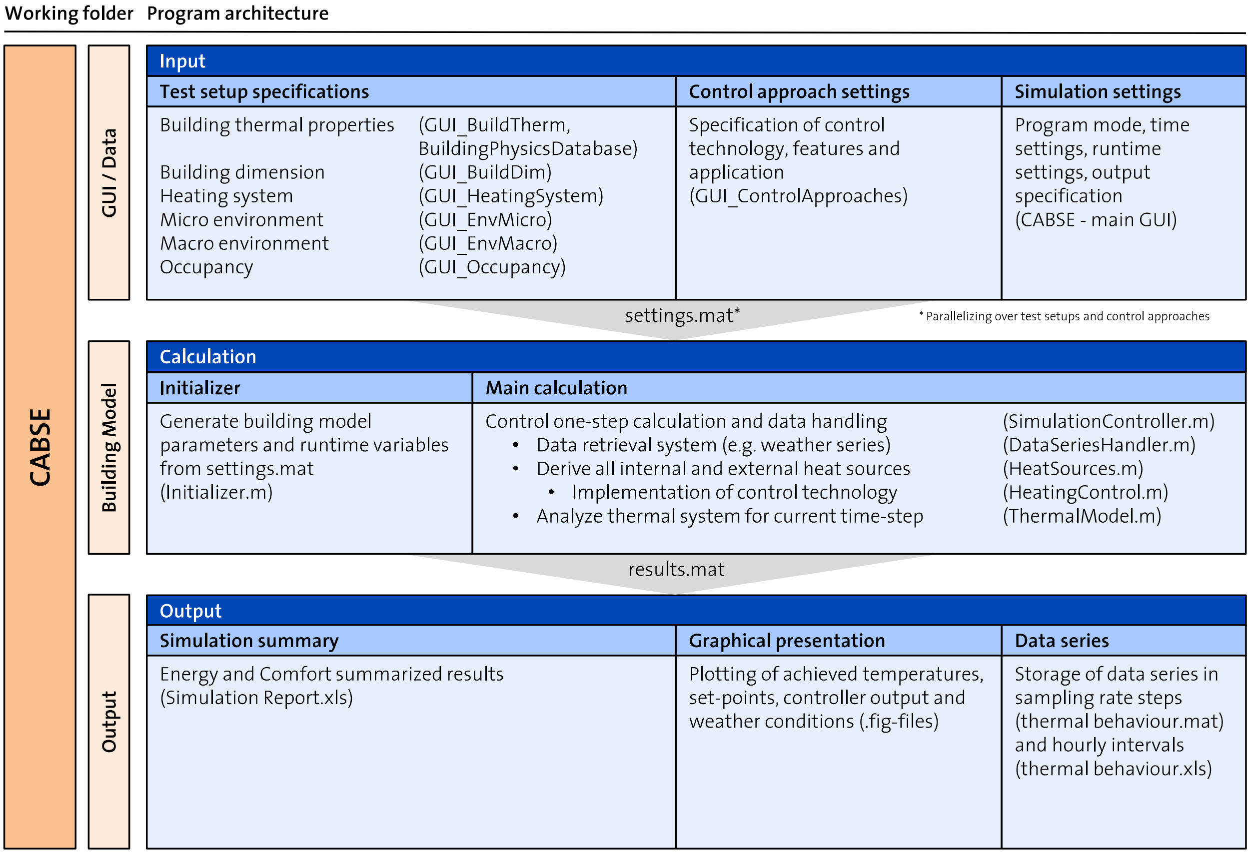


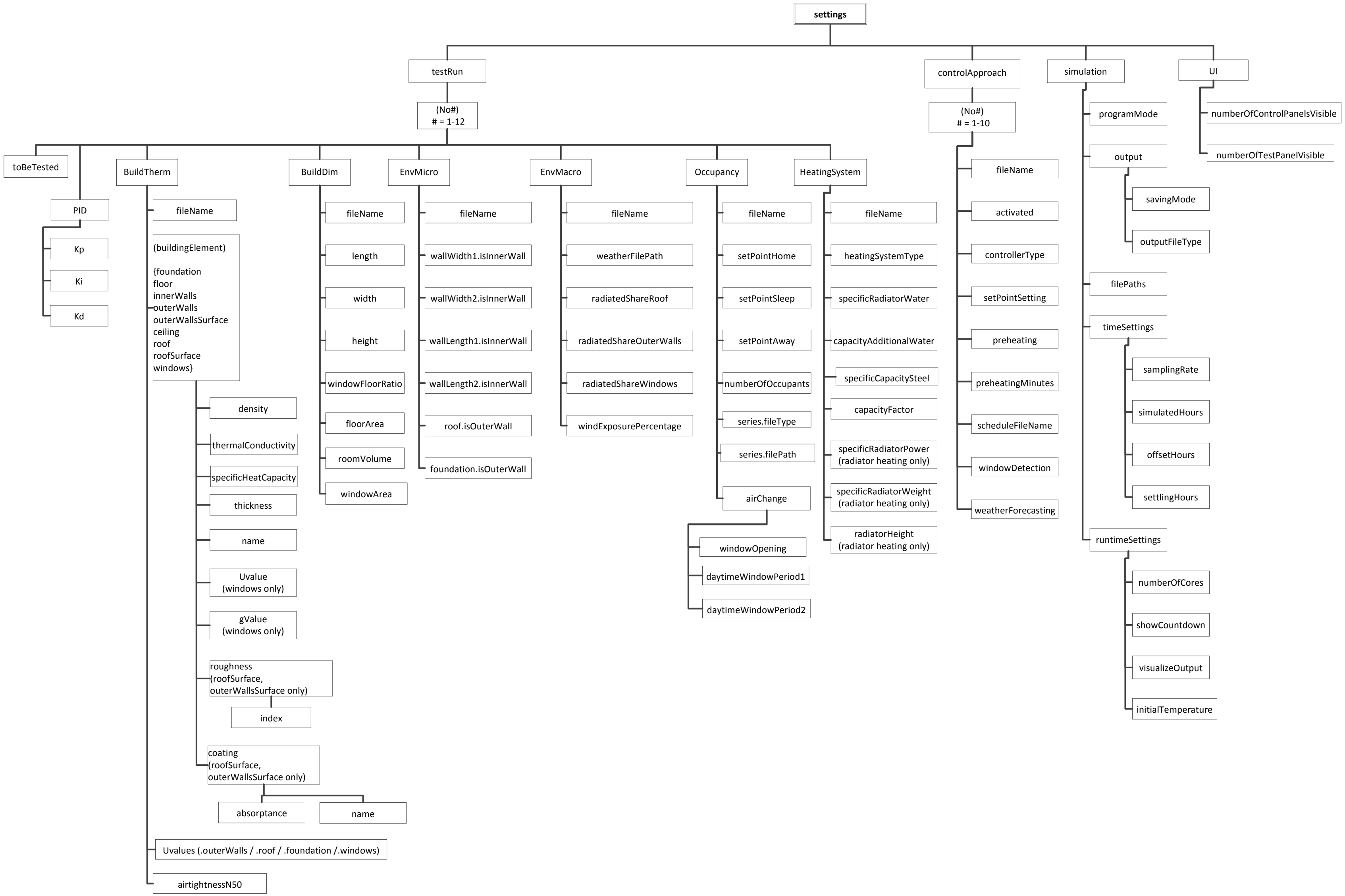
Figure 15: CABSE program architecture shows the modular structure of the implementation. Each folder features one program module and each filename (brackets) is dedicated to one program sequence. The communication between program modules is enabled by Mat-Files

The building model module performs all calculation steps. It inputs the settings file (s. Figure 16) and initializes the run time variables as well as the RC parameters. After the initialization, the calculation is looped over the number of simulation steps. These are for a typically 1 minute time steps over 1 year, approximating 525,600 calculations. One calculation step is summarized in the following:

1. Retrieve current data points, i.e. the occupant comfort temperatures as well as the hourly weather data points on solar irradiation, outside air temperature, ground temperature and wind speed. As the database contains hourly data, a linear interpolation on the data is performed to obtain data on a per minute basis.
2. Update heat sources according to the current system state (s. Appendix C, II)
3. Calculate time-variant RC parameters (s. Appendix C, II)
4. Update building model equations and analyze for current time-step (s. Appendix C, I)
5. Store one-step results and input these results for the upcoming calculation step

Following the simulation calculations, the output is generated. It contains summarized energy and comfort evaluation figures, graphical representations as well as complete data series on the temperatures.

Figure 16: Data structure of the building model settings, which is the input for the simulation and contains the user-defined selection for the simulation run



2.3.4 CABSE validation

To ensure that CABSE accurately reproduces real-life behavior, the created building models have been validated. This comprised calibration with empirical data, discussion with building model experts and cross checks with energy consumption information of households.

2.3.4.1 Calibration with empirical data

The building models in CABSE are calibrated along the empirical data of the households (s. 2.3.4). At first in this process, parameters are entered that best describe the selected test household based on a survey given to all sample households as well as data that was logged inside the building. Empirical input parameters include e.g. size of the apartment, construction date, insulation standard, heating system type, temperature set points as chosen by tenants, floor level of the unit, outside temperature, solar irradiation, and occupancy times. Second, the model has been calibrated across the remaining variables, i.e. thermal inertia, weather impact and actual heating system performance, minimizing the coefficient of variation of the root mean squared deviations CV(RMSD) between simulated and actual in-room temperature [Tahmasebi et al., 2012]. A graphical crosscheck has been conducted over a randomly selected ten-day period for each household.

Figure 17 depicts the final calibration results of one household, showing a good representation of reality. When comparing the obtained average deviation (CV(RMSD)) of 2.4% with similar work, it appeared to be well suited for the investigation [Tahmasebi et al., 2012].

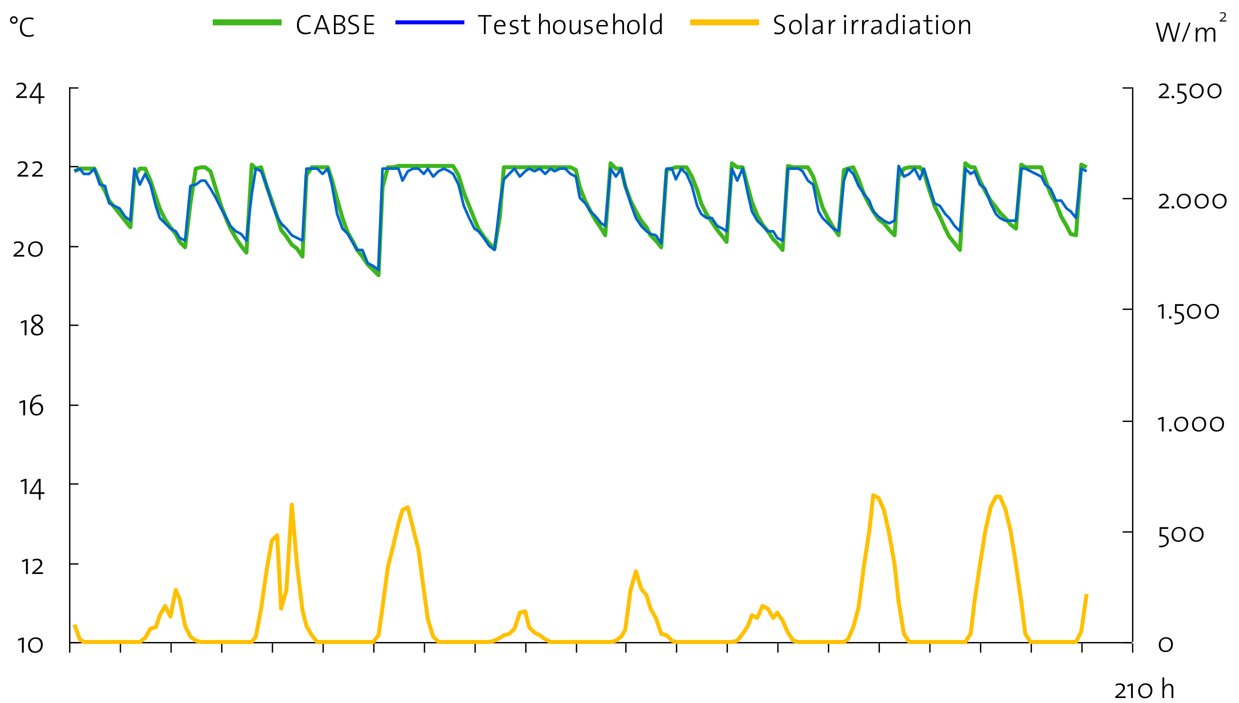


Figure 17: CABSE calibration results of one household – comparison of logged in-room temperature (in °C) with simulated in-room temperature (in °C) and solar irradiation over nine consecutive days shows very good representation of reality

2.3.4.2 Discussions with building model experts

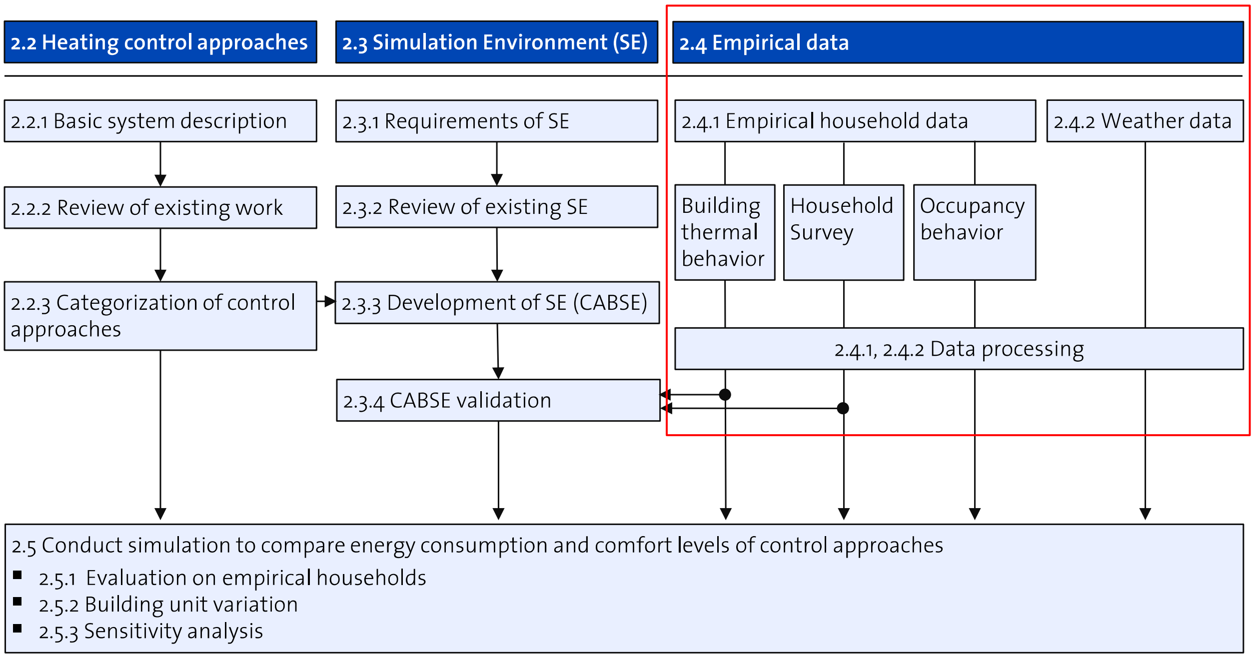
In addition, expert interviews on calibration and simulation results have been conducted and the model's dynamic behavior has been compared to well-known building simulation tools such as TRNSYS and EnergyPlus. The correctness of the thermodynamic behavior was confirmed. Therefore, a simplified system with constant conditions, e.g. outdoor temperature and air change has been evaluated within simulation runs in the required heating power to achieve a certain room temperature. The heating power derived from several simulation runs has been compared to calculated heating load derived from the building envelope and air change specifications (s. heating load calculation in 2.3.3.4). The deviation between these two values has been observed to be below 1.5% in each of the tested settings[30].

2.3.4.3 Energy-cross check for selected households

The simulation results in terms of energy consumption have been compared to actual annual energy consumption information of the households with further inclusion of assumption on heating system efficiencies (s. 1.1.2). The accuracy of the simulation in terms of the overall energy consumption showed a deviation in final energy consumption of 0-15%.[31]

2.4 Empirical data

The acquired empirical data ensures the correspondence of the results to reality. The data includes empirical data from households (s. 2.4.1) and weather data (s. 2.4.2). ´



[30] This included extreme condition tests with outdoor temperatures in the range of -25°C to +40°C.

[31] The final energy consumption for the heating system is not directly relatable to the net energy for space heating, as the final energy consumption includes distribution losses in the building, losses determined by the heating system efficiencies and for some households, energy for hot water. Considering solely the range of heating system efficiencies of 15 percentage points (s. Table 1), the range of deviation of absolute energy consumption is within the predicted range.

Besides to the acquisition of the data, the data needs to be processed in terms of the time domain and data quality.

2.4.1 Empirical household data

The empirical data originates from households for which a several month long observation of occupancy and thermal behavior as well as a household survey was conducted. The participation of the households has been on a voluntary base for 10 households, located in the south of Germany. They have been considered on a random selection out of over 119 electronic applications. The data acquisition has been realized by an industry partner with expertise in intelligent control approaches. The major incentive for the occupants to participate can be seen as a realization of energy savings, access to innovative technologies and energy performance evaluation of their heating system. The process steps for gaining empirical data in terms of survey data, long-term data and data processing are listed below.

2.4.1.1 Household survey

The household survey comprised a questionnaire about household and building specifications as well as telephone interviews. The data included

1. The location of the building (city)
2. The year of construction of the building
3. The insulation state, i.e. renovation state of the windows and walls
4. The architectural details (length, height, width of living area)
5. The environment: Floor level, adjacent buildings, shadowing
6. Heating system type
7. Number of people in the household
8. Annual energy consumption for space heating

2.4.1.2 Long-term household empirical data

Long-term empirical data for the 10 households has been acquired to enable the building model calibration described in section 2.3.4.1. This included logged data on occupants' behavior as well as the heating system over several months (ranging from 8-14 months). The measured variables are listed in the following.

- The actual room temperature has been measured in the controlled indoor space by a digital thermometer on a per minute basis
- Occupancy states have been collected on a per minute basis for the states 'Home', 'Sleep' and 'Away'. The occupants further specified desired temperatures for these states. The data acquisition could be conducted with smartphone devices featuring location tracking. The user interaction was low since a GPS smartphone tracking algorithm as well as fallback mechanisms on short disconnection times provided high automation. The users specified in addition to this a week-long schedule for the occupant states home, sleep and away on a 30 minute resolution with desired temperatures for each of the states. They have been applied for the programmable and nighttime control approach.

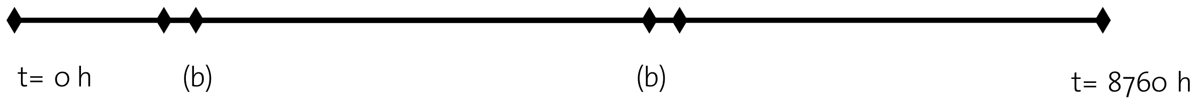
- The data on the controller output has been collected on a 15 second interval, ranging from 0 to 100% of the heater output. The heating system is remotely connected to the data acquisition systems.

2.4.1.3 Data processing

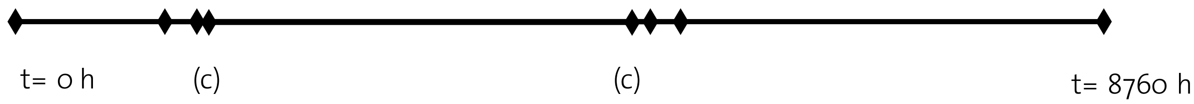
Data processing is necessary to generate annual occupancy patterns from the empirical data as the simulation period is one year. As the datasets did not face issues in terms of downtimes and errors, the following extrapolation steps were conducted for the occupancy data of each of the households.

1. Raw data: Field data spans over several months within one year (a)

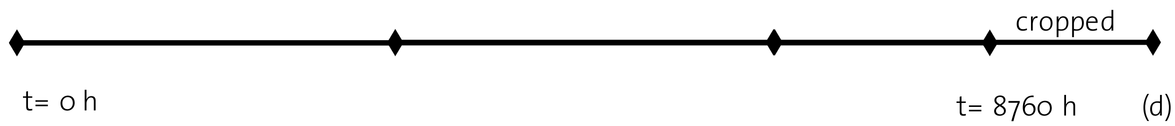
2. Cropped raw data: As the data includes system setup phases, a time period with normal operation mode is cropped (b)



3. Cropped raw data, week complete: For the later adaption of weekly programmable schedules, the data is further cropped (c) to start with the beginning of a week and finish with the end of the week



4. This data is extrapolated (multiplied) to a full-year long occupancy file (d)[32]



5. The resulting occupancy data (e) is year-long and applied for the simulation runs

2.4.2 Weather data

Weather data is required for an accurate reproduction of the building environment in the simulation. The weather data has been obtained ex-post from the weather service (Deutscher Wetter Dienst) for the location of the households for the year of the data acquisition. This data comprised accurate and hourly weather information on the following variables:

- Outside air temperature [°C]

[32] It is assumed that the occupancy patterns in the several month long data acquisition period sufficiently represents the overall occupancy behavior.

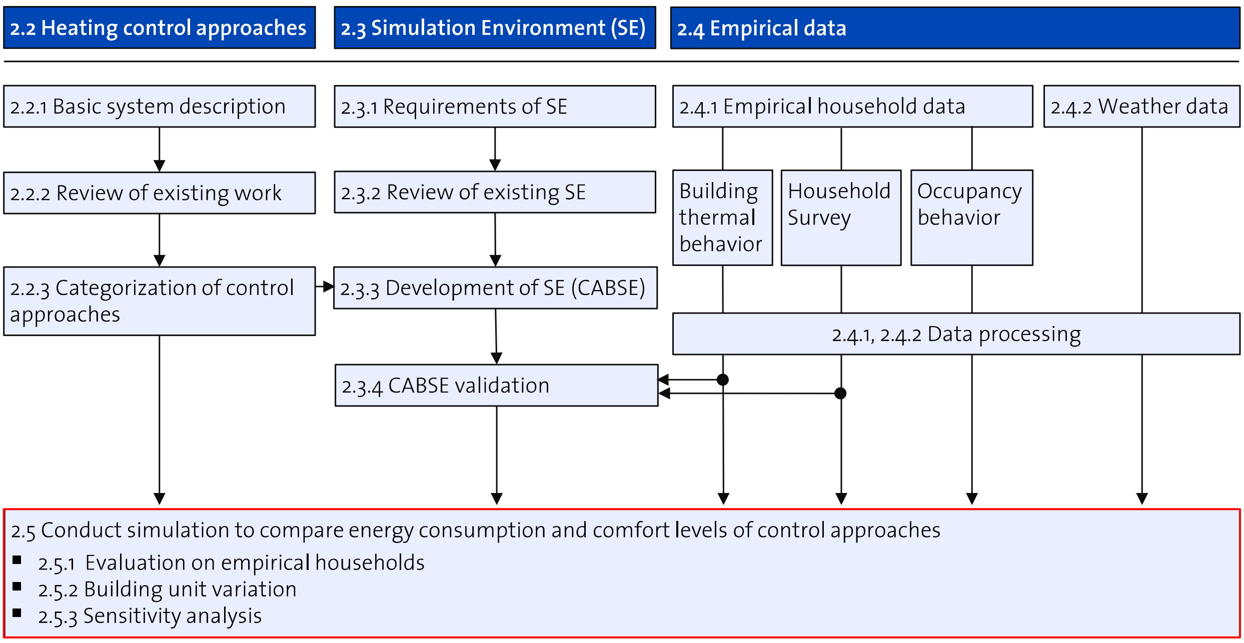
- Wind speed [m/s]
- Solar irradiation [W/m²]
- Ground temperature in 1 m below the ground [°C]

The hourly weather data has been linearly interpolated to gain data points on a per minute basis that match the simulation time-steps. An additional inspection of the temperature profiles of the measured indoor temperatures and the acquired outdoor temperatures validated the weather data. The indoor temperature matches the ex-post weather data in its steeps and drop-offs with a lag of less than 20 minutes. This is comprehensible for two reasons:

- The building doesn't immediately react to weather influences like solar irradiation or temperature changes due to the great thermal mass. In fact, assuming on average 20 minutes of latency, the ex-post weather data shows a close correlation to indoor temperature changes.
- In a dialogue with the German weather service, it has been indicated that the weather situation within a city with the size of Munich might as well be varying to a small extent between the weather station and the individual households. This is mainly for the reason, that weather stations are commonly placed on the outskirts of the cities or at its airports. Despite this, the data of the weather stations reflect the climate of the cities very well.

Based on these insights, the weather data has been found to be well suited for the research.

2.5 Simulation operation



This section describes the simulation operation in its individual simulation runs. The simulation is composed of the analysis of the empirical households (s. 2.5.1), a variation along building unit types (s. 2.5.2) and a subsequent sensitivity analysis of individual variables (s. 2.5.3). This ensures that an extensive range of influencing factors is taken into consideration and the performance of the heating control approach based on the real-world examples can be evaluated.

2.5.1 Evaluation on empirical households

To gain a range of insights for distinct real-world households, the archetypical heating control approaches are tested for each of the empirical households in terms of energy and comfort (refer to section 2.5.4). The household characteristics are listed in Table 4. They are varying in one or more building and occupancy specifications (s. Figure 18)[33].

Table 4: Excerpt of empirical households characteristics - see appendix for a full description

Test-house	Energy standard	Relation to adjacent structures	Floor area [m²]	Number of occupants	Vacancy time [% to total time]
1	WSVO 1982	Intermediate level	70	2	39.6
2	WSVO 1977	Intermediate level	75	2	34.0
3	EnEV 2002	Ground floor	150	2	18.3
4	WSVO 1982	Ground floor	55	1	45.0
5	WSVO 1982	Intermediate level	90	3	24.6
6	WSVO 1982	Intermediate level	139	6	27.4
7	WSVO 1982	Intermediate level	75	1	35.7
8	WSVO 1977	Ground floor	65	2	45.5
9	WSVO 1977	Upper level	45	1	42.2
10	WSVO 1995	Ground floor	65	1	45.6

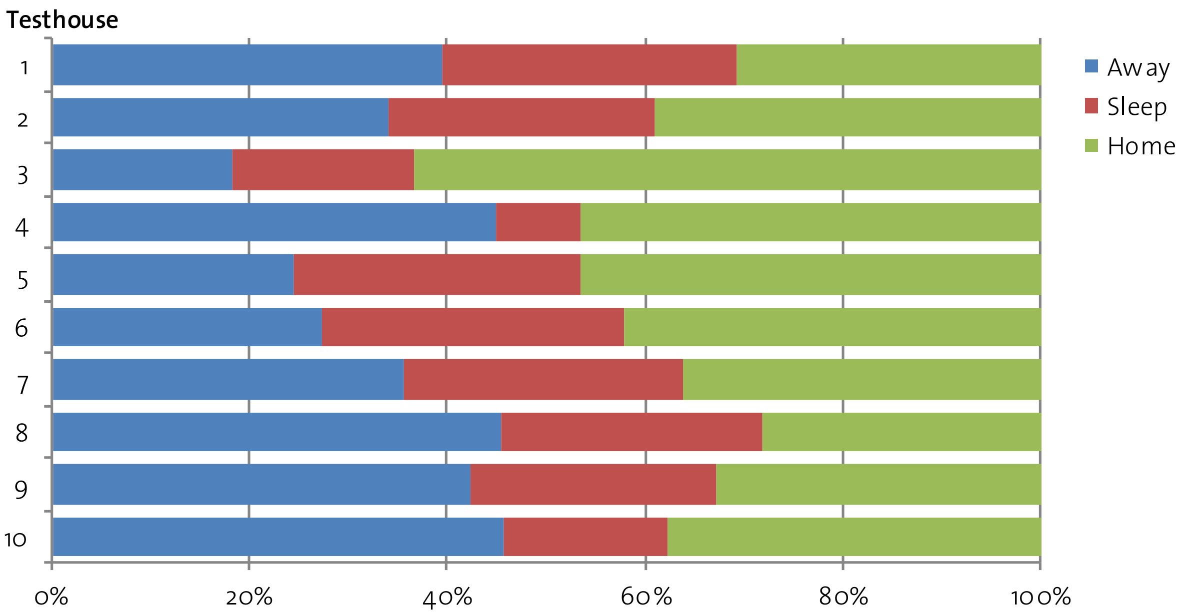


Figure 18: Relative frequency of occupant states (total time of occupant state to simulation time)

[33] An ex-ante selection of the entire household characteristics is not possible, as the nature of the heating system and the occupants are described over time.

2.5.2 Building unit variation

In order to gain results in respect to building unit types not covered in the empirical sample, a performance comparison of heating control approaches in perspective to the German building stock has been conducted (s. Figure 19). Therefore, a typology of various building types has been deployed with a defined reference parameterization.

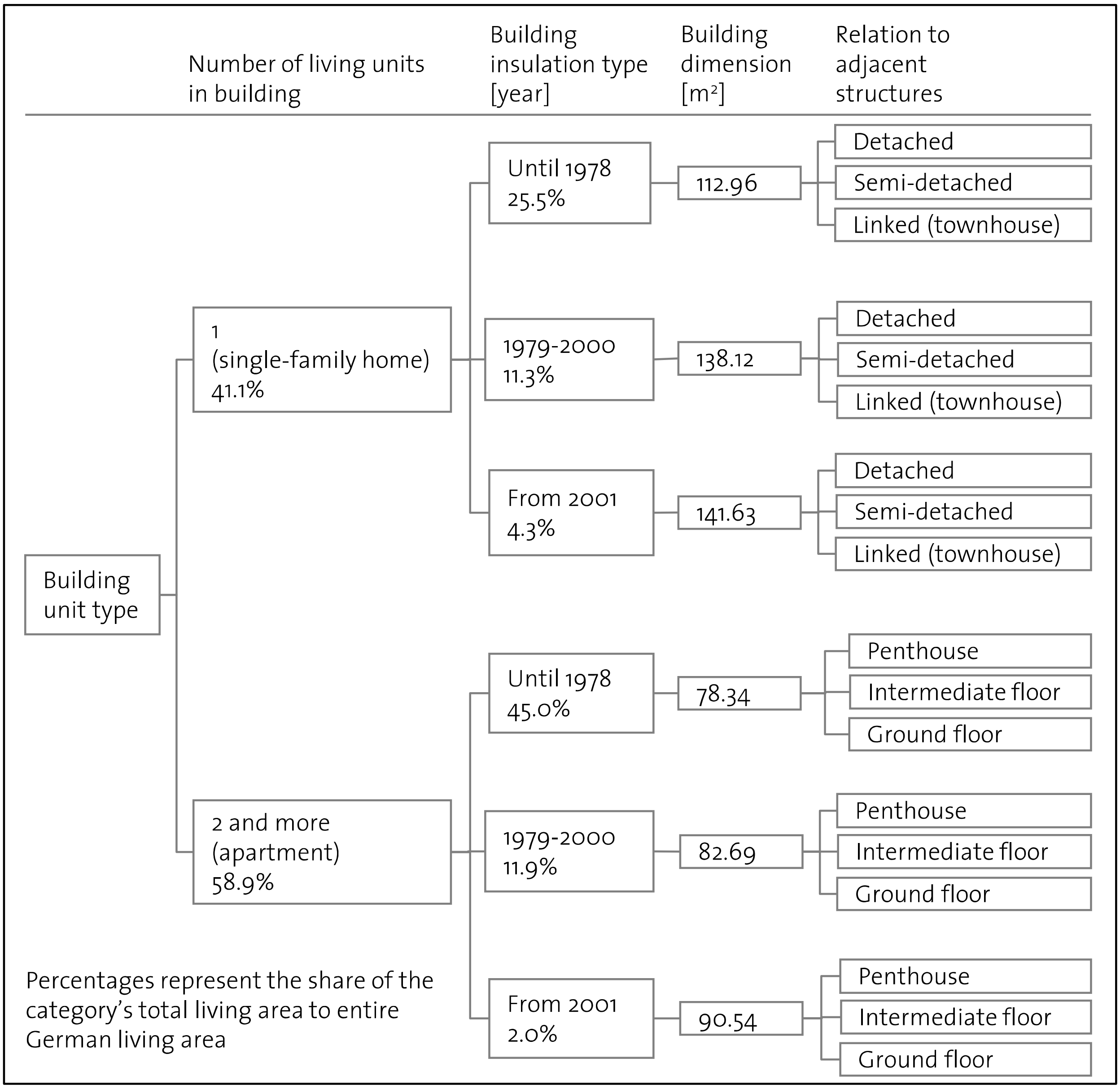


Figure 19: Segmentation of building stock along various building unit types

The building unit types are in accordance to the typology of statistical sources [Statistisches Bundesamt, 2010]. The typology is composed of the number of living units in the building, building insulation type, building dimension and relation to adjacent structures [Institut Wohnen und Umwelt, 2010; Statistisches Bundesamt, 2010]. The share of total living area for one building category as well as the average building dimensions are derived from [Statistisches Bundesamt, 2010].This source classifies the adjacent structures in an aggregation of single and double family homes, where detached buildings make up for 68.4%, semi-detached buildings for 16.1% and linked buildings for 15.5% of the total number of buildings. For multi-family homes, the majority of buildings (59.2%) are built as enclosed structure. For these, the relation to adjacent structures for one living unit has been defined as a variation of the floor level in an enclosed structure: penthouse with roof, intermediate floor and ground floor with ground contact. Based on the typology of Figure 19, the building properties are implemented in the simulation environment. The location and occupancy patterns are chosen to the following with the purpose of providing validated and representative parameterization derived from literature and empirical evidence:

- Location: The location has been set to Munich, as for this city accurate weather data could be acquired on all relevant weather variables with a further validation for the empirical households (s. 2.4.2).
- Occupancy: The occupancy with the median vacancy times among the empirical set has been chosen, i.e. household 2. The overall vacancy time is 34%, which equals approximately an average absence time of eight hours per day. The occupancy pattern is presumably representing a greater range of households, as the weekly working time of this household equals the working times of 35 hours specified by several German collective agreements[34] when assuming 30 minutes commuting times.
- Heating system: The heating system has been dimensioned according to the heating load calculation method presented in section 2.3.3.4.
- Air change: The air change has been set to 0.5 per hour as stated in DIN 4108/2.[35]

2.5.3 Sensitivity analysis

To identify drivers of the energy-savings performance, a sensitivity analysis on several variables was conducted. This helps on the one side to explain how the differences in the results between the test households arise and quantifies on the other side the impact of single variables on the results. For this purpose, the reference parameterization is set along the description of section 2.5.2. The building type is set to an apartment prior 1978 on intermediate level, which is the natural environment of household 2 and furthermore represents the most common building unit type in Germany. Therefore, the chosen parameterization provides both a close match to the real world as well as a representation of a greater range of building units. The tested variables of the sensitivity analysis are described in the following.

Occupancy: The impact of the occupancy pattern is tested. Therefore, the relative vacancy time is varied, in the range of the lowest and maximum observed empirical values from 18.3% to 45.5%. The actual occupancy patterns of four household are tested, whereas all other variables are fixed to the further described values[36].

[34] As e.g. in the electrical, printing and metal industry [IG Metall, 2007]

[35] The model validation of the households revealed that actual air change rates for the households are below this requirement, in some cases less than 50% of the required rate. This is reasonable, as it needs frequent and thorough window openings also during winter times to achieve an average air change of 0.5/h.

[36] It is not possible to condense the occupancy pattern to the overall vacancy time only. The dynamic frequencies and periods of the three occupancy states determine the characteristic of the occupancy pattern. Therefore, the results are only indicating the impact of the relative vacancy times on the relative energy savings.

Impact of solar irradiation: The range of the observed, i.e. by the model validation acquired, average shares of the solar irradiation affecting the outer walls and transmitting the windows is tested. The pool of empirical datasets in terms of solar irradiation is likely representing the possible range of solar interdependences on the building, as it features shadowed, ground floor buildings as well as a penthouse with great exposure to the sun. The range of observed average share of the solar irradiation that is affecting the building envelope is thereby derived to values between 5% and 35%.

Air change rate: The air change rate is to one part caused by the natural infiltration to the windows, to another part by the occupants' window openings. The air change is varied to the lowest observed values and the maximum values.

Heating load: The dimensioning of the heating system in terms of the maximum heat output is described in 2.3.3.4. As the actual heating power available in the household varies, the impact of the under- and overdimensioning of the heating system is tested.

Window Size: The window-to-floor-ratio describes the share of window area to the floor area. This ratio varies between buildings and is therefore simulated for its influence within the observed values.

Wind speed: The wind speed affecting the building envelope has been varied from 0% to 100% to the available wind speed, which is measured at the weather station.

2.5.4 Notes on the evaluation of energy and comfort

The performance results of the heating control approaches are measured in two dimensions, energy and comfort. The energy consumption is calculated as the specific net energy for space heating per year per square meter (kWh/m^2 p.a). It is computed as the Riemann sum of the heat power entering the room on a per minute base. The results are presented as relative energy savings[37] of the considered control approach to the reference control approach (on-off)[38]. As the relative energy savings vary between households, normalized relative energy savings show how much of the energy savings potential in the specific household is achieved. Therefore, the relative energy savings of each control approach is related to the energy minimizing control approach occupancy detection and weather prediction[39].

The comfort level is calculated according to international standards, that is ISO 7730 and ASHRAE 55-2010 [ANSI/ASHRAE, 2010; ISO, 2005]. These are based on the methodology developed by Fanger [Fanger, 1970] who introduced a rating scale with the Predicted Mean Vote (PMV) for a large group of persons for thermal comfort. This rating scale ranges from -3 for cold, -2 for cool, -1 for slightly cool, 0 for natural, +1 for slightly warm, +2 for warm, and +3 for hot. The Predicted

[37] Absolute net energy consumptions can be found in the Appendix.

[38] The on-off control approach could be identified as reference control approach. This is due to the fact, that most of the heaters can only be operated in on-off mode, since a heater with a modulated flame is rare according to expert interviews. So, to actually implement a PID controller with its output requires system knowledge and advanced algorithms: The output of the flame could be modulated through puls-width modulation within the short-cycling boundaries of the heater. So, an effective PID output for the heat flow is sophisticated in its implementation and is therefore not posing the reference scenario, but remains technically possible.

[39] This control approach has been ex-post defined as the energy minimizing control approach, thereby representing the theoretical optimum for this dimension. It confirmed the hypothesis, the automatic set-point approach with weather prediction inclusion but exclusion of preheating feature will provide the minimal energy input.

Percentage of Dissatisfied (PPD) is a measure that expresses the thermal comfort level as a percentage of thermally dissatisfied people and is directly derived from the PMV. A dissatisfied person is thereby assumed to vote for either -3, -2 +2 or +3 on the rating scale. ASHRAE 55-2010 [ANSI/ASHRAE, 2010] states an acceptable thermal environment to be within a PMV of -0.5 to 0.5. This relates to a PPD of less than 10%, which is stated as the acceptable thermal environment for general comfort [ANSI/ASHRAE, 2010]. The comfort performance of the heating control approaches are measured according to this standard. Thereby, only negative temperature errors are considered, as the purpose of the heating control system is to prevent coolness. The long-term evaluation of comfort in the simulation is conducted along the calculation procedures stated in ISO7730, Annex H [ISO, 2005]: Therefore, the number and percentage of hours, during the hours that the building is occupied and the related PMV is derived. Table 5 provides four comfort classes, which are measured for each of the households (s. Appendix A. Individual characteristics and results for empirical households).

Table 5: Three classes of thermal environment according to [ISO, 2005]. Class B is required for an acceptable thermal environment for general comfort [ANSI/ASHRAE, 2010]

Comfort class	Predicted Mean Vote (PMV)	Maximum temperature error[40] in °C	Predicted Percentage Dissatisfied (PPD)
A (High)	-0.2 < PMV < 0.2	1	< 6%
B (Acceptable)	-0.5 < PMV < 0.5	2	< 10 %
C (Reduced)	-0.7 < PMV < 0.7	3	< 15%
D (Poor)	PMV > 0.7	> 3	> 15%

2.5.5 Notes on the calculation execution

The overall calculation execution needs to be adapted and optimized regarding the defined simulation runs to ensure the feasibility of the research approach. The first simulation runs revealed high calculation times, which would have resulted in an overall calculation time of about three weeks. As the calculation accuracy has been identified as appropriate and therefore not subject to change, the issue has been addressed in two steps with the aim to improve calculation tractability:

1. <u>Improvements in calculation efficiency</u>
   a. Parallelization of simulations: Each simulation runs is testing the performance of one heating control approach in one household. Thus, the simulation of 8 control approaches over 10 households is very time-consuming. Therefore, CABSE has been parallelized to test various control approaches as well as households simultaneously.
   b. Performance inspection: A programming code profiling according to the MATLAB Profiling Guidelines [Mathworks, 2013] revealed inefficient code sequences and function callings. These sequences have been changed which led to a reduction of calculation times of 20%.
2. <u>Utilization of high-performance computing</u>

[40] For typical clothing (1 clo) and activity (1 met)

> The highly parallelized environment of CABSE is well suited for the application in high-performance clusters. One example is the Brutus cluster at the ETH Zurich, which is among the fastest computers of Europe. It is a collection of many individual computers that are connected via a common network ["ETH - Informatikdienste - Clustersysteme der Informatikdienste," 2013]. CABSE has been employed on Brutus and operated via the batch system for the various simulation runs. It enabled a 128-fold improvement in calculation times due to the operation on as many computational nodes with only minor overhead times.

Consequently, the calculation time has been reduced to only a few hours.

3 Results

The results are sectioned into the results among the 10 test households (s. 3.1)[41], the variation of the building unit (s. 3.2) as well as the sensitivity analysis of further variables (s. 3.3). They are presented in terms of the energy savings as well as the resulting comfort levels as introduced in section 2.5.4. Furthermore, the trade-off between energy savings and comfort is addressed.

3.1 Results for empirical households

The relative energy savings of the control approaches are presented in Table 6 for each of the 10 household. A detailed list of the results for the individual households is shown in the Appendix.

Table 6: Result summary for energy savings of the empirical sample across 10 households. The percentages indicate the relative energy savings of the heating control approach to the reference control approach (on-off).

	Control approach						
Test-house	PID controller (stand-alone)	Nighttime temperature setback	Programm-able thermostat	Occupancy-state detection	Occupancy-state prediction	Occupancy-state detection with weather prediction	Occupancy-state prediction with weather prediction
1	2.6%	14.2%	21.7%	25.1%	20.5%	29.6%	25.2%
2	3.0%	15.3%	23.2%	27.3%	23.9%	31.4%	28.0%
3	5.6%	9.8%	9.8%	12.3%	11.1%	13.7%	12.3%
4	4.4%	-0.8%	15.2%	19.2%	18.4%	19.7%	18.9%
5	2.2%	8.9%	14.6%	15.8%	13.2%	16.8%	14.2%
6	5.0%	16.0%	20.0%	29.2%	25.4%	33.2%	29.0%
7	1.2%	10.6%	18.4%	22.8%	20.7%	24.7%	22.2%
8	6.4%	23.1%	36.6%	42.2%	38.8%	47.0%	43.9%
9	1.0%	5.5%	13.6%	18.2%	16.8%	19.8%	18.2%
10	6.1%	14.5%	22.1%	25.3%	22.7%	27.8%	25.3%

The reference control approach (on-off) resulted in the highest energy consumption across all households. The relative energy savings for the PID controller reached from 1.0% to 6.4%. For the nighttime setback control approach, the energy savings varied significantly, from -0.8%[42] to 23.1%.

[41] Note that statements on average results among the empirical sample do not reflect the average household of the building stock, as the empirical sample is biased towards a few specific, but frequently occurring building types.

[42] Note that for one household, the temperature for sleep times has been set occasionally higher than the awake (Home) times, which is rather unrealistic. This matches the study on programmable thermostats, where it has

Possible reasons for this great range are explained in the discussion chapter (s. 4.1). Programmable thermostats, with the possibility to define desired temperatures for vacancy times, provide on average relative energy savings of 19.2% and increase the relative energy savings towards the nighttime control approach on average by 7.8 percentage points.

Considering intelligent control approaches, occupancy-state detection enabled higher energy savings than programmable thermostats for all households with an average percentage point difference of 4.2%. Comparing occupancy-state prediction to programmable thermostats revealed ambiguous differences in energy savings: While occupancy-state prediction reduced energy consumption in 8 of the 10 households, it imposed a minor increase in relative energy consumption in four households. The weather prediction feature further increased relative energy savings by 2.6 percentage points on average compared to the corresponding control approaches without this feature. Remarkably, in 5 of the 10 households the relative energy savings potential exceeded 25 % and in 3 of the 10 households 30% when employing occupancy-state detection with weather forecasting instead of an on/off control approach. The discussion section explains reason for the different outcomes for the individual households (s. 4.1).

In order to evaluate how well the heating control approaches are actually serving for comfortable thermal conditions, the resulting comfort levels of the control approaches have to be evaluated. Table 7 provides the number of hours per year that provide not acceptable thermal conditions for general comfort (according ASHRAE 55-2010). This corresponds to a Predicted Percentage of Dissatisfied of over 10%

Table 7: Comfort results for the 10 empirical households. The numbers indicate the hours per year, for which thermal conditions are below acceptable conditions (according ASHRAE 55-2010)

Test-house	Control approach							
	On-off controller (stand-alone)	PID controller (stand-alone)	Nighttime temp. setback	Programm-able thermostat	Occupancy-state detection	Occupancy-state prediction	Occupancy-state detection with weather prediction	Occupancy-state prediction with weather prediction
1	6	6	91	281	245	73	371	197
2	2	1	239	498	239	55	372	203
3	0	0	6	7	21	11	27	14
4	6	6	0	714	26	1	31	4
5	1	1	85	168	79	2	120	9
6	0	1	108	178	185	18	340	129
7	4	4	3	98	75	33	109	52
8	15	18	683	877	313	113	519	349
9	18	18	8	272	201	104	225	122
10	0	0	0	10	47	23	66	38

been reported, that in some cases, the energy consumption is increasing and that many users have difficulties to set correct programs. As the nighttime setback control approach is considered as a programmable thermostat with only two set points, this could explain the increased energy consumption.

The constant set point control approaches, i.e. on-off and PID resulted in high comfort levels with a total of less than one day per year below the thermal recommendation. At normal operation, they do not deviate to an extent that is beyond acceptable comfort conditions, as represented by household 3 and 10. However, occupants reset the home temperature set point occasionally to adjust for varying comfort requirements, which causes the heating system to adapt for this. These controller types were approximately equal in comfort performance except in household 8, where the PID controller performed marginally worse. This is due to the PID parameterization as explained in section 4.1.

Manual set point variation approaches, i.e. nighttime temperature setback and the programmable thermostats achieved significant lower comfort levels. For programmable thermostats, the number of hours of not acceptable thermal conditions for the majority of households is over 100. Household 4 shows higher comfort for the nighttime temperature setback approach. In this household, the temperature for the sleep time has been set higher than for the daytime. For this household as well as for household 7 and 9, the programmed nighttime temperature prevented rare events of low thermal comfort during night times after occupants set the home temperature unusually low over a short time. In the common case though, the temperature is too low after the night time, which causes this control approach to perform worse in terms of comfort.

Intelligent heating control approaches achieved better thermal conditions than programmable thermostats on average. For occupancy-state detection, the number of hours with unacceptable thermal conditions has been lowered by 25% in a median comparison to programmable thermostats, for occupancy-state detection by 81%.

A combined figure for the relative energy savings and comfort reveals the trade-off between the two. Figure 20 shows for each of the households the normalized relative energy savings on the horizontal axis and the comfort in terms of the share of occupancy time with acceptable thermal conditions on the vertical axis. It is visible that intelligent heating control features position in the upper right corner, relating to high energy savings and high comfort level. The programmable thermostats provide ambiguous results considering these two dimensions. For 8 of the 10 households, an intelligent heating control approach is available that provides both higher comfort level as well as energy savings[43] than programmable thermostats. In the case of household 8, the occupancy-state prediction with weather prediction control approach resulted in low comfort level. This outcome is discussed in regard to the heating system dimensioning in the following chapter (s. 4.1) and provides an important implication for the employment of intelligent heating control approaches. The standalone controller types on-off and PID represent the highest comfort levels, but also the highest energy consumption. The performance in energy-savings and thermal comfort is consistently high across the empirical households in the case of the occupancy-state prediction control approach.

[43] In the remaining two households, i.e. 3 and 10, the programmable thermostats have been programmed in order to maximize comfort, therefore not enabling intelligent heating control approach to outperform in both dimensions. For these households, all of the intelligent heating control approaches provided higher energy savings, with only marginally decreased comfort.

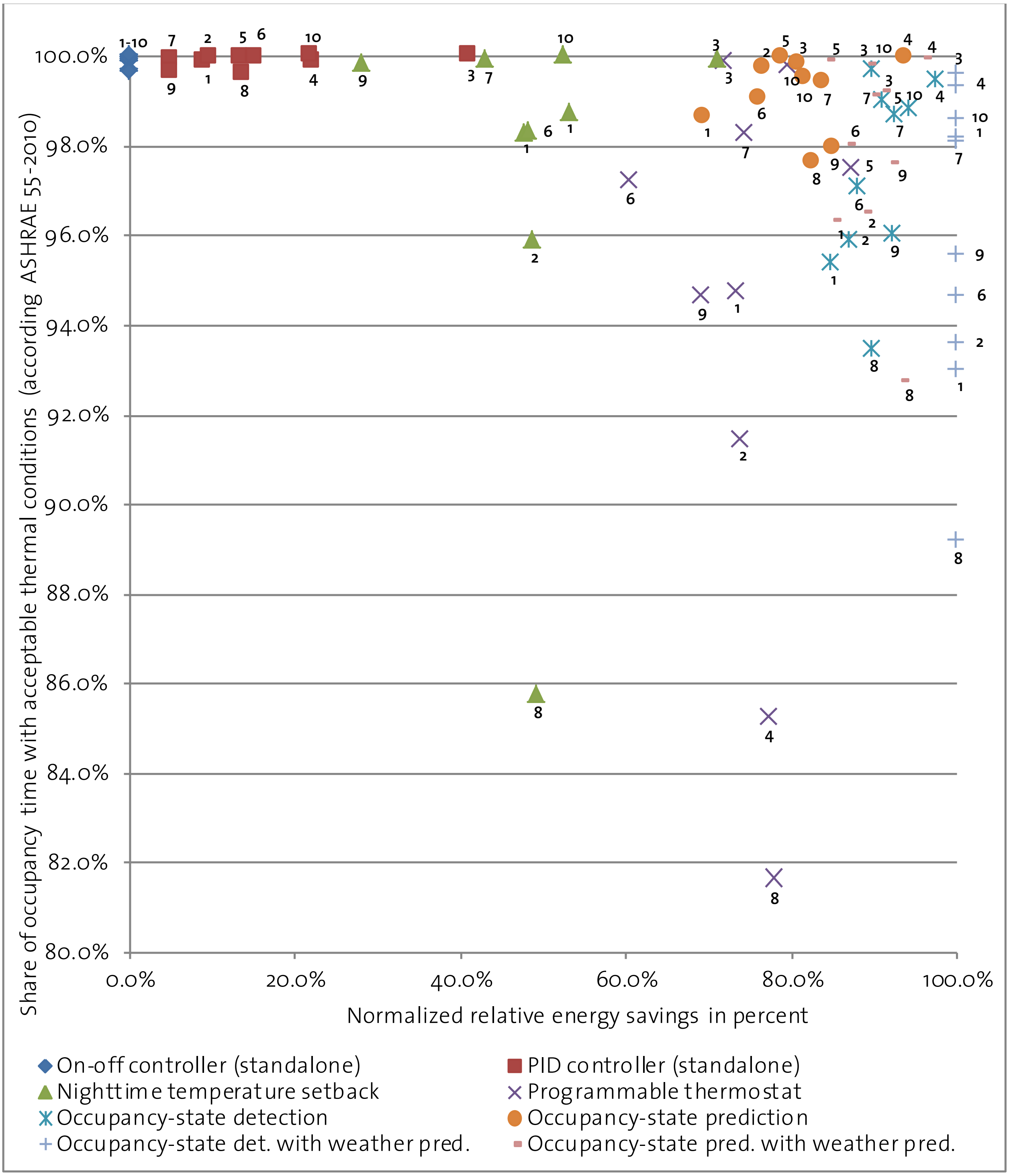


Figure 20: Results for energy savings and comfort for 10 empirical households. The relative energy savings are normalized to the energy-savings maximizing control approach (occupancy-detection and weather prediction). Tags state the household number

Figure 21 shows the average results for the empirical households for comfort and energy savings. On average, all of the four considered intelligent heating control approaches performed better in terms of comfort conditions and energy savings than programmable thermostats. Across the intelligent heating control approaches, a further trade-off between energy-savings and comfort is revealed, depending on the occupancy-prediction as well as the weather prediction feature.

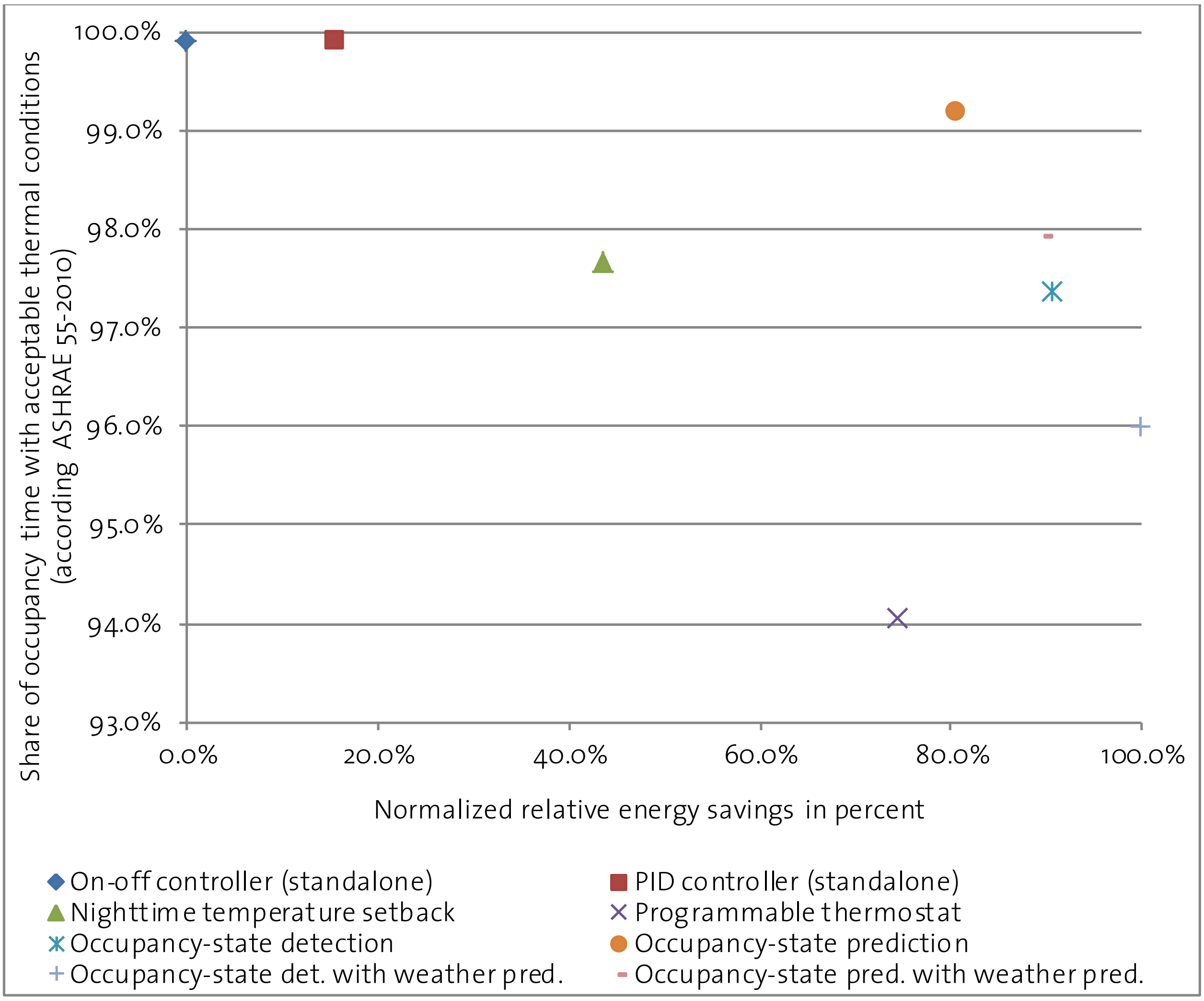


Figure 21: Average results for energy savings and comfort for 10 empirical households. The relative energy savings are normalized to the energy-savings maximizing control approach (occupancy-detection and weather prediction)

3.2 Results for building unit variation

The results on the building unit indicate, in which settings the greatest relative energy savings can be achieved by intelligent heating control approaches. The overall maximum energy savings potential, achieved by the occupancy detection and weather prediction approach is summarized in Figure 22. The results for the individual heating control approaches for different building units can be found in Figure 35 and Figure 36. Note that these only apply to the above mentioned chosen parameterization (s. 2.5.2). Combined with the subsequent sensitivity analysis, it is possible to highlight factors and use cases for which the introduction of intelligent heating control approaches is particularly favorable.

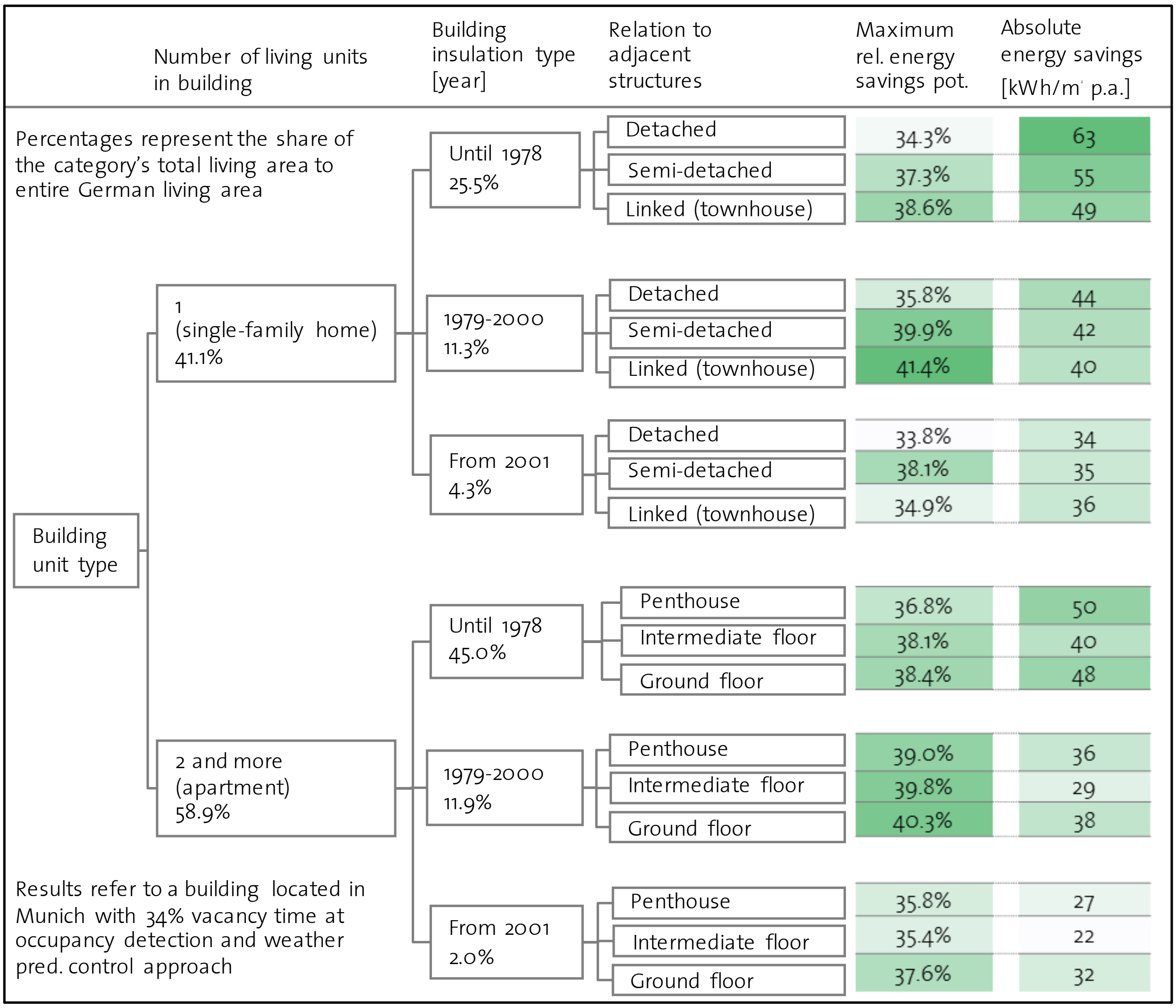


Figure 22: Maximum relative energy savings potential for building unit variation along German building stock. Results refer to a building located in Munich with 34% vacancy time at occupancy detection and weather prediction control approach

The maximum relative energy savings potential ranged from 33.8% to 41.4% for the considered building units. It can be found that building units with more adjacent structures enable for greater relative energy savings than the comparable building unit with less adjacent structures. The reasons for this are explained in the discussion section (s. 4.2). Furthermore, old building types enable greater absolute energy savings since the absolute energy consumption is above new insulation standard. For the detached single family houses, this difference is 85% or 29 kWh/m² per annum. The least absolute energy-savings potential is for apartments built after 2000 on an intermediate floor level. The additional simulation result charts in the Appendix (Figure 35 and Figure 36) reveal that the relative performance between the set point variation approaches in terms of the relative energy savings does not vary significantly for the various building units.

3.3 Results for sensitivity analysis

The sensitivity analysis has covered the occupancy pattern, weather exposure, heating system dimensioning as well as the air change.

3.3.1 Vacancy time

For the sensitivity analysis of the vacancy time, four actual household occupancy patterns have been tested. The vacancy times of these households range from 18.3% to 45.5%. Figure 23 shows the results for the relative energy savings among the control approaches. The relative energy savings potential ranged over 29.0 percentage point in case of the occupancy detection and weather prediction control approach. The percentage point difference in energy savings is lower for greater shares of vacancy times. The discussion section mentions possible reasons for this (s. 4.3). For the constant heating approach (PID controller), no effect of the vacancy times on the energy savings has been found.

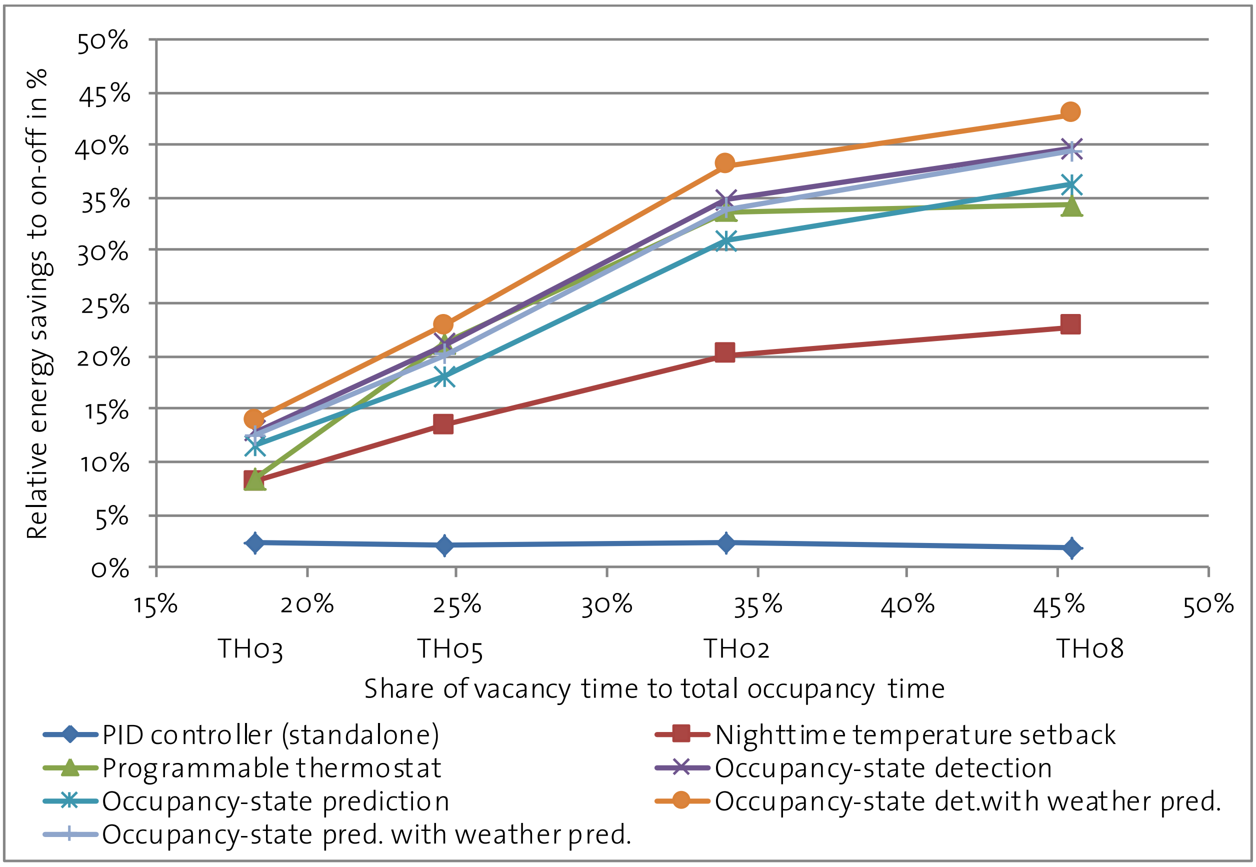


Figure 23: Relative energy savings for different vacancy times. The vacancy times are related to a specific occupancy pattern of the household stated in the tag

3.3.2 Impact of solar irradiation

The households differed in their weather exposure, measured in the average share of solar irradiation that is affecting the building envelope. The range of the observed values has been tested in the sensitivity analysis. For the highest average share of solar irradiation on the building envelope, i.e. 35%, the relative energy savings are by 2.4% percentage points greater than at the lowest share i.e. 5%. So, the greater the weather exposure of the building, the greater the achievable relative energy savings. This is further explained in the discussion section.

3.3.3 Air change rate

The air change has been varied between 0.1/h to 0.5/h. The former value is the lowest observed air change rate for the empirical households; the latter is the recommended air change rate by DIN 4108-2 which exceeds the air change rate of 9 of 10 households. For an air change rate of 0.5/h, the relative energy savings are by 2.1% percentage points greater than the air change of 0.1/h. Thus, the greater the air change in the building, the greater the achievable relative energy savings.

3.3.4 Maximum heat output

The required maximum heat output of the heating system is derived from the heating load according to the calculation procedure described in section 2.3.3.4. It has been observed that the maximum heat outputs of the households ranged between 70% and 200% of the calculated optimal value. This can be the result of an overdimensioned or malfunctioning heating system[44]. The relative energy savings for the underdimensioned heating system are by 7.1 percentage points higher than for the overdimensioned heating system. This outcome explains the high relative energy saving potential of household 2, as further described in the discussion section. Note that the underdimensioned system is performing worse in terms of the resulting comfort level. Thus, a powerful heating system combined with intelligent heating control approaches lowers the relative energy savings but performs better in terms of the achievable comfort.

3.3.5 Wind speed

The wind speed affecting the building envelope has been varied from 0% to 100% to the available wind speed measured at the weather station. There has been no effect on the energy savings potentials identified and the change in the overall energy consumption is well below 1%.

3.3.6 Comparison of sensitivities

Figure 24 states the impact of the influencing factors on the relative energy savings for the occupancy detection with weather prediction control approach[45]. The single greatest influencing factor on relative energy consumption is the occupancy pattern, which greatly determines the energy savings potential of the household. The impact on the comfort is negative though, meaning that the application of intermittent heating in a household with long vacancy times is worse for the comfort than in the case of short vacancy times. This is for the reason, that overall long vacancy times go along with an increasing number of heat-ups, which decrease comfort (s. 4.3). Intelligent heating control approaches perform better both in terms of the relative energy savings and comfort, the greater the solar irradiations as well as the more heated adjacent structures are available. The possible cause is mentioned in the following discussion chapter.

[44] An investigation for the household with the lowest maximum heat output lead to the result, that the low power output was caused by a malfunctioning in the software, restricting the maximum heat output to 2/3 of the required value.

[45] Building insulation standard and building adjacent structure sensitivities refer to the maximum range of results for the building unit variation in terms of the insulation type and adjacent structures.

Influencing factor	Range of maximum relative energy savings potential (percentage points)	Drivers of relative energy savings potential	Impact on comfort
Occupancy pattern (vacancy time)	29.0	Increased vacancy	↘
Building insulation standard	6.5	Older insulation standard	↘
Building adjacent structures	5.6	More adjacent structures	↗
Air change	2.2	Increased air change	↘
Solar irradiation exposure	2.1	Strong solar exposure	↗
Wind exposure	0.1	No effect	→
Maximum heat output	7.1	Reduced max. heat output	↘

Figure 24: Impact of various influencing factors on energy consumption and comfort. Arrows indicate an increase, decrease or constancy of comfort level measure in the share of occupancy time with acceptable comfortable environment according to ASHRAE 55-2010

4 Discussion

The discussion chapter is structured along the results of the simulation process, i.e. the empirical households (s. 4.1), the building unit variation (s. 4.2) as well as the sensitivity analysis (s. 4.3). It concludes with further remarks on the research results (s. 4.4).

4.1 Empirical households

The results of the empirical households make several conclusions possible. First of all, the maximum relative energy savings potential greatly varies between the empirical households, from 13.7% in household 3 to 47.0% in household 8. This can explained with the insights of the sensitivity analysis by comparing the different settings of household 3 and household 8. Household 3 features the lowest observed vacancy time and household 8 the greatest observed vacancy time of the empirical sample. From the occupancy sensitivity analysis, a percentage point difference in the relative energy savings of 29.0 is therefore reasonable. As the percentage point difference between the households is 33.3 and therefore greater than the mentioned 29.0, additional causes for the difference in the relative energy-savings potential might be relevant. One cause could be determined as the underdimensioned heating heating system in household 8, which is 70% of that of a normal dimensioned system in terms of the maximum heat output. As the sensitivity analysis for the maximum heat output showed a maximum percentage point difference of 7.1%, it is assumed to be relevant for the remaining 4.3 percentage point difference. In the specific case of these two households, the building unit type and weather exposure factors have been concluded to be of minor importance for the energy-savings potential. The importance of the occupancy pattern has also been stated in [Oldewurtel et al., 2013].

For the manual set point variation approaches, various conclusions can be drawn. One observation is that their energy-efficiency performance cannot be generalized as it depends on the user programming behavior. This could be especially observed in the case of the nighttime control approach, where the relative savings potential varied from -0.8% to 23.1%. In the former, the user required higher nighttime temperatures than daytime temperatures. Considering the inaccurate programming schedule of this household which resulted in a low comfort level for programma ble thermostat approach, this result in line with further work on this topic [Meier, 2010; Peffer et al., 2011]. Occupants have difficulties to employ programmable schedules, mainly because of misunderstandings of thermostats or because of improper design of user-interfaces. Therefore, the results for programmable thermostats are ambiguous: In some households, the performance in terms of energy and comfort has been good, while in others it resulted in the worst comfort across all control approaches. The results for intelligent heating control approaches with the prediction feature have been much more consistent in their comfort performance, as the share of occupancy-time with acceptable thermal conditions has been above 97.5% for all households. The prediction feature could significantly decrease the hours of not acceptable thermal conditions. Comparing occupancy-state prediction to occupancy-state prediction, these hours have been decreased by over 67%. This feature is therefore concluded to be a key element for providing high comfort for the occupants. The subpar performance of programmable thermostats can be further explained by the fact that many persons cannot predict their accurate arrival times due to e.g. traffic congestions or unexpected events in their daily schedule. Furthermore, even when assuming the case that people know their daily routine very well, there is an additional effort to program thermostats, which can be related to follow-up costs caused by this control approach. The programming behavior of the occupants indicates that user interaction issues are relevant. These are visible as short spikes of temperature set points, e.g. to very high temperatures above 25 °C. The energy star program has been discontinued in 2009 [Peffer et al., 2011], which gives further evidence, that the promised advantages of programmable thermostats are majorly a trade-off with negative side-effects, i.e. user-interaction issues, decreased comfort or failed acceptance.

The weather prediction feature resulted in lower energy consumption with a percentage point difference for the relative energy savings of 2.6 on average. It resulted in lower comfort levels for all households, but to a different extent. For households with a slight overdimensioned heating system, that is 3, 4 and 5 it marginally lowered comfort but in the case of household 8 with a serious underdimensioning, it greatly increased the hours with not acceptable thermal conditions. This is caused by the limitation for the maximum heat output of the weather prediction feature to allow for positive heat inputs by the weather. In the case the solar irradiation is not sufficiently heating the room, a low maximum heat output cannot provide for a comfortable thermal environment in a short time frame. This can be only prevented with sophisticated control algorithms that also implement the knowledge of the dynamic thermal characteristics of the building in relation to the weather circumstances. It is concluded, that the weather prediction feature should not be employed without further knowledge of the building and heating system. The implementation and setup costs are thus increased for this feature.

The PID controller type could prove as the superior controller compared to the on-off controller. It created energy savings in median of 3.7% compared to the reference control approaches. It prevents the typical oscillation of the on-off controller around the set points and thus does not frequently overheat. The PID controller lowers the heating power before the set point is reached. In a faulty PID parameterization, the heating power is limited too much before the inside temperature has reached the set point. This has been observed in household 8, where the heating system was underdimensioned. In this case, the default PID parameters should have been adjusted to achieve faster rise times. It is concluded that the initial setup costs for PID controllers are higher than on-off controllers, specifically for use cases deviating from a standard. Considering the better performance of the majority of the households even for a standard parameterization, the PID controller is clearly preferable. It has to be further mentioned that in field application, a PID controller might not be able to proportionally control the heat output. This is for the reason that the flame inside a gas heater is not modulating as well as a PID outputs, in many cases they are emitting either 100% or 0% of the maximum power. This is due to the fact, that proper efficiency and emission reduction can only be achieved at predefined flame operation. In theory, this could be fully averted with puls-width modulation of the burning process, where the frequency of the flame operation is adjusted [Richards et al., 1999]. This frequency adjustment is limited though to achieve longer life-times of the furnaces. Therefore, the interface of the PID controller to the heater needs to be considered with special regard to this circumstance.

4.2 Building unit variation

The discussion topics for the building units arise from the variation regarding adjacent structures as well as the building insulation. In the case of the variation of the building insulation type according to the energy standards, no substantial difference for relative energy savings for different insulation types has been found. Considering in contrast the absolute energy savings, they are substantially higher for old building types, as their energy consumption level is much greater than for new buildings. Thus, the payback period of intelligent heating control technologies is lower in old buildings, since the savings in energy costs can more than double the ones for new buildings. Considering the great energy-savings potential for old buildings, this gives reason to provide incentives for the implementation intelligent heating control approaches from a policy-maker perspective. As mentioned in 1.1.2, the refurbishment rate for building insulation is low and does not suffice to meet the energy-efficiency goals. A retrofit of the heating control technologies in old buildings can therefore provide a low-cost option to improve energy-efficiency.

It has been noted in the results section, that a building unit achieves greater relative energy savings when it is surrounded by more adjacent structures, assuming these structures are constantly heated. This can be explained by the increased heat transfer when employing intelligent heating control approaches: The greater the temperature difference between the building units, the greater the heat transfer. This temperature difference is greater when employing intelligent heating control approaches as they increase the time and magnitude for temperature differences to adjacent building units Therefore, a so called free rider problem [Kim et al., 1984] arises: As the energy consumption is lowered for one building unit, the surrounding building units with constant set points are faced with slightly increased energy consumption as their heat transfer towards the lower heated room is increased. With a great diffusion of intelligent heating control technologies, the free rider problem is reduced to a marginal level and only reflects different occupancy patterns and set-points. For these arguments, an additional incentive for changing early to the intermittent heating technologies arises for building units with heated adjacent structures. As no work on this topic has been found, the significance of this finding can be examined by further research.

4.3 Sensitivity analysis

The sensitivity analysis on occupancy patterns in terms of the vacancy times revealed that with greater vacancy time relative energy savings potential increases. This is an expected result since with greater vacancy of the building, the periods when intermittent heating can be applied is increased. This has been found similarly in other work [Oldewurtel et al., 2013]. The analysis further revealed that the marginal percentage point increase for relative energy savings is lower for greater shares of vacancy times. This can be explained by the necessity, to heat vacant building units even when occupants are not at home. While for short vacancy times, the heating system can be completely turned off, it has to be turned on again for longer vacancy times to achieve a minimal temperature, for two reasons:

1. The building structures needs to be heated above a minimum temperature, as a damage to the structure and appliances could be caused by too low temperatures [Cho, 2007].

2. The temperature needs to be kept at certain level to keep heat-up times low: The higher the temperature differences of the away to the home set points, the longer it takes to heat up the room. This decreases comfort, even in the case of occupancy prediction control approaches, as the prediction time and accuracy is limited [Scott et al., 2010].

Furthermore, the increased energy savings for overall long vacancy times go along with decreased comfort. This is due to the fact that more vacancy times normally require more frequent heat-ups. Only in the case of long absence periods like vacations, the number of heat-ups is not increasing. Thus, intelligent heating control approaches are most beneficial for households with long vacancy times, but the need for accurate prediction algorithm becomes even more relevant for these cases.

The sensitivity analysis showed another insight regarding influencing factors of the environment. In the case of factors that are promoting the heating system, that is solar irradiation or adjacent heated structures, the relative energy savings are higher compared to the case without these factors. This is for the reasons, that these factors contribute heat power during the heat-up periods. Thereby, these factors accelerate the time to reach the set point which in turn raises the comfort level. The weather prediction feature is built on this circumstance, as it lowers the heat output of the space heater to increase the contribution of the naturally available heat sources for the heat-up process. The energy-savings are achieved in a trade-off to the comfort level and can therefore only be justified, if the occupants are willing to accept this trade-off. Summing these observations up, it can be stated that for the intermittent heating approaches it is beneficial in terms of energy savings as well as comfort level if the promoting factors for the heat power are available. Intelligent control approaches can utilize on this fact and optimize the control algorithm e.g. in the case of weather prediction, but the maximum heating output should not be decreased too an extent where it is not compensated by other available heat sources. The necessity to implement proper or even additional maximum heat output when utilizing intermittent heating has been recently acknowledged by standards for the heating system dimensioning (DIN EN 12831).

In addition, the sensitivity analysis revealed a minor impact of the weather exposure on the relative energy-savings potential. This analysis has not included to effect of the climate region on the energy-savings potential. Lu et al. states a high impact of the climate region on the energy savings, ranging from 25%-47% [Lu et al., 2010]. To enable a comparison to this work, it is recommended to conduct a sensitivity analysis that includes different climate regions within Europe.

4.4 Further remarks on the research results

This section discusses the results in perspective to further work as well as emphasizes the importance of the comfort evaluation. In general, the research results reflect the findings and conclusions of prior work well and did not reveal contradictions, as described below. The research results, specifically the reported high relative energy savings potentials of over 25% are in line with prior work where energy savings on average of 28% [Lu et al., 2010] and 34% [Oldewurtel et al., 2013] was reported. The occupancy-state detection technology presented in [Lu et al., 2010] with average savings of 28% based on a study in the U.S. in 8 households, compared to an average of 23.7% for the empirical sample of this thesis. The study is encouraging, as it shows that the occupancy-detection approach can be implemented with low-cost sensors with even higher energy-savings[46]. This is supported when comparing the results to work on Model Predictive Control (MPC). The above described energy-savings potential of 34% in [Oldewurtel et al., 2013] are realized by a sophisticated control system, which demands a costly implementation process. The mentioned work describes, that the energy-efficiency potential can be captured to a large part by instantaneous occupancy measurements, e.g. through sensors. Therefore, sophisticated features such as occupancy-prediction are not raising the energy-efficiency. This result has been similarly found in the simulation results presented in this thesis: Occupancy-state detection has the greatest impact on the energy-efficiency, while the weather prediction feature could only slightly increase energy-savings with the described accompanying disadvantages. The occupancy-state prediction feature had negative impact on the energy performance, but greatly improved the comfort level, as described below.

In another research project, the comfort has been measured in terms of MissTime, that is the time that the house is occupied but too cold [Scott et al., 2011]. The therein presented occupancy-prediction technology reduced MissTime by a factor of 6-12 compared to the scheduled approach. MissTime is analog to the presented measure in Table 7, which states the hours of unacceptable thermal conditions during occupancy times. The median factor equals 5.8 for the empirical sample. The conclusion in comparison to this work is interesting in two ways: First, the occupancy-prediction feature has been identified as significant contributor to the comfort level in both works. Second, the investigation in Scott et al. shows that the occupancy-prediction feature is implementable in real-world with similar results to the simulation. It supports the validity of the assumptions for the occupancy-prediction control approach. Comparing the performance of the occupancy-prediction approach with work on GPS arrival prediction [Gupta et al., 2009], it becomes apparent that even a well-functioning occupancy-prediction approach will decrease comfort to a certain extent. This is for the reason that the heat-up time is usually longer than the predicted time to arrival. Gupta et al. state a median commute time of 24.3 minutes of the U.S. and a median of 88 minutes for the heat-up time. This is in line with the thermal responses of the heating systems of the empirical households, where heat-up times are usually 90 minutes or above.

The results have revealed that there is a trade-off between energy-savings and the achievable comfort level, which is best described along Figure 21. While the standalone control approach on-off and PID perform very well regarding the comfort, they are also responsible for the highest energy consumption. Comparing the performance to programmable thermostats and nighttime temperature setback approaches, it is obvious that energy-savings are majorly traded in for the comfort levels. In further work it has been shown that this trade-off is to an extent, which is not acceptable for occupants, therefore preventing the success of programmable thermostats [Meier et al., 2010; Peffer et al., 2011]. This trade-off is mentioned by similar work [Scott et al., 2011]. With the evolution of intelligent heating control approaches, this trade-off has been overcome to the greatest part. Considering occupancy-state prediction approaches, significant energy-savings are achieved with only marginally decreased comfort. Based on individual preferences, it can be left to the occupants decision, whether he is willing to accept decreased comfort for further energy-savings, e.g. with the application of the weather prediction feature. As a minor trade-off among

[46] It has to be mentioned, that the settings of the compared research might differ in terms of climate conditions, system setup and occupancy pattern which impacts the average energy-savings potential.

the various intelligent heating control approaches has been revealed, this has implications for companies developing technologies for intelligent heating control approaches. These can implement various features, e.g. occupancy-state prediction or weather prediction in a way which leaves the customer to decide, which of the features he actually is willing to use.

The comfort performance is likely to be a crucial factor to realize higher-order energy-savings. As mentioned above, many users are not satisfied with their programmable thermostats. The EnergyStar endorsement for programmable thermostats was discontinued in 2009 for the reason that many occupants are unable to operate them properly [Peffer et al., 2011]. The diffusion of programmable thermostats is inhibited due to the poor performance, including achievable comfort levels. In contrast, due to automatic operation as well as the significantly raised comfort levels, intelligent heating control approaches have overcome the prime concerns for programmable thermostats. This is promising for a potential diffusion of technologies of such approaches, but needs further investigation. It is not clear, which attributes of intelligent heating control approaches are most important for customers, and in what extent they are willing to accept trade-offs in terms of energy-savings and comfort. Therefore, a conjoint analysis can reveal customer preferences, which gives further insight for technology selection and diffusion [Green et al., 1978]. With more insights on the technology diffusion process of intelligent heating control approaches, it is possible to evaluate the higher-order energy-efficiency potential, e.g. for the household sector of Germany or the European Union. Therefore, an evaluation for further weather regions needs to be conducted. The representative building units of this region should be employed similarly to the building unit variation, possibly with an enlarged empirical sample. An assessment for the location of other continents like America or Asia has to go along with an adaption of the methodology. This is for the reason that the assumptions on the heating systems and controller operation need to be adjusted, as HVAC control systems are more common in these regions.

5 Conclusion

This thesis investigated the energy-efficiency potential of intelligent heating control approaches in the residential sector with focus on temperate climate zones. Therefore, a categorization of heating control approaches based on existing research has been derived and long-term empirical building and occupancy data of ten households has been acquired. Within a developed simulation environment, the energy consumption and achievable comfort levels for each of the households has been evaluated for the archetypical heating control approaches. The multi-faceted simulation process generated findings that expand the current scientific knowledge and has implications for policy-makers, businesses and further research.

The results clearly speak in favor of intelligent heating control approaches. Across all empirical households, intelligent heating control approaches resulted in the lowest energy consumption. For the majority of households, the energy efficiency potential exceeded 20% and are 26.4% on average for the 10 empirical households. For 5 of the 10 empirical households the potential has been determined to be above 25%, which could be observed for only 1 household when employing a programmable thermostat. In 3 of the 10 households, the relative energy savings exceeded 30% for the occupancy-state detection with weather prediction control approach.

While the research has been conducted under the assumption, that the diffusion of technologies implementing intelligent control approaches is affected by the occupant satisfaction, a measure on the occupant comfort has been introduced. **The comfort evaluation revealed that intelligent heating control approaches overcome to a great extent the trade-off of between energy-savings and achievable comfort level seen for standalone controller types and programmable thermostats.** When applying the ASHRAE standard for thermal comfort throughout one year, programmable thermostats imposed a total of over 1 week, i.e. 168 h, of not acceptable thermal conditions[47] during occupancy times for 7 of the 10 empirical households. For occupancy-state prediction, this was the case in none of the households. In fact, in 5 of the 10 households, the time of not acceptable thermal conditions throughout the year for occupancy-state prediction was below 1 day and was thereby in the range of constant set point approaches like the standalone on-off or PID-controller. The results confirm the findings of further studies, that state that people are facing problems when programming thermostats, which results in poor comfort level and therefore not acceptable thermal conditions [Meier et al., 2010; Peffer et al., 2011]. As this thesis evaluated the performance of the heating control approaches in terms of energy-savings and comfort levels, further research needs to be conducted to examine the relevance of the comfort level on technology diffusion. This could be considered e.g. in a conjoint analysis on customers to investigate the technology selection based on various criteria, e.g. energy-savings, thermal comfort or user-interfaces. This can give further direction in terms of product development for intelligent heating control approaches as well as enable for a projection of energy savings for the

[47] This equals comfort class C or below with a Predicted Percentage of Dissatisfied of over 10% (s. 2.5.4)

overall household sector. For an estimation of higher-order energy-savings, e.g. the household sector of Germany or the EU, further weather regions need to be investigated, possibly with an enlarged set of empirical data. This work could include combined heating and cooling approaches, as HVAC systems are more relevant for countries with hotter climate.

The prediction feature of intelligent heating control approaches is especially relevant to provide a high comfort level. Within the empirical sample, the occupancy-state prediction approach decreased the number of hours of unacceptable thermal conditions on average by over 2/3 compared to the occupancy-state detection approach. Therefore, it is recommended for companies involved in product development of intelligent heating control technologies to devote special focus on this feature. This can be in regard to algorithms for arrival prediction that learn user patterns, improved hardware to provide high uptimes or fallback procedures for failures. It has to be mentioned, that short commute times of occupants can limit the benefit of this feature, as heat-up times are usually higher than the predicted time to arrival.

The building unit variation showed that with a poor insulation of the building construction, higher absolute energy savings, therefore higher cost savings, can be achieved. The insulation type mainly determines the absolute energy consumption of the building. For old building types, the absolute energy savings can be double the savings in comparison to new building types. This has implications for policy-makers, who can offer incentives to implement heating control technologies in old building types. This would enable for great energy savings for buildings that have not been subject to refurbishments. This is attractive to occupants, as the payback period for their investment is low and the cost-savings in energy consumption accrue over the following years. The variation of the building unit further showed, that the **relative energy savings for intelligent heating control approaches are greater when adjacent structures provide a constant heated room**. This might have implications for technology diffusion: The first adopters of the technologies will benefit from additional energy savings while imposing more energy consumption for the neighboring building unit. The significance of this finding remains to be investigated.

As part of the sensitivity analysis, vacancy time has been identified has the most important driver for the energy-savings potential of intelligent heating control approaches. Particularly favorably is the employment in household with great vacancy times, which allow for higher relative energy savings. The sensitivity analysis revealed a range of over 29 percentage points for the relative energy savings potential within the observed vacancy times. This has important practical implications, as with the evaluation of the occupancy pattern prior to the application of intelligent heating control approaches, the relative energy savings potential can be predicted to a great extent. This can be performed e.g. with the evaluation of an average week-long schedule of the occupants. Within the sensitivity analysis, **the impact of the building to the weather has been shown to be of minor significance for the energy savings potential**. A general tendency to greater relative savings has been found for greater weather exposure, that is in terms of solar irradiation or air change. **The weather prediction feature lowered energy consumption but was accompanied by lower comfort levels.** This feature enabled an increase in relative energy savings potential for the households of 2.6 percentage points on average. This feature raises the implementation costs as it needs further system knowledge and can, if not set up appropriately, impair the overall performance in terms of the comfort level. For these reasons **it is questionable, whether the weather prediction feature is appropriate for the application in heating control technologies for**

the residential sector. This feature needs to be tested within actual technical solution in terms of the installation costs, weather data acquisition and long-term performance.

Special caution for the application of intelligent heating control approaches should be exercised for households with underdimensioned heating systems in terms of the maximum heat output. This has been revealed particularly in respect to one empirical household. As this household faced a significant underdimensioning of the heating system, the intelligent heating control approaches provided high energy savings but greatly at the expense of comfort. Due to the increased frequency of heat-up times for the intelligent control technologies, it has been inferred that the employment of intelligent heating control approaches should go along with a proper dimensioning of the heating systems. This is acknowledged by a recent norm for heating load calculations, which states the requirement of additional heat-up power in the case of intermittent heating (DIN EN 12831).

Implementation topics of the technologies related to the heating control approaches become more relevant with upcoming product developments. Generally this comprises the compatibility to existing heating systems, the system setup, e.g. in terms of the controller algorithms, the user interfaces as well as long-term performance. A further field study with industry experts can focus on these topics to reveal possible product options for heating control approaches for the prevailing heating systems in buildings. This can include individual, single-room control for households, which has not been part of this investigation. Furthermore, it is desirable to find default PID parameterization and algorithms that provide stable system behavior for all use cases, including various heating systems. This is desirable considering the overall performance of the PID controller in terms of energy consumption and comfort level.

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References

Alamdari, F., & Hammond, G. P. (1983). Improved data correlations for buoyancy-driven convection in rooms. *Building Services Engineering Research and Technology*, *4*(3), 106–112.

ANSI/ASHRAE. (2010). Standard 55: Thermal Environmental Conditions for Human Occupancy.

Arbeitsgemeinschaft Energiebilanzen e.V. (2011a). Auswertungstabellen zur Energiebilanz für die Bundesrepublik Deutschland 1990 bis 2010.

Arbeitsgemeinschaft Energiebilanzen e.V. (2011b). Anwendungsbilanzen für die Endenergiesektoren in Deutschland in den Jahren 2009 und 2010.

Arbeitsgemeinschaft Energiebilanzen e.V. (2011c). Energieverbrauch in Deutschland - Daten für das 1. Quartal 2011.

Awbi, H. B., & Hatton, A. (1999). Natural convection from heated room surfaces. *Energy and Buildings*, *30*(3), 233–244.

Bennett, S. (1993). Development of the PID controller. *Control Systems, IEEE*, *13*(6), 58–62.

Berliner Energie Agentur GmbH. (2011). Energiekonzept 2020, Langfassung.

Boyd Jr., R. (1959). Space heating system and apparatus. *US Patent 2,882,383*.

Bundesministerium für Wirtschaft und Technologie. (2012). Emissionen von Kohlendioxid, Stickstoffoxiden, Schwefeldioxid, Kohlenmonoxid und Gesamtstaub nach Quellkategorien.

Carlson, E. (1979). Night set-back thermostat. *US Patent 4,154,397*.

Chen, T. Y. (2002). Application of adaptive predictive control to a floor heating system with a large thermal lag. *Energy and Buildings*, *34*(1), 45–51.

Cho, T. (2007). Prediction of cyclic freeze–thaw damage in concrete structures based on response surface method. *Construction and Building Materials*, *21*(12), 2031–2040.

Comscore. (2012). EU5 Smartphone Penetration Reaches 55 Percent in October 2012. Retrieved December 17, 2012, from http://www.comscore.com/Insights/Press_Releases/2012/12/EU5_Smartphone_Penetration_Reaches_55_Percent_in_October_2012

Crawley, D B, Lawrie, L. K., Pedersen, C. O., & Winkelmann, F. C. (2004). EnergyPlus: an update. *Proceedings of SimBuild*, 4–6.

Crawley, Drury B., Hand, J. W., Kummert, M., & Griffith, B. T. (2008). Contrasting the capabilities of building energy performance simulation programs. *Building and Environment*, *43*(4), 661–673.

Donovan, P. (2010). Programmable thermostat. *US Patent 20100198425*.

Dounis, a. I., & Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment—A review. *Renewable and Sustainable Energy Reviews*, *13*(6-7), 1246–1261.

eGain. (2013). eGain Forecasting. Retrieved April 10, 2012, from http://www.egain.se

EnergyPlus. (2012). EnergyPlus Engineering Reference.

ERSS. (2006). Surface Colour - Solar absorptance. Retrieved April 07, 2013, from http://energyratingsoftwaresupport.com.au

ETH - Informatikdienste - Clustersysteme der Informatikdienste. (2013). Retrieved April 07, 2013, from https://www1.ethz.ch/id/services/list/comp_zentral/cluster/index_EN

Fanger, P. O. (1970). *Thermal comfort: Analysis and applications in environmental engineering*. Danish Technical Press, Copenhagen, Denmark.

Fox, A., Griffith, R., & Joseph, A. (2009). Above the clouds: A Berkeley view of cloud computing. *UC Berkeley Reliable Adaptive Distributed Systems Laboratory*.

Girod, B., Van Vuuren, D. P., & Hertwich, E. G. (2013). Global climate targets and future consumption level: an evaluation of the required GHG intensity. *Environmental Research Letters*, *8*(1), 14016.

Green, P. E., & Srinivasan, V. (1978). Conjoint Analysis in Consumer Research: Issues and Outlook. *Journal of Consumer Research*, *5*(2), 103–123.

Gupta, M., Intille, S., & Larson, K. (2009). Adding GPS-Control to Traditional Thermostats: An Exploration of Potential Energy Savings and Design Challenges. *Pervasive Computing*, 95–114.

IG Metall. (2007). Manteltarifvertrag für Beschäftigte zum ERA-TV Edelmetallindustrie, 1–30.

Incropera, DeWitt, Bergman, & Lavine. (2007). *Fundamentals of Heat and Mass Transfer*. (John Wiley & Sons, Ed.) (6th editio., pp. 257–2070).

Institut Wohnen und Umwelt. (2010). *Datenbasis Gebäudebestand*.

International Energy Agency. (2011). *Technology Roadmap Energy-efficient Buildings: Heating and Cooling Equipment*.

International Energy Agency. (2012). Worldwide Trends in Energy Use and Efficiency Energy.

ISO. (2005). ISO7730: Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.

Johnson, W. S. (1883). Electric Tele-Thermoscope. *US Patent 281,884*.

Kim, O., & Walker, M. (1984). The free rider problem: Experimental evidence. *Public Choice*, *43*(1), 3–24.

Korado. (2012). Radik Plan Heizkörper, *8*, 90–91.

Levine, M. R., Russo, J. T., Cairo, A. C., & Rigotti, V. H. (1986). Programmable thermostat. *US Patent 4,606,401*.

Lu, J., Sookoor, T., Srinivasan, V., & Gao, G. (2010). The Smart Thermostat: Using Occupancy Sensors to Save Energy in Homes. In *Proceedings of SenSys* (pp. 211–224).

Mack, C. a. (2011). Fifty Years of Moore's Law. *IEEE Transactions on Semiconductor Manufacturing*, *24*(2), 202–207.

Mathworks. (2013). Profiling for Improving Performance. Retrieved April 10, 2013, from http://www.mathworks.de/de/help/matlab/matlab_prog/profiling-for-improving-performance.html

Meier, A. (2010). How People Actually Use Thermostats. *Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings*.

Meier, A., Aragon, C., Hurwitz, B., & Mujumdar, D. (2010). How People Actually Use Thermostats. In *ACEEE Summer Study on Energy Efficiency in Buildings*.

Minergie. (2010). Leistungsgarantie Haustechnik.

Montgomery, R., & McDowall, R. (2008). *Fundamentals of HVAC Control Systems*. ASHRAE Learning Institute.

Neitzel, M., & Klöppel, S. (2012). Modernisierungskompass.

Nest. (2013). Nest Learning Thermostat. Retrieved April 10, 2013, from http://www.nest.com

Oldewurtel, F., Parisio, A., Jones, C. N., & Gyalistras, D. (2012). Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, *45*, 15–27.

Oldewurtel, F., Parisio, A., Jones, C. N., & Morari, M. (2010). Energy efficient building climate control using stochastic model predictive control and weather predictions. In *American Control Conference (ACC), 2010* (pp. 5100–5105).

Oldewurtel, F., Sturzenegger, D., & Morari, M. (2013). Importance of Occupancy Information for Building Climate Control. *Applied Energy*, *101*, 521–532.

OptiControl. (2012). OptiControl Website. Retrieved February 09, 2013, from http://www.opticontrol.ethz.ch

Pang, X., Bhattacharya, P., & O'Neill, Z. (2011). Real-time building energy simulation using energyplus and the building controls virtual test bed. In *Proceedings of Building Simulation* (pp. 14–16).

Peffer, T., Pritoni, M., Meier, A., Aragon, C., & Perry, D. (2011). How people use thermostats in homes: A review. *Building and Environment*, *46*(12), 2529–2541.

Pistohl, W. (2009). *Handbuch der Gebäudetechnik 2*. Werner Verlag.

Richards, G. A., Janus, M., & Robey, E. H. (1999). Control of Flame Oscillations with Equivalence Ratio Modulation. *Journal of Propulsion and Power*, *15*(2), 232–240.

Roots, W. K., & Woods, J. T. (1969). On-Off Control of Thermal Processes. *IEEE Industrial electronics and control instrumentation*, *IECI-16*(2), 136–146.

Schimschar, S., Blok, K., Boermans, T., & Hermelink, A. (2011). Germany's path towards nearly zero-energy buildings—Enabling the greenhouse gas mitigation potential in the building stock. *Energy Policy*, *39*(6), 3346–3360.

Schweizerischer Ingenieur und Architektenverein. (2011). 2040: SIA Effizienzpfad Energie.

Scott, J., Brush, A. J. B., Krumm, J., & Meyers, B. (2011). PreHeat: Controlling Home Heating Using Occupancy Prediction. In *International Conference on Ubiquitous Computing*.

Scott, J., Krumm, J., Meyers, B., Brush, A. J., & Kapoor, A. (2010). Home Heating Using GPS-Based Arrival Prediction. *MSR Technical Report, Cambridge, UK: Microsoft Research*.

Siroky, J., Oldewurtel, F., Cigler, J., & Prívara, S. (2011). Experimental analysis of model predictive control for an energy efficient building heating system. *Applied Energy*, *88*(9), 3079–3087.

Statistisches Bundesamt. (2010). Mikrozensus - Zusatzerhebung 2010. Bestand und Struktur der Wohneinheiten Wohnsituation der Haushalte.

tado°. (2013). tado° intelligent heating control. Retrieved April 10, 2013, from http://www.tado.com

Thorsteinsson, J. (1967). Automatic set-point control for thermo-stats in room-heating systems. *US Patent 3,352,490*.

University of Wisconsin. (2013). TRNSYS. Retrieved February 09, 2013, from http://www.trnsys.com

Ure, A. (1830). On the Thermostat or Heat Governor, a Self-Acting Physical Apparatus for Regulating Temperature. *Abstracts of the Papers Printed in the Philosophical Transactions of the Royal Society of London*, *3*.

Ziegler, J., & Nichols, N. (1942). Optimum settings for automatic controllers. *American Society of Mechanical Engineers*, (November 1942).

Ziegler, R. N. (1976). Automatic temperature setback system for controlling a heating unit. *US Patent 3,972,471*.

Appendix

A. Individual characteristics and results for empirical households

I. Household 1

a. Household profile

Table 8: Building information of household 1

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1982
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m^2]	70
Heating system	Radiator
Weather exposure[48]	Strong

Table 9: Occupancy information of household 1

Occupancy specification	Parameter value
Number of occupants	2
Share of vacancy times to total time in %	39.6
Share of sleep times to total time in %	29.8
Share of presence times to total time in %	30.6
Maintained window air change [1/h]	0.3

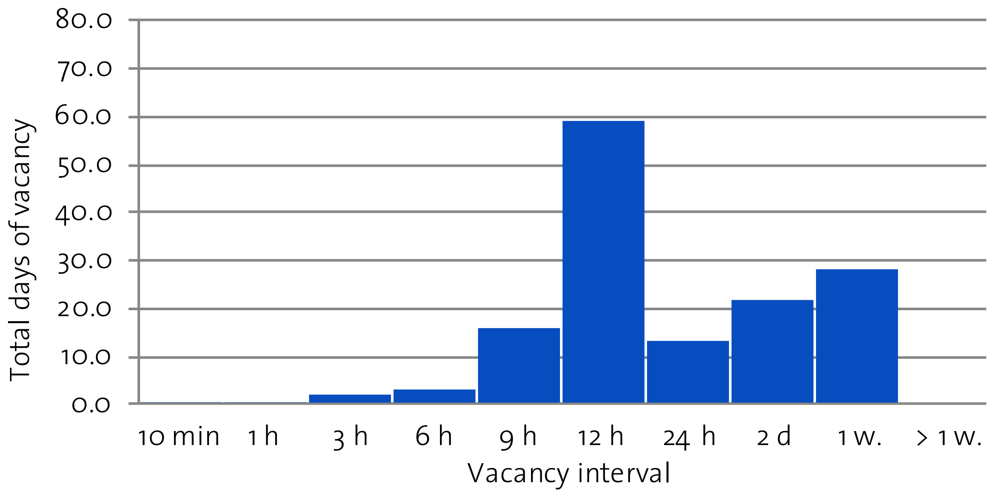


Figure 25: Occupancy pattern of household 1 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

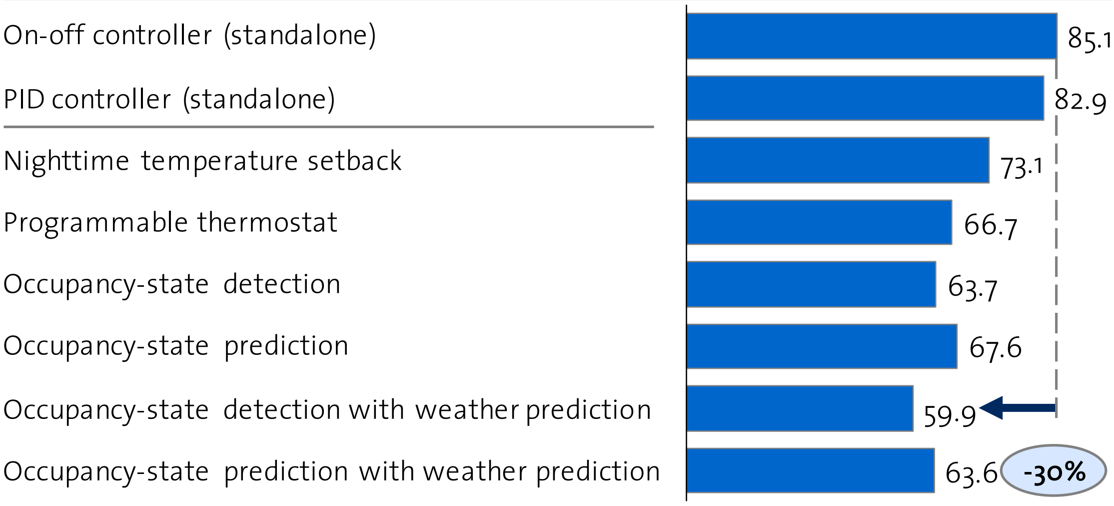
[48] Classification along the average share solar irradiation on the building envelope (s. 2.3.3.4). This measure is stated as low for < 10%, medium for 10-25% and strong for > 25%.

b. Results

The model calibration resulted in a CV(RMSD) of 3.67%.

Comparison of net energy required for indoor heating

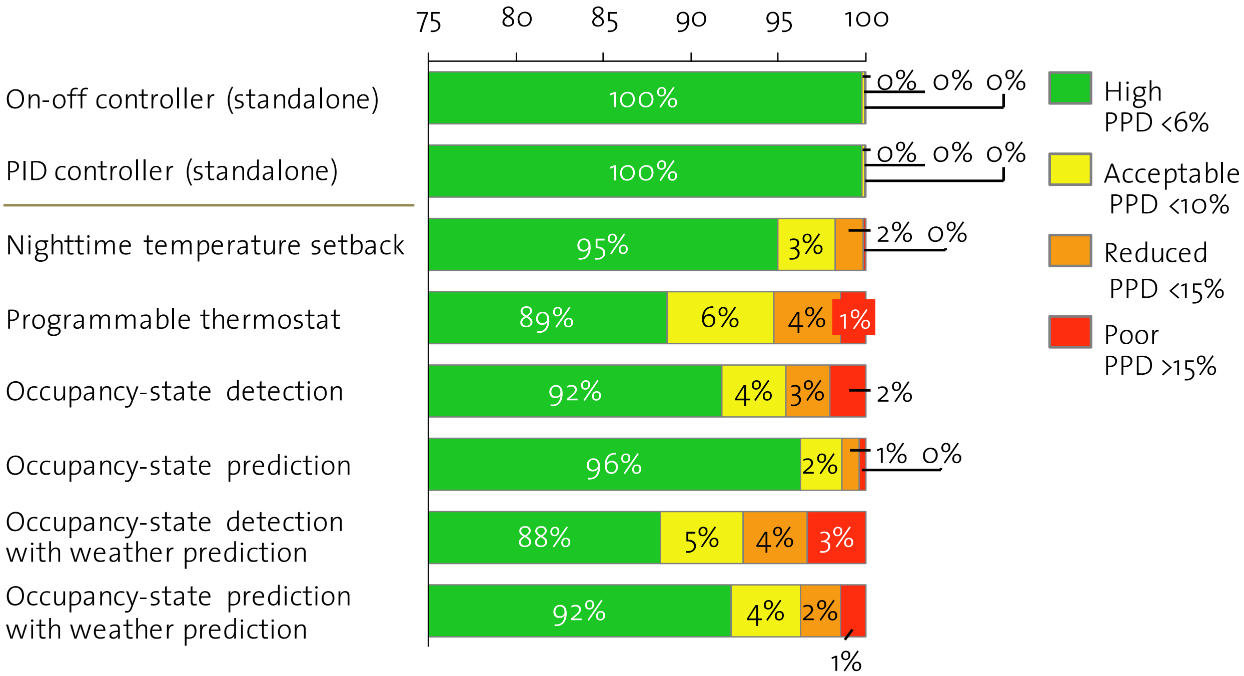
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



II. Household 2

a. Household profile

Table 10: Building information of household 2

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1977
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m^2]	75
Heating system	Radiator
Weather exposure	Medium

Table 11: Occupancy information of household 2

Occupancy specification	Parameter value
Number of occupants	2
Share of vacancy times to total time in %	34.0
Share of sleep times to total time in %	27.2
Share of presence times to total time in %	38.9
Maintained window air change [1/h]	0.5

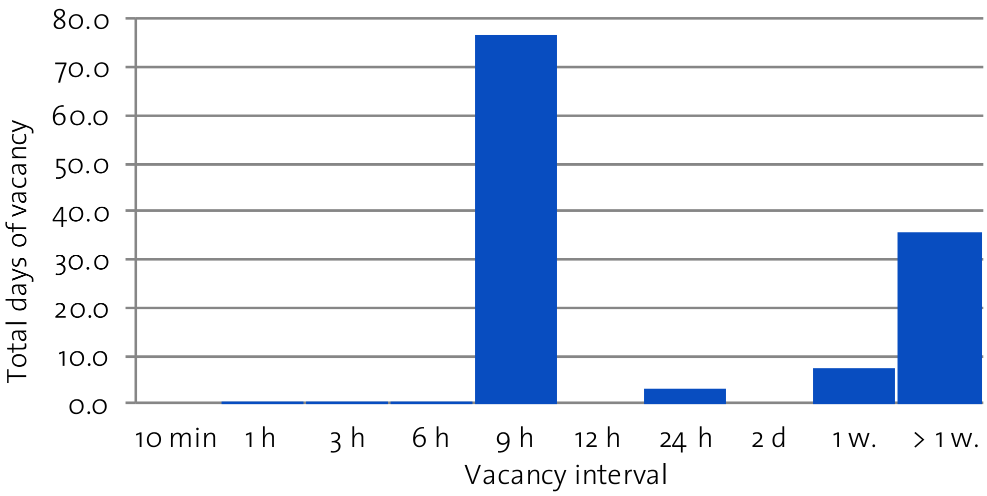


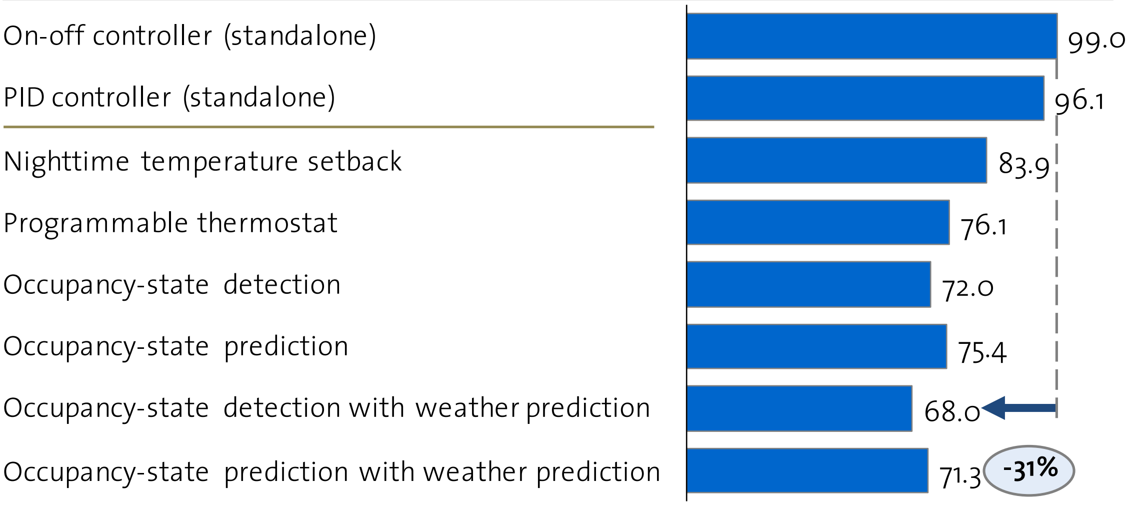
Figure 26: Occupancy pattern of household 2 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 2.23%.

Comparison of net energy required for indoor heating

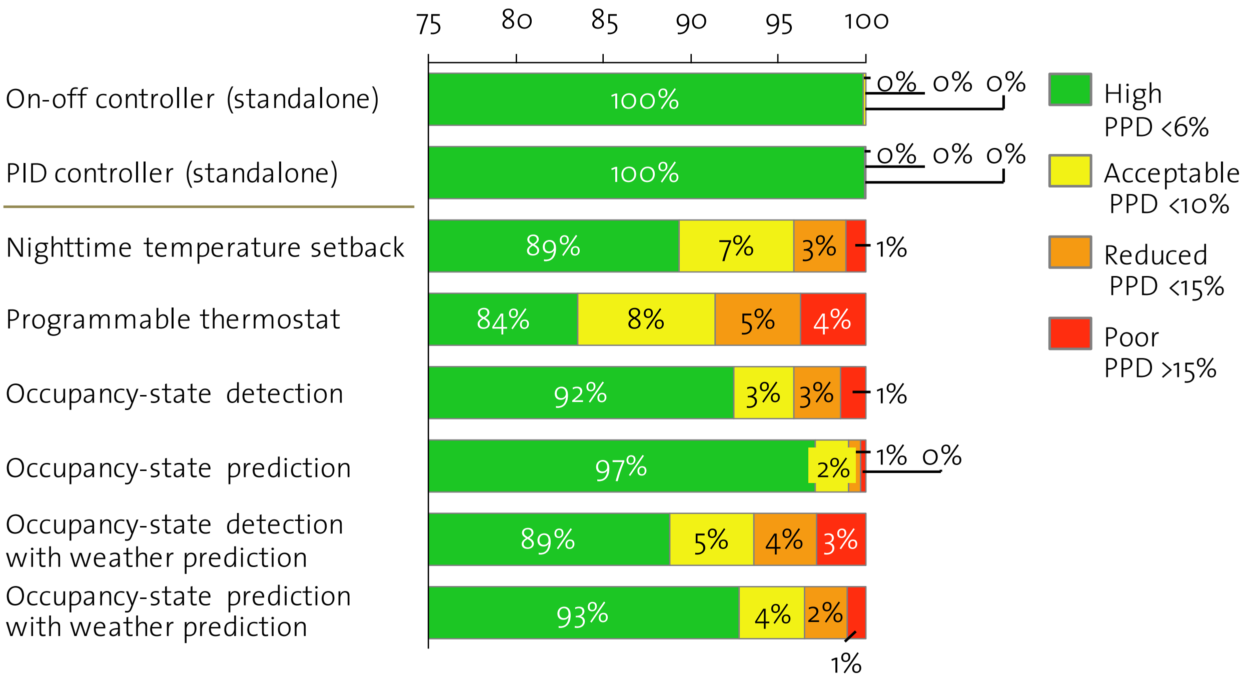
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



III. Household 3

a. Household profile

Table 12: Building information of household 3

Building specification	Parameter value
Location	Munich
Energy standard	Energieeinsparverordnung 2002
Number of living units in building	More than 1 (multi-family house)
Floor level	Ground
Floor area [m^2]	150
Heating system	Radiator
Weather exposure	Low

Table 13: Occupancy information of household 3

Occupancy specification	Parameter value
Number of occupants	2
Share of vacancy times to total time in %	18.3
Share of sleep times to total time in %	18.4
Share of presence times to total time in %	63.3
Maintained window air change [1/h]	0.15

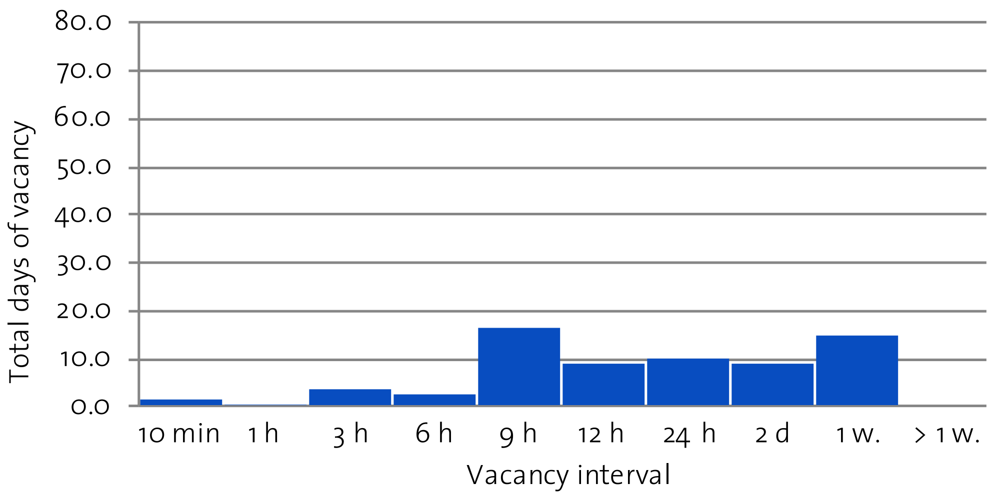


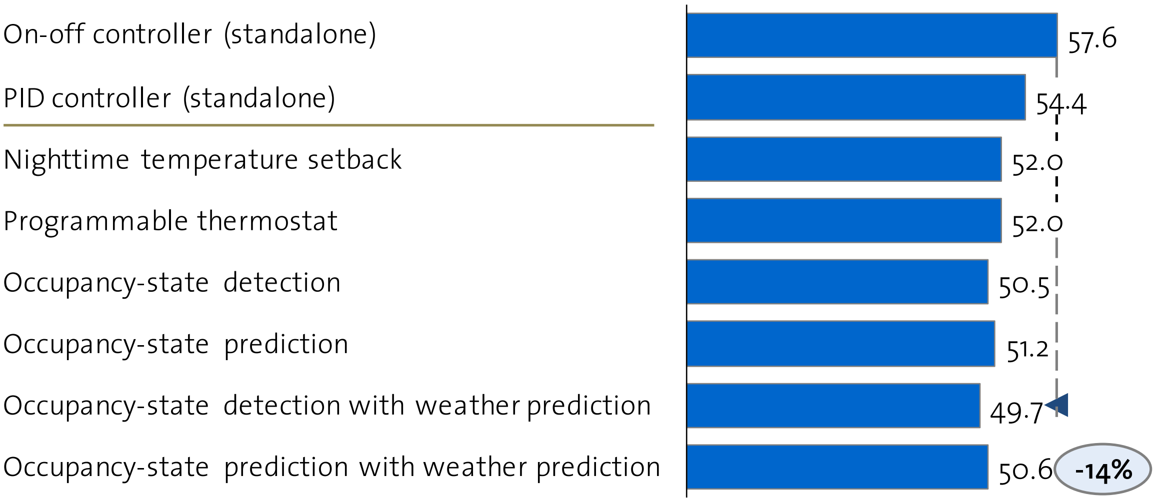
Figure 27: Occupancy pattern of household 3 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 2.33%.

Comparison of net energy required for indoor heating

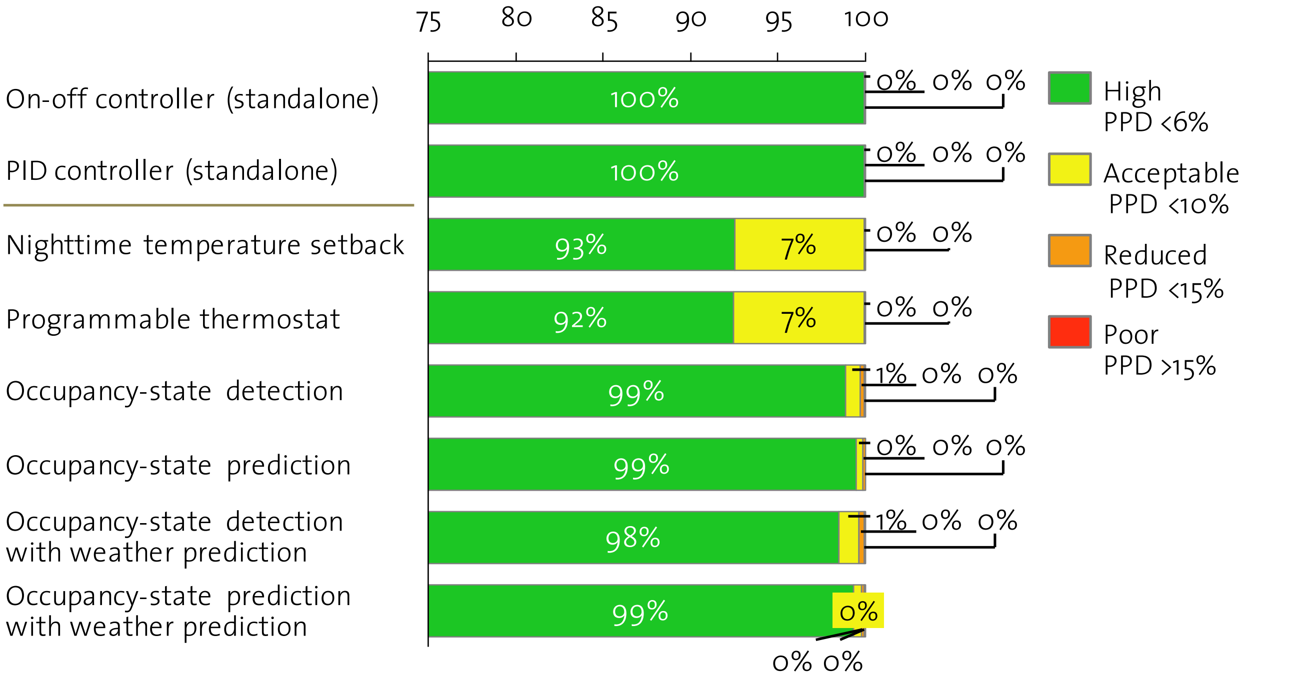
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



IV. Household 4

a. Household profile

Table 14: Building information of household 4

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1982
Number of living units in building	More than 1 (multi-family house)
Floor level	Ground
Floor area [m²]	55
Heating system	Radiator
Weather exposure	Low

Table 15: Occupancy information of household 4

Occupancy specification	Parameter value
Number of occupants	1
Share of vacancy times to total time in %	45.0
Share of sleep times to total time in %	8.6
Share of presence times to total time in %	46.4
Maintained window air change [1/h]	0.15

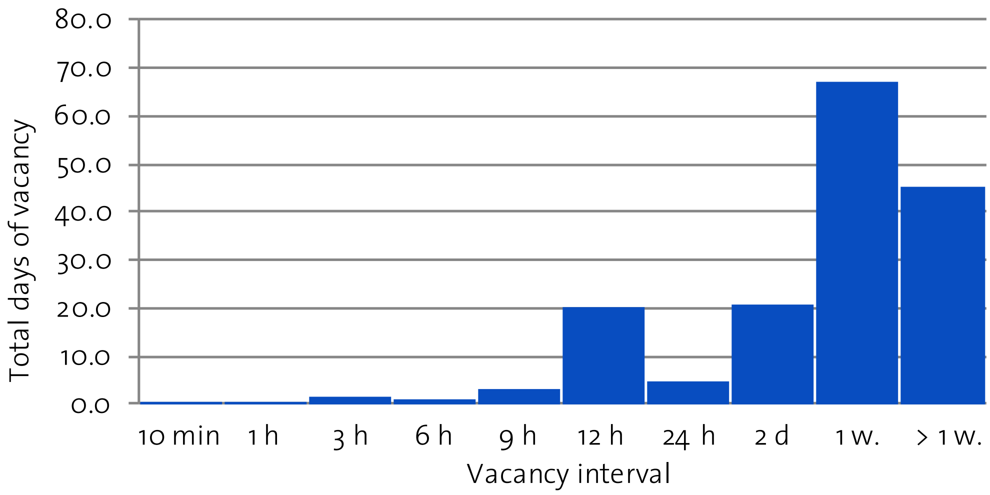
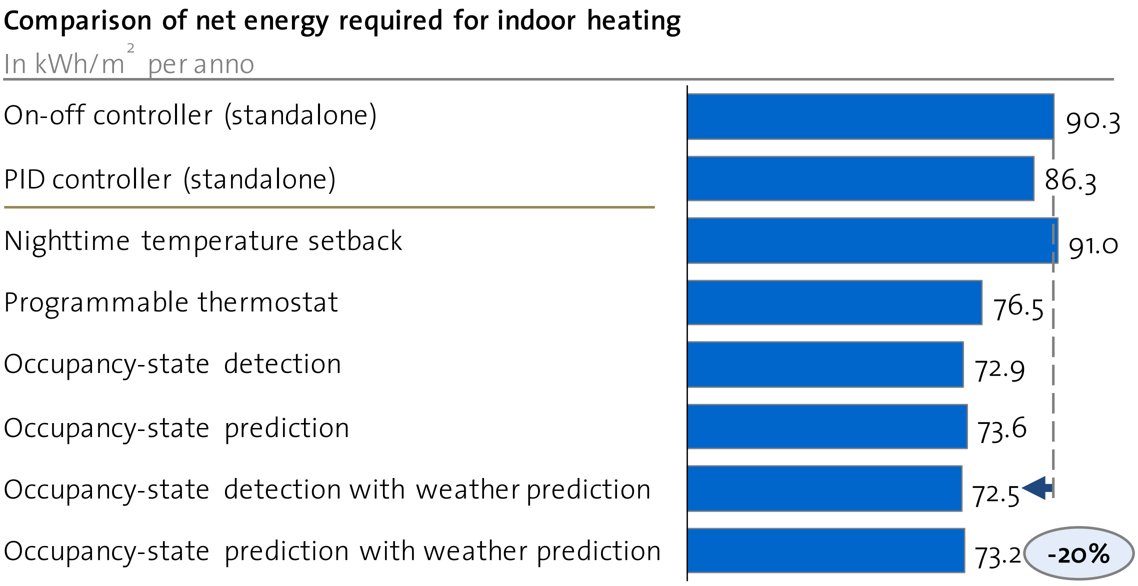
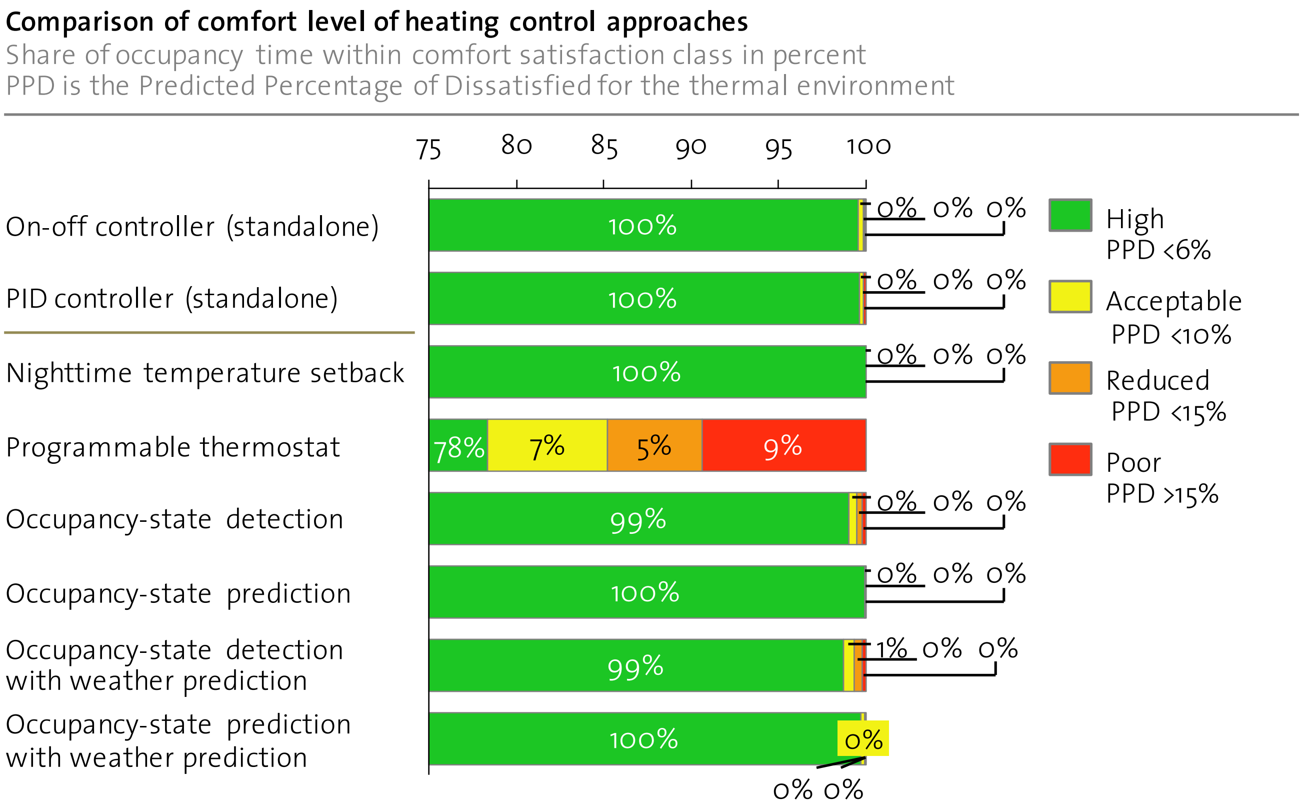


Figure 28: Occupancy pattern of household 4 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 1.84%.





V. Household 5

a. Household profile

Table 16: Building information of household 5

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1982
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m^2]	90
Heating system	Radiator
Weather exposure	Low

Table 17: Occupancy information of household 5

Occupancy specification	Parameter value
Number of occupants	3
Share of vacancy times to total time in %	24.6
Share of sleep times to total time in %	28.8
Share of presence times to total time in %	46.6
Maintained window air change [1/h]	0.15

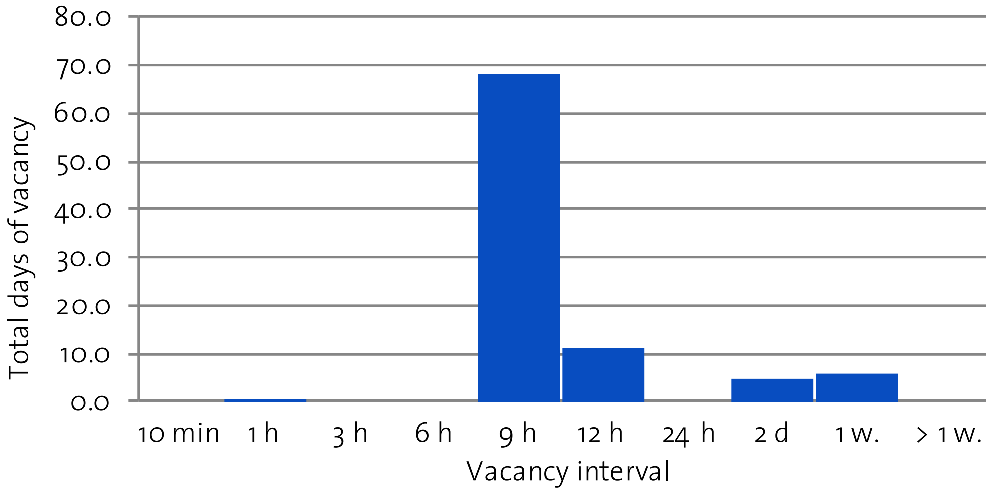


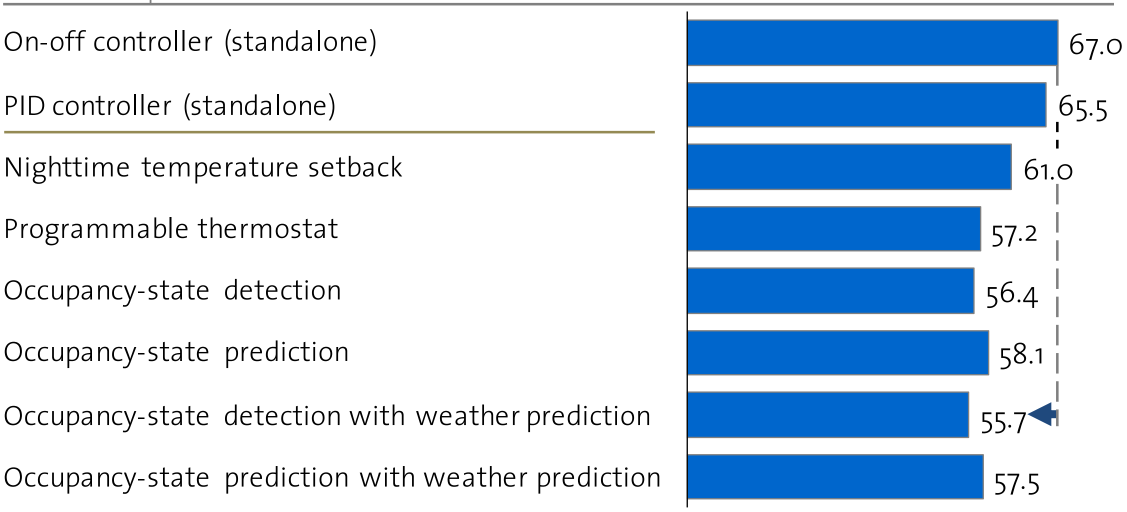
Figure 29: Occupancy pattern of household 5 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 1.08%.

Comparison of net energy required for indoor heating

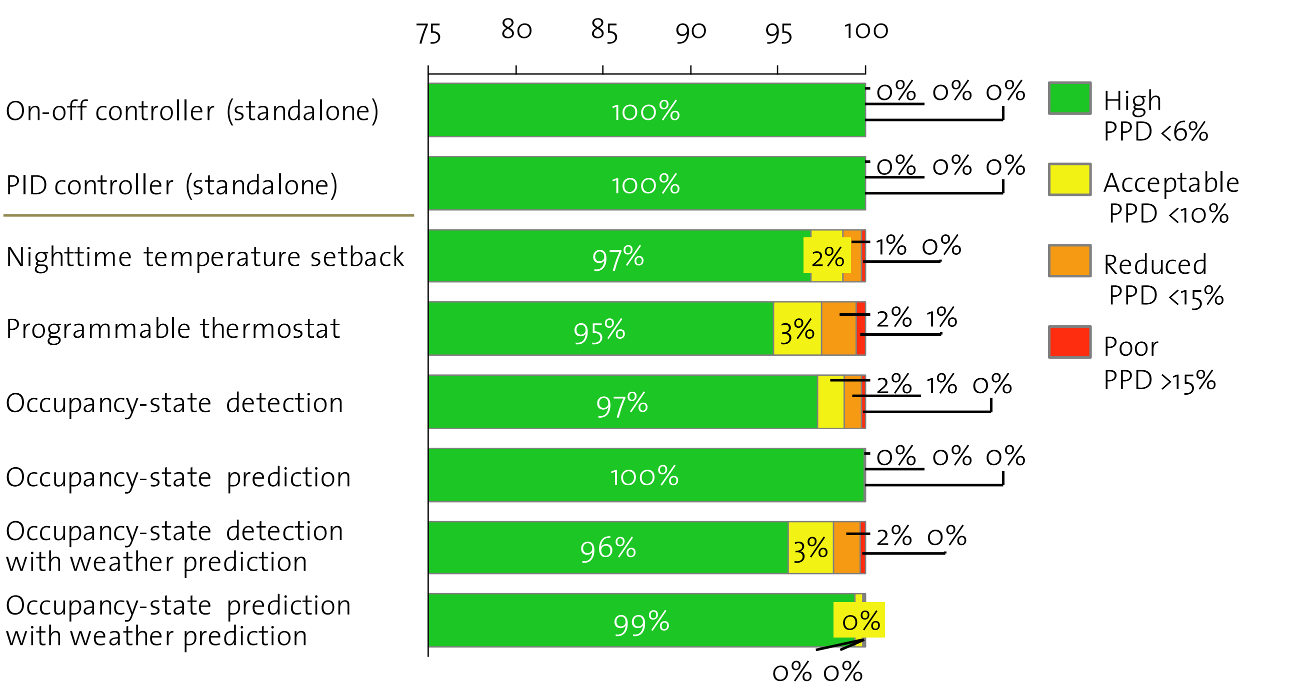
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



VI. Household 6

a. Household profile

Table 18: Building information of household 6

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1982
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m^2]	139
Heating system	Radiator
Weather exposure	Medium

Table 19: Occupancy information of household 6

Occupancy specification	Parameter value
Number of occupants	6
Share of vacancy times to total time in %	27.4
Share of sleep times to total time in %	30.5
Share of presence times to total time in %	42.1
Maintained window air change [1/h]	0.6

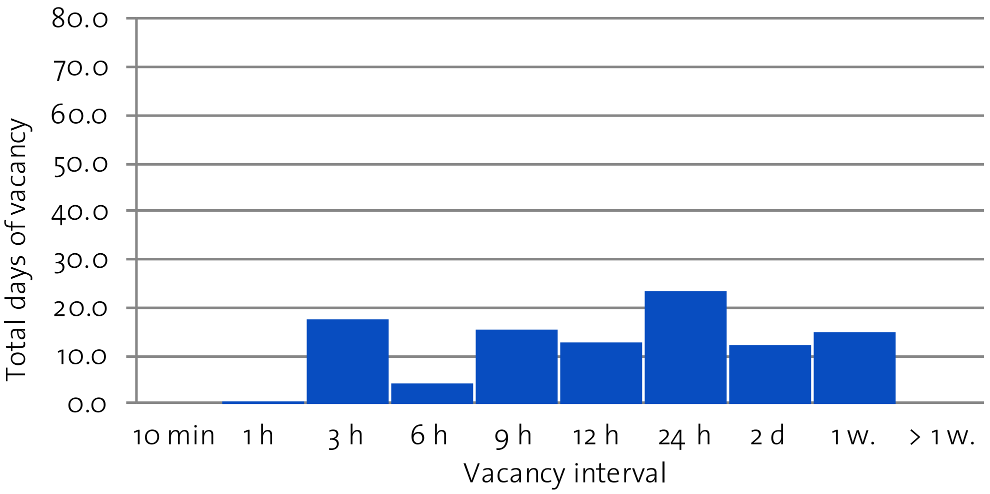


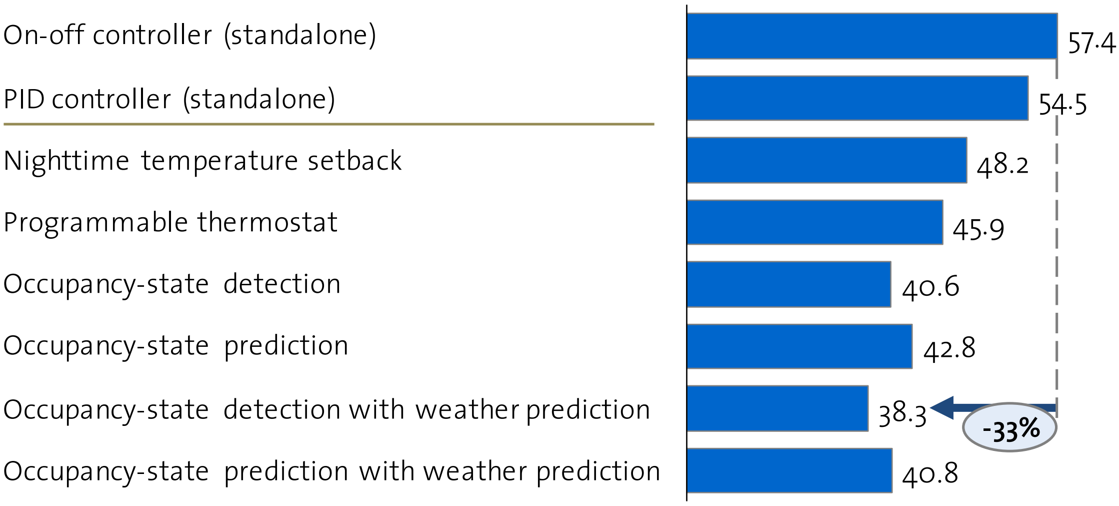
Figure 30: Occupancy pattern of household 6 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 2.81%.

Comparison of net energy required for indoor heating

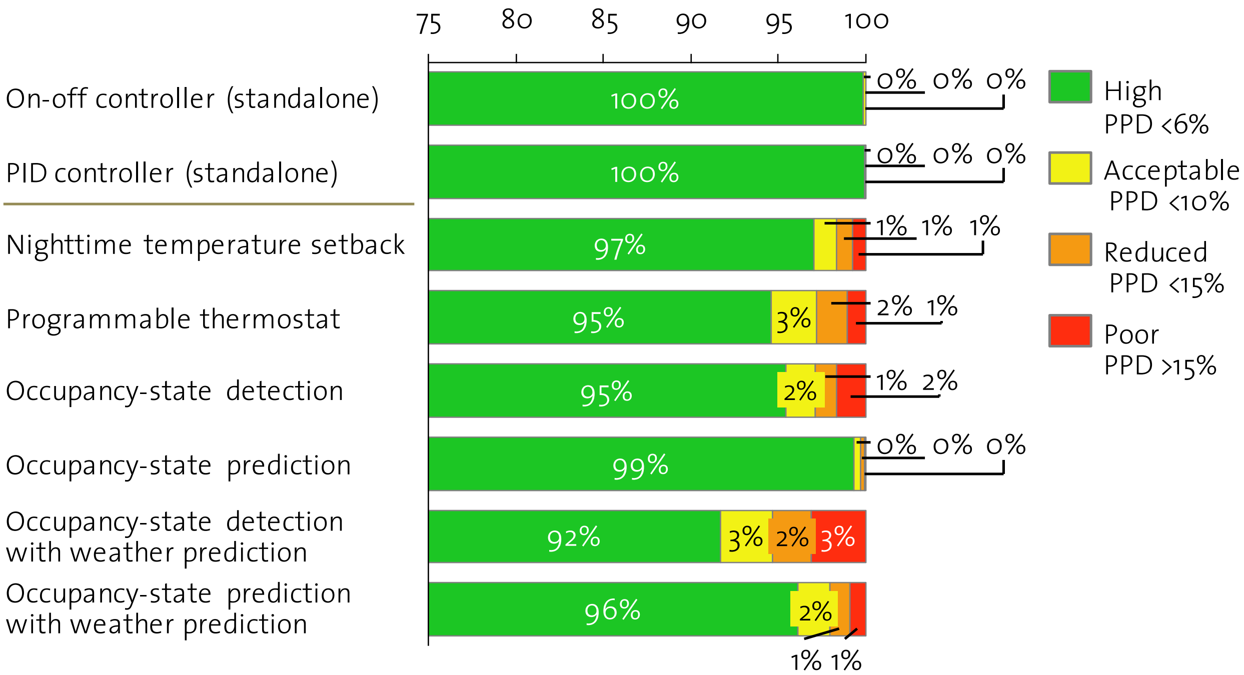
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



VII. Household 7

a. Household profile

Table 20: Building information of household 7

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1982
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m²]	75
Heating system	Radiator
Weather exposure	Low

Table 21: Occupancy information of household 7

Occupancy specification	Parameter value
Number of occupants	1
Share of vacancy times to total time in %	35.7
Share of sleep times to total time in %	28.1
Share of presence times to total time in %	36.2
Maintained window air change [1/h]	0.1

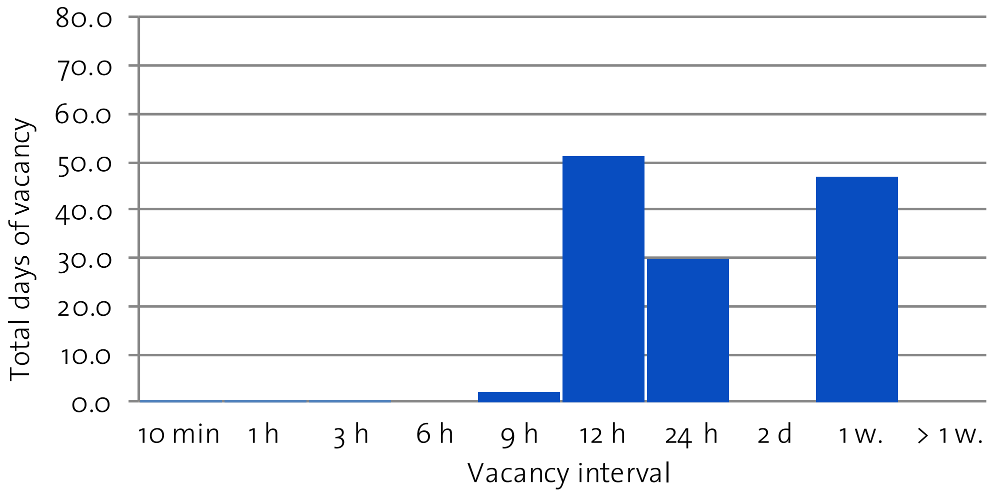


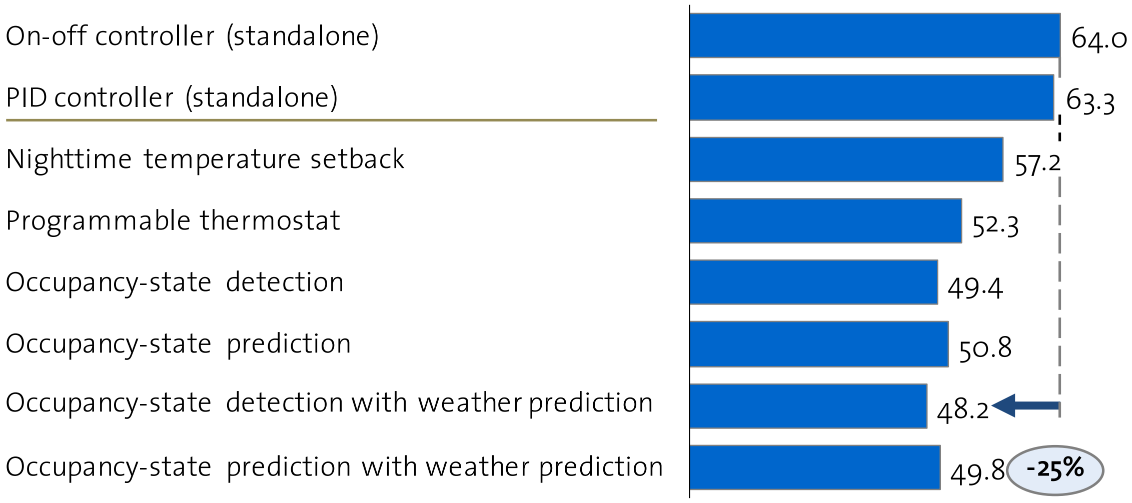
Figure 31: Occupancy pattern of household 7 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 2.41%.

Comparison of net energy required for indoor heating

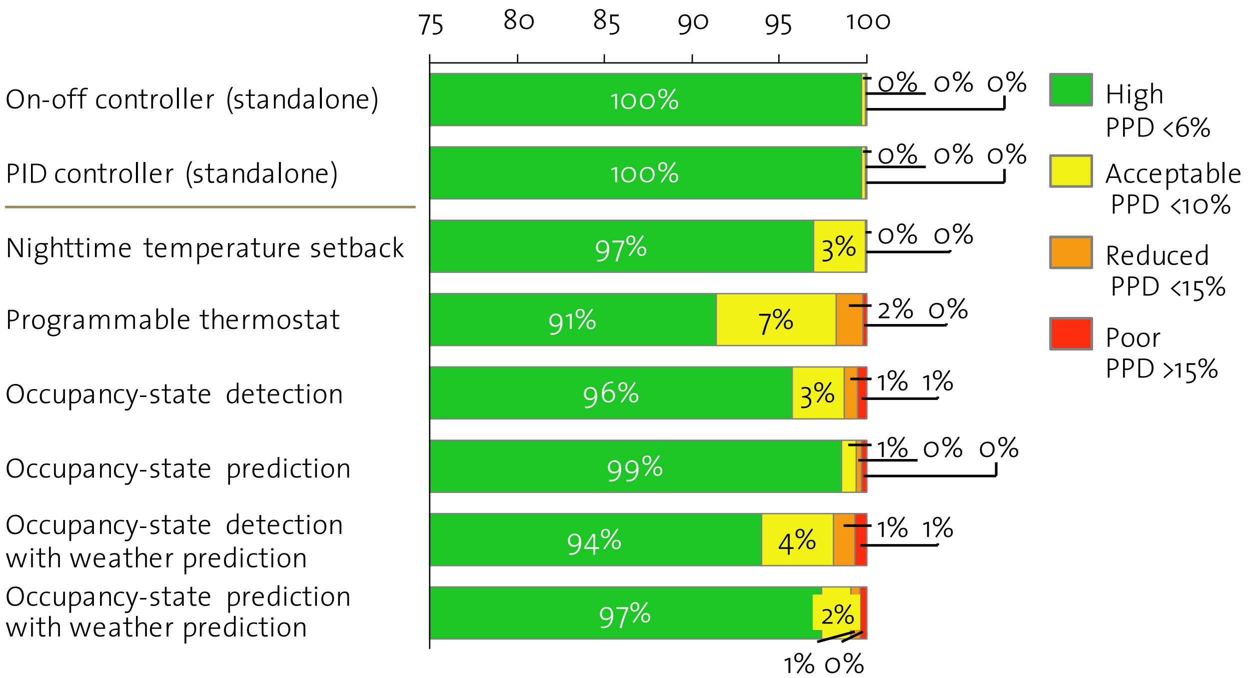
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



VIII. Household 8

a. Household profile

Table 22: Building information of household 8

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1977
Number of living units in building	More than 1 (multi-family house)
Floor level	Ground
Floor area [m^2]	65
Heating system	Radiator
Weather exposure	Low

Table 23: Occupancy information of household 8

Occupancy specification	Parameter value
Number of occupants	2
Share of vacancy times to total time in %	45.5
Share of sleep times to total time in %	26.3
Share of presence times to total time in %	28.1
Maintained window air change [1/h]	0.15

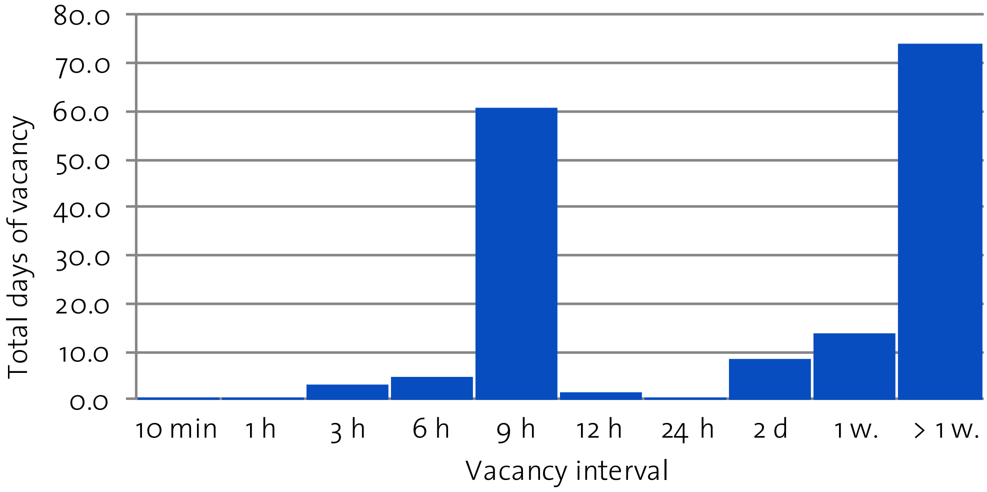


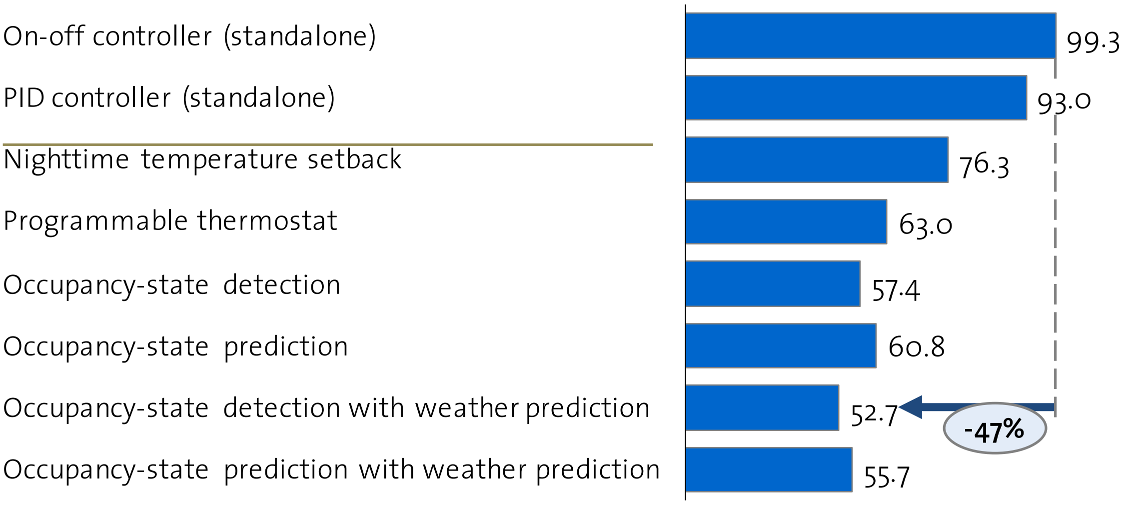
Figure 32: Occupancy pattern of household 8 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 3.30%.

Comparison of net energy required for indoor heating

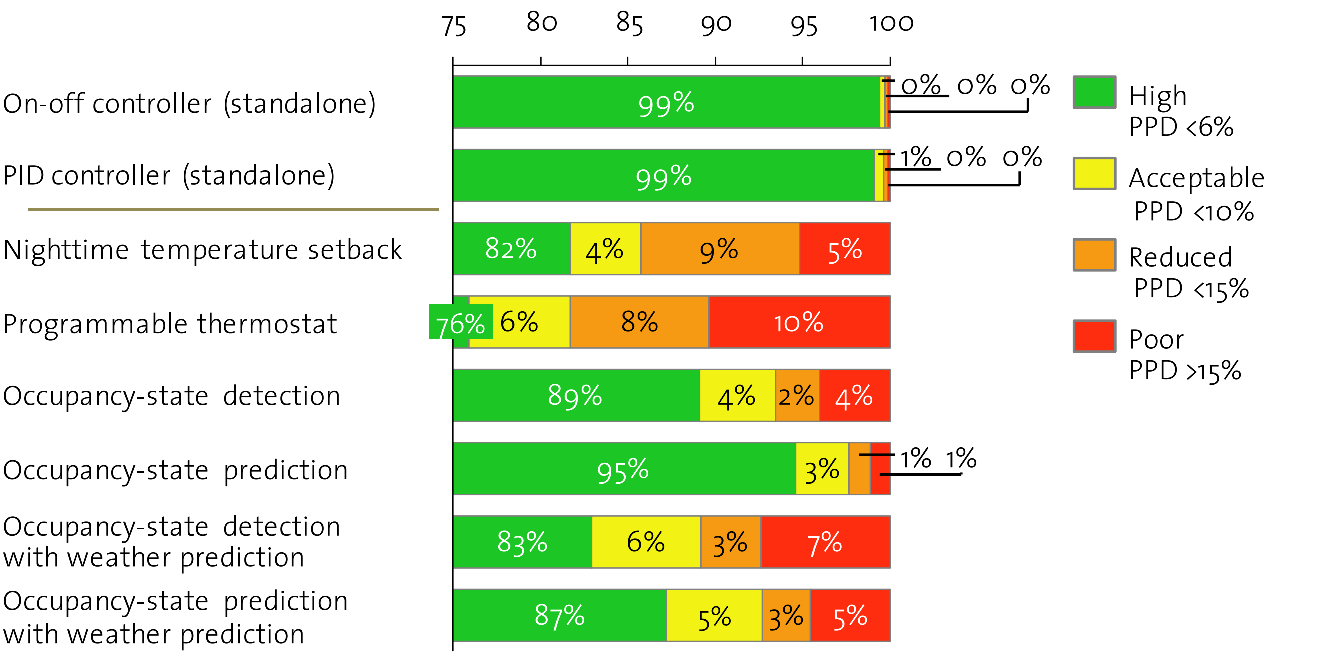
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



IX. Household 9

a. Household profile

Table 24: Building information of household 9

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1977
Number of living units in building	More than 1 (multi-family house)
Floor level	Upper
Floor area [m^2]	45
Heating system	Radiator
Weather exposure	Strong

Table 25: Occupancy information of household 9

Occupancy specification	Parameter value
Number of occupants	1
Share of vacancy times to total time in %	42.2
Share of sleep times to total time in %	25.1
Share of presence times to total time in %	32.7
Maintained window air change [1/h]	0.2

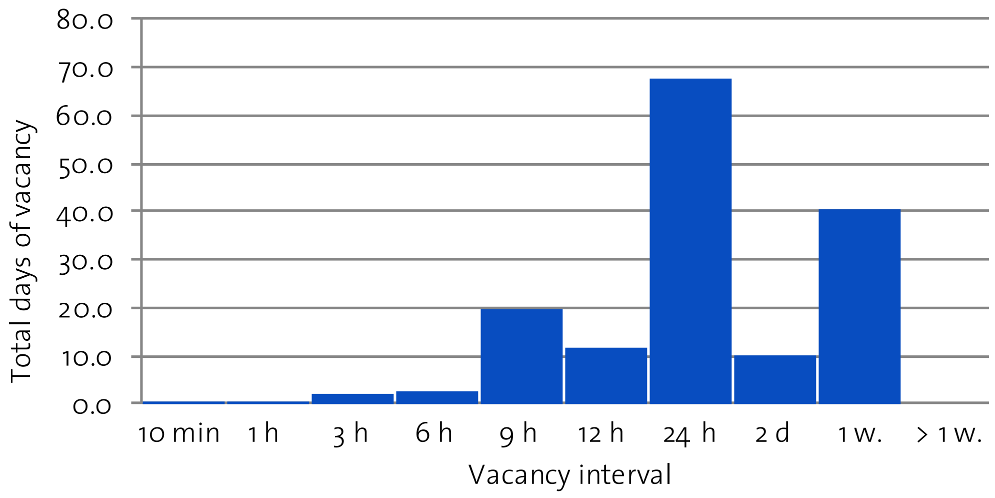


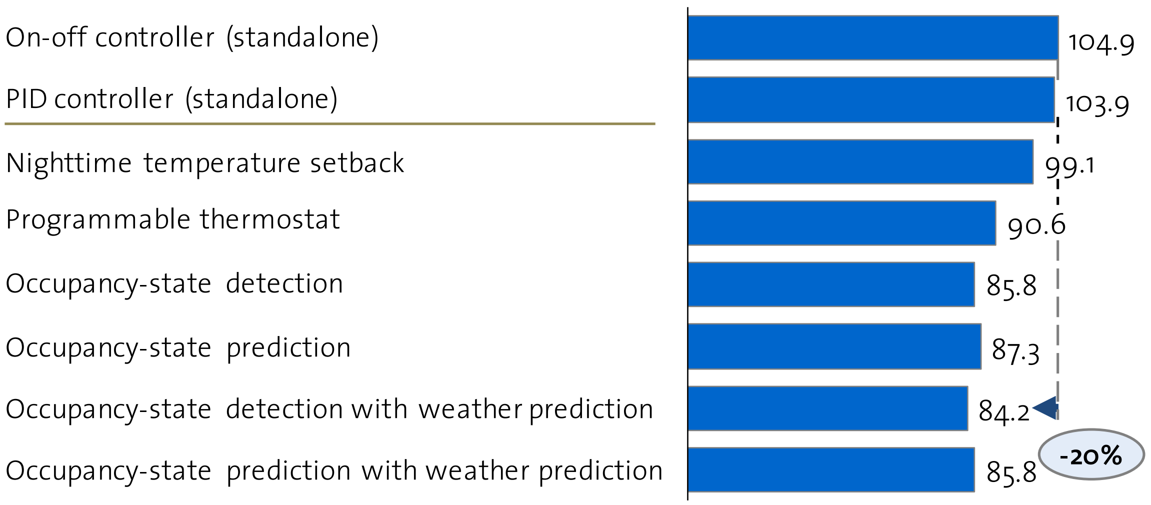
Figure 33: Occupancy pattern of household 9 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

b. Results

The model calibration resulted in a CV(RMSD) of 2.71%.

Comparison of net energy required for indoor heating

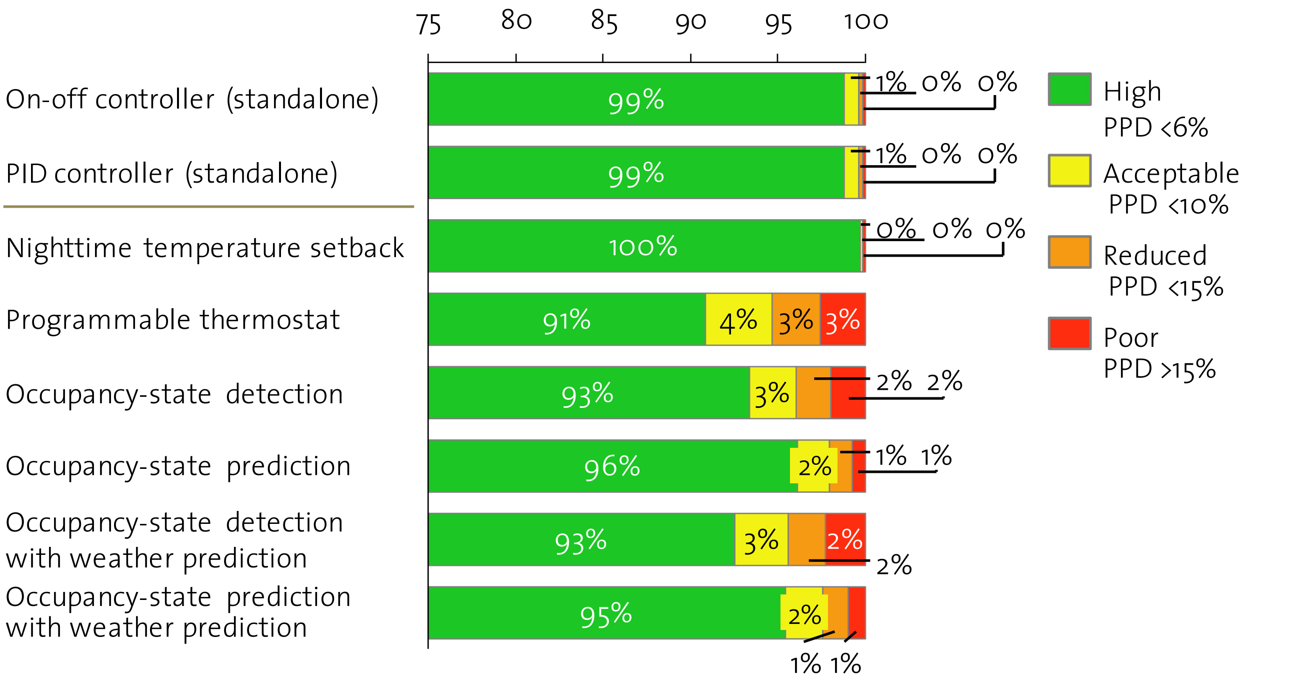
In kWh/m² per anno



Comparison of comfort level of heating control approaches

Share of occupancy time within comfort satisfaction class in percent

PPD is the Predicted Percentage of Dissatisfied for the thermal environment



X. Household 10

a. Household profile

Table 26: Building information of household 10

Building specification	Parameter value
Location	Munich
Energy standard	Wärmeschutzverordnung 1995
Number of living units in building	More than 1 (multi-family house)
Floor level	Intermediate
Floor area [m²]	65
Heating system	Radiator
Weather exposure	Medium

Table 27: Occupancy information of household 10

Occupancy specification	Parameter value
Number of occupants	1
Share of vacancy times to total time in %	45.5
Share of sleep times to total time in %	16.7
Share of presence times to total time in %	37.7
Maintained window air change [1/h]	0.2

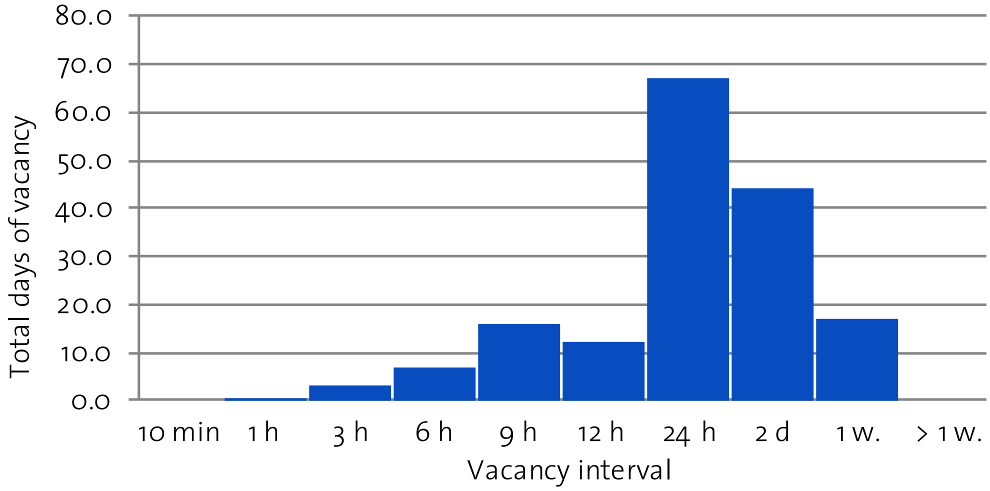
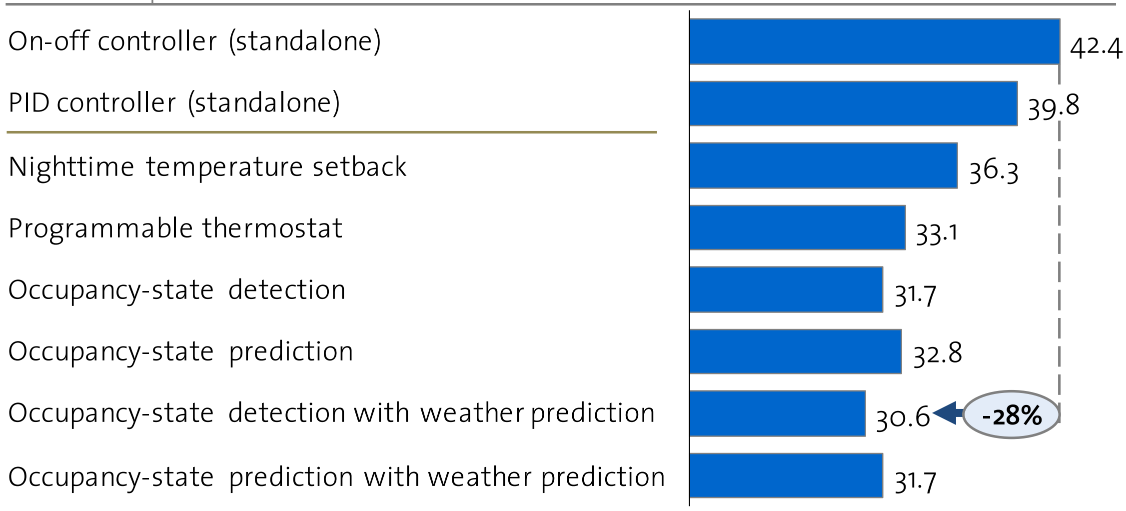


Figure 34: Occupancy pattern of household 10 described by the total days of vacancies for each vacancy interval (number represents the upper boundary of the specific vacancy interval)

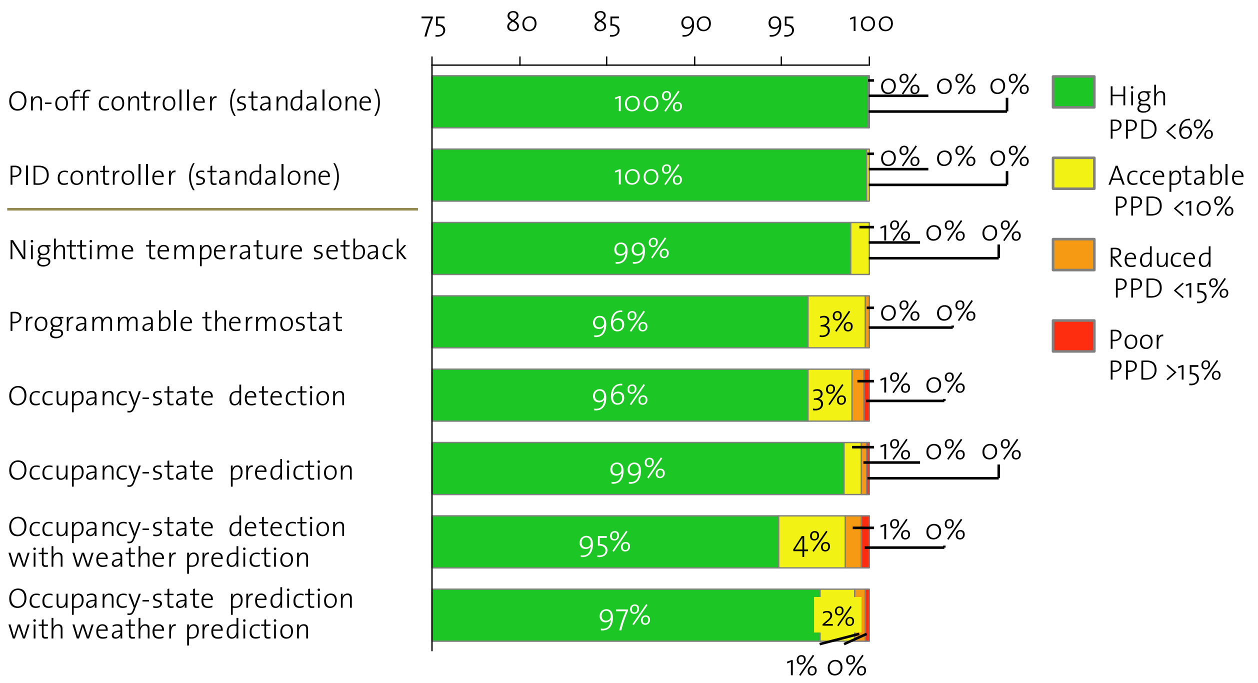
b. Results

The model calibration resulted in a CV(RMSD) of 1.92%.

Comparison of net energy required for indoor heating
In kWh/m² per anno



Comparison of comfort level of heating control approaches
Share of occupancy time within comfort satisfaction class in percent
PPD is the Predicted Percentage of Dissatisfied for the thermal environment



B. Additional simulation result charts

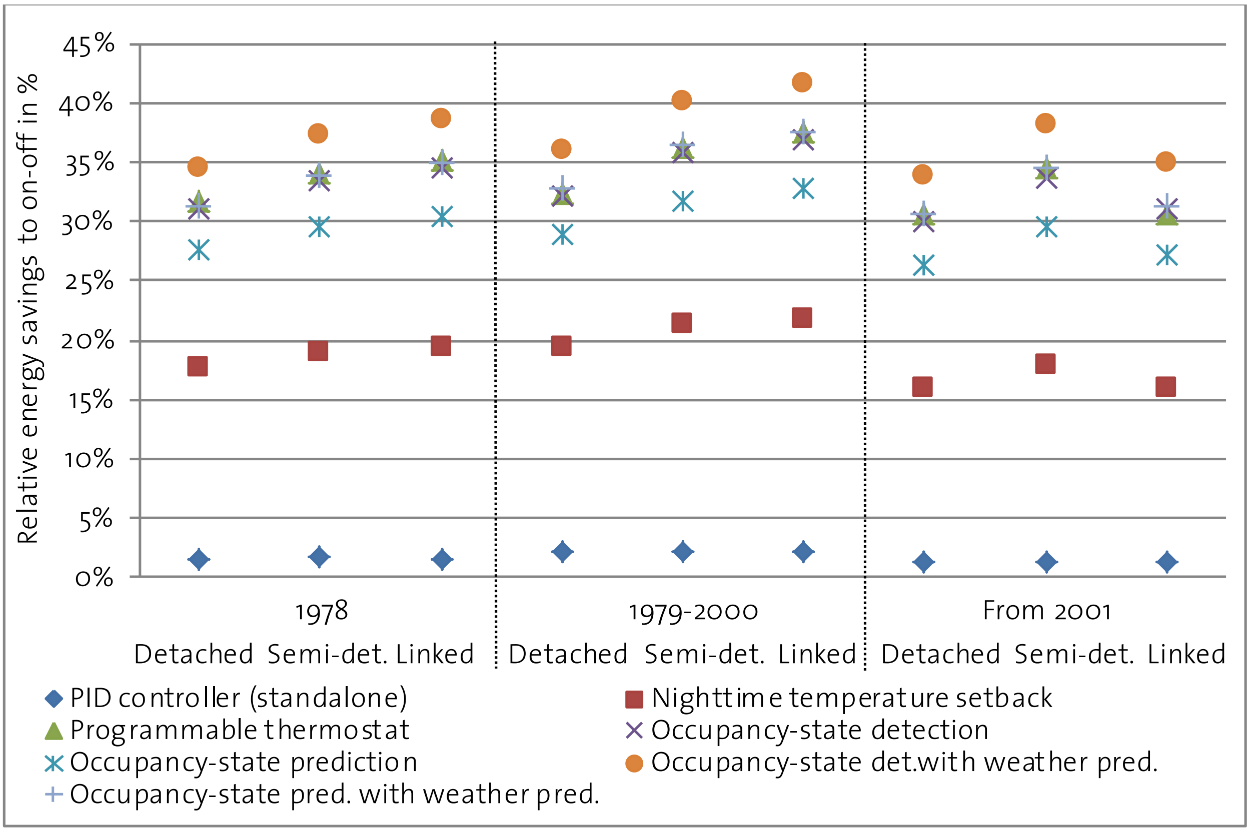


Figure 35: Relative energy savings for building units in single-family buildings

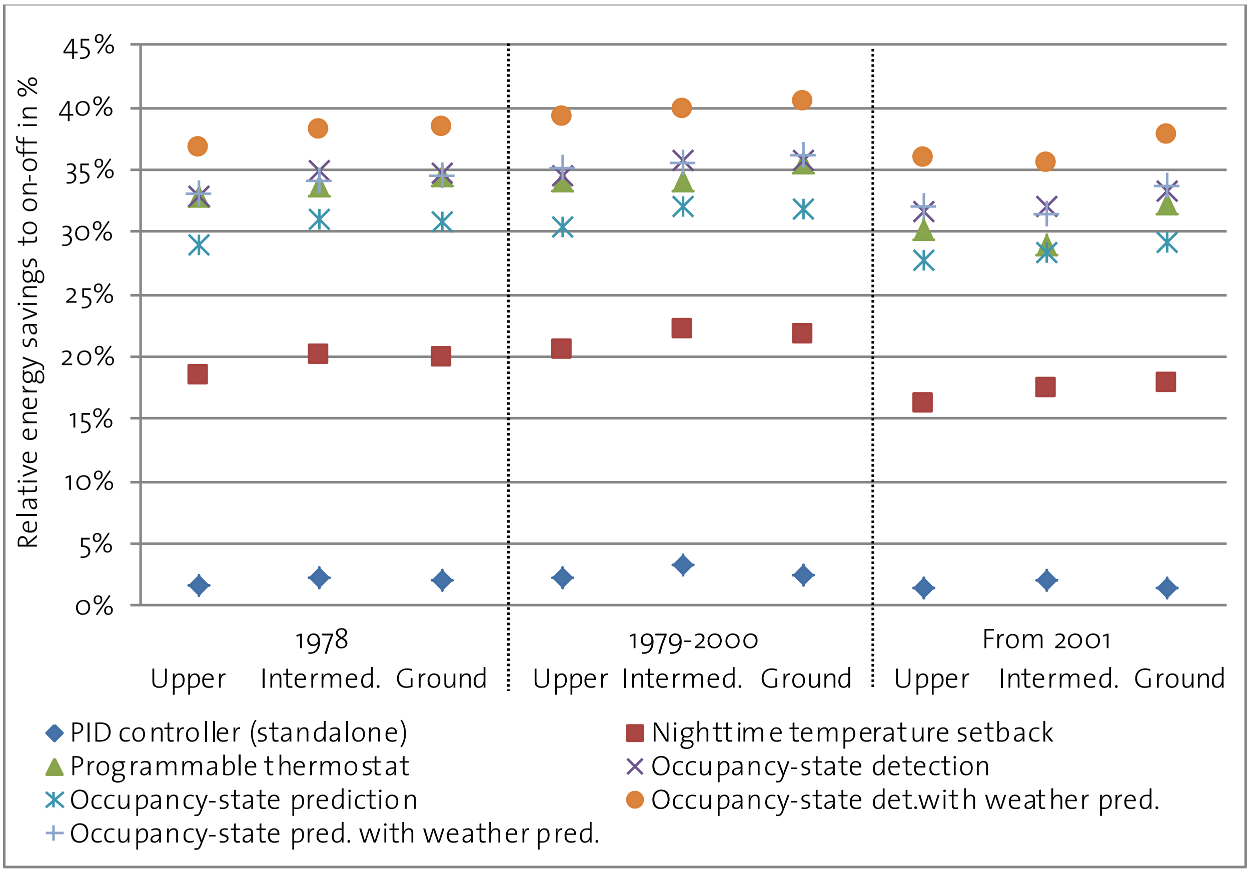


Figure 36: Relative energy savings for building units in multi-family buildings

C. Model Equations

I. Resistance-Capacitance model equations

Abbreviations:

- T: Temperature
- C: Heat capacity
- h: Heat transfer coefficient
- R: Thermal resistance
- ceil: ceiling
- oW: outer walls
- iW: inner walls
- roofSurf: roof surface
- found: foundation

Room node

$$C_{room}\frac{dT_{room}}{dt} = \frac{T_{ceil1} - T_{room}}{\frac{1}{h_{ceil}} + R_{ceil1}} + \frac{T_{oW1} - T_{room}}{\frac{1}{h_{oW}} + R_{oW1}} + (T_{air} + T_{room}) * U_{windows} + \frac{T_{iW} - T_{room}}{\frac{1}{h_{iW1}} + R_{iW1}}$$

$$+ \frac{T_{floor} - T_{room}}{\frac{1}{h_{floor}} + R_{floor1}} + \frac{T_{heater} - T_{room}}{\frac{1}{h_{heater}}}$$

$$+ heat_{internal\ gains} + heat_{air\ change} + heat_{window\ transmission}$$

Ceiling nodes

$$C_{ceil1}\frac{dT_{ceil1}}{dt} = \frac{T_{room} - T_{ceil1}}{\frac{1}{h_{ceil}} + R_{ceil1}} + \frac{T_{ceil2} - T_{ceil1}}{R_{ceil2} + R_{ceil3}}$$

$$C_{ceil2}\frac{dT_{ceil2}}{dt} = \frac{T_{ceil1} - T_{ceil2}}{R_{ceil2} + R_{ceil3}} + \frac{T_{ceil3} - T_{ceil2}}{R_{ceil4} + R_{ceil5}}$$

$$C_{ceil3}\frac{dT_{ceil3}}{dt} = \frac{T_{ceil2} - T_{ceil3}}{R_{ceil4} + R_{ceil5}} + \frac{T_{roof} - T_{ceil3}}{R_{ceil6} + R_{roof1}}$$

Roof node

$$C_{roof}\frac{dT_{roof}}{dt} = \frac{T_{ceil3} - T_{roof}}{R_{ceil6} + R_{roof1}} + \frac{T_{roofSurf} - T_{roof}}{R_{roof2} + R_{roofSurf1}}$$

Roof surface node

$$C_{roofSurf}\frac{dT_{roofSurf}}{dt} = \frac{T_{roof} - T_{roofSurf}}{R_{roof2} + R_{roofSurf1}} + \frac{T_{air} - T_{roofSurf}}{R_{roofSurf1} + \frac{1}{h_{roofSurf}}}$$

$$+ \text{heat}_{\text{solar irradiation on roof surface}}$$

Outer wall nodes

$$C_{oW1}\frac{dT_{oW1}}{dt} = \frac{T_{room} - T_{oW1}}{\frac{1}{h_{oW}} + R_{oW1}} + \frac{T_{oW2} - T_{oW1}}{R_{oW2} + R_{oW3}}$$

$$C_{oW2}\frac{dT_{oW2}}{dt} = \frac{T_{oW1} - T_{oW2}}{R_{oW2} + R_{oW3}} + \frac{T_{oW3} - T_{oW2}}{R_{oW4} + R_{oW5}}$$

$$C_{oW3}\frac{dT_{oW3}}{dt} = \frac{T_{oW2} - T_{oW3}}{R_{oW4} + R_{oW5}} + \frac{T_{oWSurf} - T_{oW3}}{R_{oW6} + R_{oWSurf}}$$

Outer wall surface nodes

$$C_{oWSurf}\frac{dT_{oWSurf}}{dt} = \frac{T_{oW3} - T_{oWSurf}}{R_{oW6} + R_{oWSurf1}} + \frac{T_{air} - T_{oWSurf}}{R_{oWSurf2} + \frac{1}{h_{oWSurf}}} + \text{heat}_{\text{solar irradiation on outer wall}}$$

Interior wall node

$$C_{iW}\frac{dT_{iW}}{dt}=\frac{T_{room}-T_{iW}}{\frac{1}{h_{iW}}+R_{iW1}}+\frac{T_{room2}-T_{iW}}{R_{iW2}+\frac{1}{h_{iW2}}}$$

Floor node

$$C_{floor}\frac{dT_{floor}}{dt}=\frac{T_{room}-T_{floor}}{\frac{1}{h_{floor}}+R_{floor1}}+\frac{T_{found}-T_{floor}}{R_{floor2}+R_{found1}}$$

Foundation nodes

$$C_{found}\frac{dT_{found}}{dt}=\frac{T_{floor}-T_{found}}{R_{floor2}+R_{found1}}+\frac{T_{ground}-T_{found}}{R_{found2}}$$

Heater

$$C_{heater}\frac{dT_{heater}}{dt}=\frac{T_{room}-T_{heater}}{\frac{1}{h_{heater}}}+heat_{space\ heater}$$

II. Resistance-Capacitance variable equations

The following equations describe the calculation of the RC variables and the heat sources.

Equation 5: Thermal resistance (time-invariant)

$$\text{Thermal resistance} = \frac{\text{thickness}}{\text{area} * \text{thermal conductivity}} \left[\frac{K}{W}\right],$$

Equation 6: Heat capacity (time-invariant)

$$\text{Heat capacity} = \text{specific heat capacity} * \text{density} * \text{thickness} * \text{volume} \left[\frac{W}{m * K}\right]$$

Equation 7: Heat transfer coefficient (time-variant)

$$\text{Heat transfer coefficient } (t) = \text{specific heat transfer coefficient } (t) * \text{area}$$

Equation 8: Specific interior[49] heat transfer coefficient[50] (time-variant)

$$\text{Specific interior heat transfer coefficient } (t) = c * \left|\text{temperature}_{\text{indoor}}(t) - \text{temperature}_{\text{building element}}(t)\right|^{k}$$

Equation 9: Heat by internal gains[51]

$$\text{Heat}_{\text{internal gains}}(t) = \text{standard internal gain} * \text{occupant state scaling factor } (t)$$

Equation 10: Heat on surface areas

$$\text{Heat}_{\text{solar irradiation on surface}}(t) = \text{solar absorptance}_{\text{surface material}} * \text{area}_{\text{surface material}} * \varnothing \frac{\text{radiated surface area}}{\text{total surface area}} * \text{solar irradiation } (t)$$

---

49 Exterior heat transfer coefficient are calculated from the surface roughness and wind speed according to (Reference and Calculations 2012 , s. simple combined algorithm)

50 Constant c and exponent k are adapted from (Alamdari and Hammond 1983; Awbi and Hatton 1999)

51 Internal gains arise from equipment and persons, depending on the occupants' states. The standard internal gain is derived from DIN 18599 which states 50Wh/m²d for single-family houses and 100Wh/m²d for multi-family houses. To regard varying internal gains depending on the occupancy, the occupant state scaling factor is assumed to be 25% for the away state, 75% for the sleep state and 100% for the home state.

Equation 11: Heat from window transmission

$$\text{Heat}_{\text{window transmission}}(t) = \emptyset \frac{\text{radiated window area}}{\text{total window area}} * \text{gValue}_{\text{window}} * \text{area}_{\text{window}} * \text{solar irradiation}(t)$$

Equation 12: Heat from air change[52]

$$\text{Heat}_{\text{air change}}(t) = \text{air change rate} * (\text{outside temperature}(t) - \text{room temperature}(t)) * \text{heat capacity}_{\text{air inside building}}$$

Equation 13: Heat from space heater

$$\text{Heat}_{\text{space heater}}(t) = \text{controller output}(t)^{53} * \text{maximum heat output}$$

[52] The air change rate sums the natural infiltration and occasional window openings. The minimum air change requirements are in compliance with DIN 4108-6

[53] The controller output is derived by Equation 1 and Equation 2, respectively

III. Heating system equations

The following equations describe the calculation procedure to derive the heating load as well as the heat capacity of the heating system.

Equation 14: Heat capacity of heating system[54]

$$C_{\text{Heating System}} = C_{\text{Radiator}} + C_{\text{Water in radiator}} + C_{\text{Water in pipes}}$$

with

$$C_{\text{Radiator}} = \begin{cases} v_{\text{Water per power}} * \psi_{\text{Heating load}} & \text{for floor heating} \\ v_{\text{Water per length}} * L_{\text{Radiator}} & \text{for radiator heating} \end{cases}$$

$$C_{\text{Water in radiator}} = \begin{cases} C_{\text{floor}} & \text{for floor heating} \\ c_{\text{Steel}} * V_{\text{Steel}} * \rho_{\text{Steel}} & \text{for radiator heating} \end{cases}$$

$$C_{\text{Water in pipes}} = c_{\text{Water}} * V_{\text{Water in pipes}}$$

C_i	Heat capacity of element i
c_i	Specific heat capacity of element i
$v_{\text{Water per measure m}}$	Specific volume of water per measure m
ρ_i	Density of element i
L_i	Length of element i

Equation 15: Heating load calculation, [Pistohl, 2009]

$$\psi_{\text{Heating load}} = \psi_T + \psi_I$$

$\psi_{\text{Heating load}}$	Heating load [W]
ψ_T	Transmission heat losses [W]
ψ_I	Infiltration heat losses [W]

Equation 16: Transmission heat loss calculation, [Pistohl, 2009]

$$\psi_T = \sum A_k * (U_K + 0.10) * F_x * (\Theta_{int,i} - \Theta_e)$$

A_K	Area of the construction element K
U_K	Heat transfer coefficient of the construction element K
F_x	Temperature correcting factor, [Pistohl, 2009]
$\Theta_{int,i}$	Standard room temperature, 20° C (DIN EN 12831)[55]
Θ_e	Standard outside temperature for the city, [Pistohl, 2009]

[54] Equations and parameterizations derived from [Pistohl, 2009] and [Korado, 2012]

[55] The standard room temperature is required to be reached with the heating system

Equation 17: Infiltration heat loss calculation, [Pistohl, 2009]

$$\psi_I = \sum 0.27 * n * V_e * (\Theta_{int,i} - \Theta_e)$$

n	Average air change, 0.7/h [Pistohl, 2009]
V_e	V_e : exterior volume, V_e = 1.25 * interior building volume [Pistohl, 2009]

D. Building physics database

Table 28: Building materials and thermal properties [Pistohl, 2009]

Material name	Density in kg/m³	Thermal conductivity in W/(m*K)	Specific heat capacity in J/(kg*K)
Concrete	2000	1.350	1000
Cork	200	0.050	1300
Carpet	200	0.060	1300
Linoleum	1200	0.170	1400
Air	1.23	0.025	1008
Bronze	8700	65.000	380
Steel	7800	50.000	450
PVC	1390	0.170	900
Foam rubber	70	0.060	1500
Hard rubber	1200	0.170	1400
Silicone foam	750	0.120	1000
Polyurethane foam	70	0.050	1500
Stucco	1300	0.570	1000
Cement	1800	0.400	1000
Gravel	1800	2.000	1000
Marble	2800	3.500	1000
Plywood	500	0.130	1600

Table 29: Window thermal specifications, derived from DIN 18599-2.

Window type	U-factor in K*m²/W	g-value
Single glazing	5.80	87%
Double glazing	2.90	78%
Triple glazing	2.00	70%
Heat absorbing double glazing	1.40	67%
Heat absorbing triple glazing	0.80	50%
Sun-blocking double glazing	1.30	48%
Sun-blocking triple glazing	1.20	25%
Passive house window	0.85	50%

Table 30: The roughness specifications of the surface materials are adapted from [EnergyPlus, 2012] "Outdoor/Exterior convection"

Roughness	D	E	F
Very rough (e.g. stucco)	11.58	5.894	0.000
Rough (e.g. brick)	12.49	4.065	0.028
Medium rough (e.g. concrete)	10.79	4.192	0.000
Medium smooth (e.g. clear pine)	8.23	4.000	-0.057
Smooth (e.g. smooth plaster)	10.22	3.100	0.000
Very smooth (e.g. glass)	8.23	3.330	-0.036

Table 31: Solar absorptance of surface coatings [ERSS, 2006]

Surface coating	Solar absorptance
Paint - white	23%
Paint - light cream	30%
Galvanized iron (new)	32%
Paint - pink	49%
Paint - light green	50%
Copper (aged)	57%
Concrete (dry)	62%
Fibro cement (weathered)	65%
Tiles - concrete (uncolored)	65%
Tiles - clay (light red)	66%
Galvanized iron (weathered)	75%
Paint - light grey	75%
Brick (red pressed clay)	79%
Tiles - clay (dark purple)	81%
Tiles - concrete (light brown)	85%
Tiles - concrete (black)	91%
Paint - black	96%

Table 32: U-factors for building elements in K*m²/W according to thermal building codes

Thermal building code	Outer walls[56]	Windows	Roof	Ground
Wärmeschutzverordnung 1977		1.45	0.45	0.9
Wärmeschutzverordnung 1982		1.2	0.3	0.55
Wärmeschutzverordnung 1995	0.5	1.8	0.3	0.5
Energieeinsparverordnung 2002	0.45	0.25	0.5	1.7
Energieeinsparverordnung 2009	0.24	0.24	0.3	1.3
SIA 380/1 2009 (Swiss)	0.25	0.25	0.25	1.3

Table 33: Heat transfer coefficients in K*m²/W according to DIN EN ISO 6949

Heat transfer coefficient	Upward heat flow	Horizontal heat flow	Downward heat flow
$R_{interior\ surface}$	0.10	0.13	0.17
$R_{exterior\ surface}$	0.04	0.04	0.04

[56] In Wärmeschutzverordnung 1977 and 1982, the insulation of the outer walls and windows are described by combined U-factors.

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