Model-based Assessment of Heat Pump Flexibility

Tobias Wolf
Abstract

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Today's energy production is changing from conventional to intermittent generation due to the increasing energy injection from renewable sources. This alteration requires flexibility in energy generation and demand. Electric heat pumps and thermal storages were found to have a large potential to provide demand flexibility which is analysed in this work. A three-fold method is set up to generate thermal load profiles, to simulate heat pump pools and to assess heat pump flexibility. The thermal profile generation based on a combination of physical and behavioural models is successfully validated against measurement data. A randomised system sizing procedure was implemented for the simulation of heat pump pools. The parameter randomisation yields correct seasonal performance factors, full load hours and average operation cycles per day compared to 87 monitored systems. The flexibility assessment analysis the electric load deviation of representative heat pump pool in response to 5 different on / off signals. The flexibility is induced by the capacity of thermal storages and analysed by four parameters. Generally, on signals are more powerful than off signals. A generic assessment by the ambient temperature yield that the flexibility is highest for heating days and the activated additional space heating storage: Superheating to the maximal storage temperature provides a flexible energy of more than 400 kWh per 100 heat pumps in a temperature range between -10 and +13 °C.
Acknowledgements

First, I want to thank my supervisor David Fischer at the Fraunhofer Institute of Solar Energy Systems ISE in Freiburg, who gave me the opportunity to write this thesis during the last 12 months. He always challenged my scientific methods and I can look back to valuable discussions about the flexibility assessment. The thesis was part of the project WP smart im Bestand: Heat Pump Field Trial – Focus Existing Buildings and Smart Control\textsuperscript{1}. The research focuses are 1) the efficiency of electric-driven heat pumps depending on different refurbishment scenarios in the field, 2) the load-shift potential of electric-driven heat pumps in the field and the required framework.

I want to thank the research team from the group of Electrically and Heat Driven Heat Pumps, namely Jeanette Wapler, Danny Günther and Robert Langner. Jeanette and Danny supported me with constructive criticism and ideas to the methodology of the heat pump validation and evaluated the plots of the flexibility assessment. Robert provided the measurement data of the WP-Effizienz and WP Monitor projects and helped me analysing the heat pump data sets.

Thanks a lot to Joakim Widén, my subject reader at Uppsala University. He gave very kind and valuable input towards the structure and understanding of my thesis and formal mistakes.

Thanks a lot to Christian and Marcus who were kind enough to read and correct my Master thesis.

I also want to thank my colleagues Thomas, Inga, Benni, Josef-Michael, Manuela and Jan for having such a great time at the Fraunhofer ISE.

Many, many thanks go to my family and good friends, who always supported me. Last but not least I want to thank my flatmates, who are an important part of my stay in Freiburg.

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<tr>
<td>amb</td>
<td>ambient</td>
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<tr>
<td>biv</td>
<td>bivalence point</td>
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<td>block</td>
<td>blocking hours</td>
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<td>env</td>
<td>storage environment</td>
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<td>lb</td>
<td>lower boundary</td>
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<td>lim</td>
<td>heating limit</td>
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<td>modelled</td>
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<td>per annum</td>
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<td>geothermal probe</td>
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<td>storage</td>
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<td>sup</td>
<td>supply</td>
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<tr>
<td>ub</td>
<td>upper boundary</td>
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<td>A</td>
<td>Air</td>
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<td>ASHP</td>
<td>Air Source Heat Pump</td>
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<td>B</td>
<td>Brine</td>
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<td>BH</td>
<td>Backup Heater</td>
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<td>DHW</td>
<td>Domestic Hot Water</td>
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<td>DHWS</td>
<td>Domestic Hot Water Storage</td>
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<td>DSM</td>
<td>Demand Side Management</td>
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<td>GSHP</td>
<td>Ground Source Heat Pump</td>
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<td>HL</td>
<td>Heating Load</td>
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<td>HP</td>
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<td>MFH</td>
<td>Multifamily House</td>
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<td>S</td>
<td>Storage</td>
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<td>SFH</td>
<td>Single Family House</td>
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<td>SG</td>
<td>Smart Grid</td>
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<tr>
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<td>Space Heating</td>
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<tr>
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<td>Terraced House</td>
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<tr>
<td>VPP</td>
<td>Virtual Power Plant</td>
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<td>W</td>
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# List of Symbols

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<td>$a$</td>
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<td>-</td>
</tr>
<tr>
<td>$b$</td>
<td>coefficient letter for linear regression</td>
<td>-</td>
</tr>
<tr>
<td>$f_{block}$</td>
<td>factor for blocking hours</td>
<td>-</td>
</tr>
<tr>
<td>$n_{block}$</td>
<td>number of blocking hours</td>
<td>h</td>
</tr>
<tr>
<td>$n_{days}$</td>
<td>number of days of the simulated year</td>
<td>-</td>
</tr>
<tr>
<td>$n_{day(t_{min})}$</td>
<td>number of the day with minimum temperature</td>
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</tr>
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<td>$n_{persons}$</td>
<td>number of persons</td>
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<td>$q$</td>
<td>specific load per person</td>
<td>kW</td>
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<td>$r$</td>
<td>correlation</td>
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<td>$t$</td>
<td>time</td>
<td>s</td>
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<td>$\bar{t}$</td>
<td>mean temperature</td>
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<tr>
<td>$v$</td>
<td>specific volume per person</td>
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<td>value of the target data set</td>
<td>-</td>
</tr>
<tr>
<td>$y$</td>
<td>value of the comparing data set</td>
<td>-</td>
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<td>$A$</td>
<td>surface area</td>
<td>m$^2$</td>
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<td>$ASHC$</td>
<td>annual specific heat consumption</td>
<td>kW h m$^{-2}$</td>
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<td>$\overline{ASHC}$</td>
<td>mean annual specific heat consumption</td>
<td>kW h m$^{-2}$</td>
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<td>$C$</td>
<td>heat capacity</td>
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<td>$FE$</td>
<td>flexible energy</td>
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<td>$Q$</td>
<td>thermal power or demand</td>
<td>kW</td>
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<tr>
<td>$Reg$</td>
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<td>$SPF$</td>
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<tr>
<td>$T$</td>
<td>temperature</td>
<td>K / °C</td>
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<tr>
<td>$V$</td>
<td>storage volume</td>
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<tr>
<td>$\eta_{HP}$</td>
<td>share of HP energy from annual thermal energy</td>
<td>%</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>specific loss</td>
<td>kW m$^{-2}$ K</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>temperature difference or deviation amplitude</td>
<td>K</td>
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To my parents.
Chapter 1

Introduction

The German energy policy of the last two decades fostered a growing share of renewable energy generation. A major growth could be observed in electricity production. The share of renewable electricity generation reached more than 27% in 2014 (BMWi, 2015). An increasing share of renewable sources such as wind or solar power is shifting the conventional, constantly available generation by fossil-fuelled or nuclear power plants towards an intermittent generation. The alternating electricity generation is clearly visible in the shape of the German electricity production profile during a week in March 2016 as shown in Figure 1.1. Grey is indicating the generated electricity by conventional sources with a high share of the total generation during the week. The yellow-coloured generation profile by solar power shows the characteristic curve with the peak at midday, while the green-coloured wind power profile is dependent on the wind regime.

![Figure 1.1: Electricity production in Germany during week 11 in 2016](https://www.energy-charts.de/power.htm)

Figure 1.1 shows that the electricity generation by conventional sources is increased in the morning and evening hours and reduced during day-times at most of the days. For instance,

on 14.03. the conventional electricity sources compensate for the increased generation by renewable sources, especially solar, during the day. Flexible electricity generation is one key solution to compensate for alternating electricity production. Energy-exchange stocks as well as regulating or balancing markets offer trading of flexibilities. Another solution to compensate for a growing share of intermittent electricity generation is the demand-side management (DSM) of electric loads. DSM is an important contribution to electric grids which distribute electrical energy in a smart and controlled way from places of generation to consumers, widely known as smart grids. DSM allows amongst others the control of electrical loads on the demand side by energy utilities or aggregators (Siano, 2014, 463f.).

In 2014 German households have consumed about 25 % of the total generated electricity in Germany (BDEW, 2015, p. 5). Because of a growing number of electrical devices the potential for DSM in households is tremendous. Nowadays, electricity demand in buildings is mostly uncontrollable and changes constantly during the course of the day, between weekdays and weekends as well as between seasons (Strbac, 2008, p. 4420). Only few appliances allow DSM, such as washing machines, dishwashers, battery storage and heat pump systems.

1.1 Heat pumps as flexible loads

In 2014 more than 7.5 million installed heat pumps were counted in the European Union. They are used for space and domestic hot water heating and air conditioning. In Germany about 700,000 operating heat pump systems, mostly electric compressor driven, were recorded in 2014 (Nowak and Westring, 2015). The high maturity of the technology qualifies them as an energy-efficient alternative to fossil-fuelled heating boilers. The thermal-electric nature of the systems qualify heat pumps to provide a relevant potential for load-shifting and flexibility generation in Germany (Papaefthymiou, Grave, and Dragoon, 2014; Fischer et al., 2014b). Some research studies assess the flexibility of single heat pump systems in different scenarios (Hong et al., 2012a; Vanhoudt et al., 2014). Since single residential heat pumps consume only few kW electric power, many heat pumps can be aggregated. Thousands of heat pumps can be combined to one heat pump pool which allows to control an electric heat pump power in MW-scale. Some research studies assess the response of heat pump pools to price signals or electricity generation profiles (Carmo, Detlefsen, and Nielsen, 2014; Leeuwen et al., 2011; Van Pruissen, Kok, and Eisma, 2015). The knowledge of these demand-side flexibilities is highly valuable because they can be traded on the same markets like generation flexibilities.
1.2 Aims of this work

The aim of this work is to generically assess the electric flexibility of a representative heat pump pool in Germany to support aggregators or energy utilities in developing business models for flexibility trading. The major researches focus on:

- Construction of a valid model to simulate the space heating and domestic hot water demand for buildings with a stochastic approach to simulate entire building pools.
- Set-up of a valid model for the simulation of heat pump systems and pools of different heat pump systems.
- Development of a methodology to assess the flexibility of a heat pump pool in response to different external signals based on the SG Ready label and the selection of characteristic parameters for flexibility determination.
- Generic presentation of the electric flexibility of a heat pump pool in response to external signals. The aim is to support aggregators and energy utilities in developing business models to trade heat pump flexibility at energy markets.

1.3 Objectives of this work

This thesis work covers the objectives as presented in Figure 1.2.

Theoretical background
- Heat pump system analysis
- Flexibility
- External signals

Space heating and DHW model
- Space heating model
- DHW model
- Validation

Heat pump pool model
- System model
- System sizing
- Verification & Validation

Flexibility assessment
- Pool composition
- Signal definition
- Simulation
- Flexibility determination

Results & Conclusion
- Verification
- Signal comparison
- Generic presentation

Figure 1.2: Overview of this work.

The theoretical background in Chapter 2 analysis heat pump systems in Germany, discusses the flexibility term and the outcomes of existing research on flexibility and describes generally external signals and introduces the signals defined by the SG Ready label.

The space heating and DHW models are set up in Chapter 3 to generate thermal load profiles. A simplified physical model is combined with the advantages of a behavioural model. Different types of buildings and occupant groups allow a quick simulation of building pools. The model is thoroughly optimised and validated with measurement data from monitoring projects.

A model for the simulation of heat pump systems is developed and described in Chapter 4. The model contains two different heat pumps, a backup heater, space heating and DHW storages and a higher-level controller. The air and ground source heat pumps are modelled
Chapter 1. Introduction

with regressions of manufacturer data, whereas the storage model is based on an energy balance. A research on recommended system sizing procedures is carried out and a randomisation of the selected system sizing procedure for simulation of heat pump pools is introduced. The characteristic values of an exemplary heat pump pool are validated with monitoring data.

For the flexibility assessment, a representative building/heat pump-pool is defined in Chapter 5 and five external signals are selected to provoke an electric load response from the pool. Characteristic parameters for electric flexibility are determined after the simulation of the building/heat pump-pool.

Finally, the simulated load profiles in response to signals are verified and analysed in Chapter 6. First the signals are compared generally and then a generic presentation of the flexibility is presented. The conclusion in Chapter 7 discusses the main outcomes of the thesis and the future work.
Chapter 2

Theoretical background

This chapter aims to present background information on heat pump systems in Germany, discusses the flexibility term in general and analysis existent research on heat pump flexibility assessment. In the last section, adequate signals to provoke flexibility of an electric-driven heat pump pool are discussed.

2.1 Heat pump system analysis

More than 700,000 heat pumps were operated in Germany in 2014. An average of about 70,000 heat pumps per year were installed in the last seven years (Nowak and Westring, 2015, p. 88). The distribution of heat pump types in different building types in Germany is analysed and presented in Figure 2.1. The analysis focuses on heat pumps which were installed after the introduction of the SG Ready label in 2013 (see Section 2.3). The distribution of heat pumps in different building types was analysed in Platt, Exner, and Bracke (2010, p. 41). 88% of the heat pumps were installed in single family houses (SFH) in 2010, 10% in terraced houses (TH) and 2% in multifamily houses (MFH). Gorris and Jacob (2013, p. 42) predicted that between 75 and 85% of heat pumps would be installed in new buildings until 2016 and respectively 15 to 25% in existing refurbished houses. The percentage range occurs due to two scenarios of market development. The share of heat pumps in refurbished houses was much higher in the past and reached a maximum of 80% in 1997. The share of air source heat pumps is increasing since 2000 and reaches a share of about 70% in comparison to 23% of ground source and 7% of ground water source heat pumps (Gorris and Jacob, 2013, p. 35).

2.2 Flexibility

Flexibility is a widely used term, in general defined by the Oxford advanced learner’s dictionary as

"the ability to change to suit new conditions or situations".\(^1\)

This definition can be transferred to the flexibility definition in the context of demand-side energy management. It is the ability to modify the energy generation or consumption of a

---

\(^1\)http://www.oxforddictionaries.com/definition/learner/flexibility, accessed on 12th February 2016
system in response to external signals specified by markets or market members (Eurelectric, 2014; Council of European Energy Regulators, 2013, p. 5). Papaefthymiou, Grave, and Dragoon (2014, p. 1) state that flexibility is a measure of the capability of power systems to maintain system stability. Demand-side flexibility can support energy system balancing especially for a short-term consideration. Peak-shaving and trading flexibilities at balancing power markets are two suitable applications.

Many technologies are able to provide flexibility, including centralised power plants, de-centralised power supply, energy storages and demand-side devices. While large energy supply or demand system can trade flexibility individually, smaller costumers are not able to participate in flexibility markets because of high barriers or lack of expertise. Aggregation is a function of the market to trade the flexibility of many de-centralised customers (Eurelectric, 2014, p. 5), often referred to as pool. Aggregators are intermediary market players and offer services to trade the flexibility of smaller customers. They play an important role for the complexity of energy markets.

### 2.2.1 Heat pumps and flexibility

Heat pumps provide significant flexibility to power systems, while offering an efficient technology according to Papaefthymiou, Grave, and Dragoon (2014, 24f.). The maximum period for load shifting shall be up to 24 hours, depending on the thermal mass of the building. A major advantage is the maturity of the heat pump technology and the fact that heat pumps are widely spread. Many scientific papers pick up the issue of heat pump flexibility assessment or demand-side management.

Some researches focus on the impact of single or a pool of heat pumps on electric grids. Nabe et al. (2011, 10f.) for instance show the influence of heat pump flexibility on demand-side management in three scenarios. The potential analysis values flexibility by determining the reduction of variable costs and CO$_2$ savings. Further it determines positive and negative balancing power in GW as annual means in years 2020 and 2030. Bhattarai et al. (2014) evaluated flexibility of a heat pump pool by simulating the power and voltage at
the distribution transformer. Carmo, Detlefsen, and Nielsen (2014, p. 1696) assessed the flexibility of an electric grid with high renewable energy penetration by introducing a wind friendliness indicator. The latter expresses the ability of heat pumps to absorb power of the supply system (wind power plant). Vanhoudt et al. (2014, 537f.) investigates a single heat pump and its impact on the generation profile of locally produced electricity.

Fischer et al. (2014b) set up a pool of air source heat pumps, which was defined to cover 10% of the German national heat load. Fischer et al. presented the flexibility potential to balance wind and solar power in two ways. At first, the mean shifted heat pump load per day in GWh for each month of the year. Second the ratio of the mean shifted load per day to the mean electric heat pump demand per day. Van Pruissen, Kok, and Eisma (2015) analysed a virtual power plant (VPP) with 150 domestic heat pumps in the Netherlands towards peak-shaving and system balancing. During the study a VPP was operated for then months and a coordination mechanism was introduced to optimize the VPP load for a near-by wind farm. It quantifies the average flexible power per month in kW and the share of heat pumps responding to the system balancing signals.

Other researches aim for a more generic representation of flexibility. Hong et al. (2012a, 10f.) investigated the flexibility potential of different heat pump systems and two building types. The flexibility is determined in hours of maximal advance of heat pump operation. Leeuwen et al. (2011, 4f.) made an analysis on the load-shifting of heat pump systems with a thermal storage. A pool of 160 heat pumps according to a typical Dutch neighbourhood in the year 2020 was assessed during an entire year. Flexibility is defined as the load shift in kWh per day provoked by a switching off signal. It is presented ambient temperature dependent and as average daily load shift for the months of the year.

2.2.2 Flexibility parameters

Adequate parameters for the determination of energy system flexibility are essential. An overview of parameters defined by the pan-European electricity association Eurelectric and the renewable energy consultancy company Ecofys GmbH are shown in Table 2.1. Huber, Dimkova, and Hamacher (2014, p. 236) name ramp magnitude and frequency and the response time to measure the flexibility of a power system. The paper states that a "trinity of ramp rate, power and energy" is a commonly used mean to describe flexibility. Lund et al. (2015, p. 787) found that the definitions of flexibility and the appropriate parameters can differ between the types of energy systems. This statement is supported by the parameters stated in Table 2.1.

As described the parameters to describe flexibility must be defined individually for each energy system. The literature review on heat pump flexibility above showed that most of the literature assesses heat pump flexibility in special scenarios. These can be local, regional or national grids with renewable energy penetration or the response to real price signals. Little research was done on generic approaches to determine the flexibility of heat
Table 2.1: Characteristic parameters of flexibility defined in general (Eur-electric, 2014) and for energy storages (Papaefthymiou, Grave, and Dragoon, 2014)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Eurelectric</th>
<th>Ecofys</th>
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<tbody>
<tr>
<td>Amount of power modulation</td>
<td>Reaction time</td>
<td>Charging / discharging capacity</td>
</tr>
<tr>
<td>Duration</td>
<td>Duration</td>
<td>Full cycle efficiency</td>
</tr>
<tr>
<td>Rate of change</td>
<td>Duration</td>
<td>Maximum period of shifting</td>
</tr>
<tr>
<td>Response time</td>
<td>Duration</td>
<td>Storage content</td>
</tr>
<tr>
<td>Location</td>
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pump pools as response to different signal types. Widely used parameters of flexibility are shifted load or flexible power. These values are often daily means dependent on the ambient temperature or average daily means per month. Other studies present the ability to balance intermittent power generation with self-defined indicators.

2.2.3 Degrees of freedom

In order to provoke flexibility in heat pump systems the degrees of freedom are of major importance. They allow the alteration of the conventional system operation. A literature review was carried out on heat pump and other thermal systems to analyse degrees of freedom used in existing research. The review showed that the room temperature set point as well as the DHW and/or the space heating storage temperatures are common degrees of freedom (see Table 2.2). Most of the research studies allow the alteration of the room temperature set point up to ±3 K (Hong et al., 2012b). That alteration offers flexibility for heat pump systems without storages and increases flexibility of systems with storages. 8 of 15 papers investigated flexible thermal energy storages. A combination of storages and room temperature set point activation has the highest potential to provide flexible power over a preferably long time. Two studies set up systems with modulating heat pumps which provide an additional degree of freedom - the heat pump power. One research integrated electric backup heaters into the flexibility assessment which offer additional power to be switched on or off.

2.3 External Signals

Effective external signals are required to alter electric heat pump consumption in response. Time-based rates and incentive-based signals are two common forms of signals (Council of European Energy Regulators (2013, 18ff.), Palensky and Dietrich (2011, p. 382)). Price-based signals provoke flexibility explicitly by dynamic price tariffs. They represent the alteration of electricity costs. Customers have the possibility to shift their electric demand to times of lower prices.

Incentive-based signals are implicit and provoke flexibility through programmed events.
Chapter 2. Theoretical background

Table 2.2: Degrees of freedom for heat pump and other thermal systems in literature.

<table>
<thead>
<tr>
<th>Research paper</th>
<th>HP type</th>
<th>room set temp.</th>
<th>SH storage temp.</th>
<th>DHW storage temp.</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bhattarai et al. (2014)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td>Focus on thermal building mass</td>
</tr>
<tr>
<td>Ellerbrok (2014)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fischer et al. (2014b)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hong et al. (2012a)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hong et al. (2012b)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Klaassen et al. (2015)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td>Two scenarios</td>
</tr>
<tr>
<td>Leeuwen et al. (2011)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td>Source pump control</td>
</tr>
<tr>
<td>Miara et al. (2014)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td>Electric backup heater</td>
</tr>
<tr>
<td>Nabe et al. (2011)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pedersen, Nielsen, and Andersen (2014)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vanhoudt et al. (2014)</td>
<td>On/Off</td>
<td>•</td>
<td></td>
<td></td>
<td>Introduction of degree minutes</td>
</tr>
<tr>
<td>Dar et al. (2014)</td>
<td>modul.</td>
<td>•</td>
<td></td>
<td></td>
<td>Two system setups</td>
</tr>
<tr>
<td>Van Pruissen, Kok, and Eisma (2015)</td>
<td>modul.</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hao et al. (2015)</td>
<td>-</td>
<td>•</td>
<td></td>
<td></td>
<td>Generalised battery model</td>
</tr>
<tr>
<td>Vanthournout et al. (2012)</td>
<td>-</td>
<td>•</td>
<td></td>
<td></td>
<td>Smart DHW storage</td>
</tr>
</tbody>
</table>

A variety of different incentive-based programmes are possible such as direct control of electric loads or demand response for emergency situations. One very common incentive-based signal regarding German heat pumps is the demand of blocking hours as explained in Section 4.2.1.

Dependent on the communication technology any signal can be transferred to heat pump devices. The German association of heat pumps set up 4 different signals to control heat pumps remotely in smart grids (Koch, 2013). Heat pumps, equipped with a controller covering the operation states according to the 4 signals, receive the so-called SG Ready label. The 4 states are defined as follows:

1. The heat pump is switched off. This operation state is compatible to 2 blocking hours.
2. The heat pump runs in the energy efficient conventional mode.
3. The heat pump operation for space heating and DHW is intensified. It is not actively switching on but suggesting to switch on within the temperature boundaries of the storages.
4. The heat pump is actively switched on if possible. Different options shall be available:
(a) The heat pump (compressor) is actively switched on.

(b) The heat pump (compressor) and electric backup heater are switched on, optional: increased storage temperatures.

Signals can not only differ by type but also by duration and frequency. Most of the research on flexibility in Section 2.2.1 is based on continuous price signals which are interpreted by the heat pump control algorithms. Incentive-based signals have usually a certain length when sent to demand response devices. The signal frequency and duration are dependent on the aim of the demand response event.
Chapter 3

Domestic hot water and space heating models

This chapter presents the model for the generation of thermal load profiles and validation results, visual mining of measurement data and the validation methods.

3.1 Overview of the model

Correctly modelling thermal load profiles is important, since 83% of the energy consumed in German households is used for space heating and DHW generation (Statistisches Bundesamt, 2014). Thermal load profiles of buildings and urban areas allow improvements in heating system sizing and the optimisation of district heating networks. The DHW demand model is based on a behavioural model, statistical data sets (Eurostat, 2000) and tapping data (Verein Deutscher Ingenieure, 2000). The space heating demand profiles are generated by using a physical 5R1C-Network model (Deutsches Institut fuer Normung, 2008) which was improved with data from the behavioural model. The validation is carried out with measurement data of monitored heat pump systems. While the DHW load profiles are additionally validated with reference load profiles, the space heating demand profiles are cross-validated with the monitoring data. The validation yields that the models are correctly simulating thermal load profiles for single houses. For aggregations of houses the thermal load profiles show smoothing effects, induced by the behavioural model based on statistical data. The validation of the model is further described in Section 3.2.

Appendix A contains a paper which discusses the DHW and space heating models in detail. The applied methodology, the two models and the results of the model validations are presented. The paper was submitted to Elsevier for review in December 2015.

3.2 Model validation

The space heating and DHW models are validated with measurement data to determine the model quality. The statistical values for the validation are presented. An introduction to and the selection of correct measurement data are described afterwards.
3.2.1 Statistical values

For the evaluation of the profiles annual sums, annual peaks, the correlation towards the mean profile and the root mean square error \((RMSE)\) are determined. Müller-Benedict (2011) defines correlation as the coherence between data sets and a target data set. Usually the Pearson-Bravais correlation is used, which is calculating the standardised coherence between the two data sets as:

\[
r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} = \frac{s_{xy}}{s_x s_y} \quad [-]\quad (3.1)
\]

where \(x\) is the value of the target and \(y\) the value of the comparing data set. The correlation is zero for no coherence and 1 or -1 for perfect positive or negative coherence.

\(RMSE\) is a measure that shows the difference between the values of a model and measurement data. It aggregates the model prediction errors for a series of data and yields a single value of quality. For the comparison of different model predictions with a measurement data set the \(RMSE\) provides a good accuracy. Nonetheless it cannot be applied to compare several models with various measurement data because the \(RMSE\) is scale-dependent and has the unit of the data. It is calculated as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{\text{mod},i} - y_{\text{mon},i})^2}{n}} \quad \text{[unit of } y\text{]} \quad (3.2)
\]

where \(y_{\text{mod}}\) are the modelled and \(y_{\text{mon}}\) are the monitored values for \(n\) predictions.

3.2.2 Measurement data

The space heating and DHW models are validated with measurement data from the WP-Effizienz and WP Monitor projects, carried out by the Fraunhofer ISE (Miara et al., 2014). The aim of these projects was the individual monitoring and analysis of heat pump systems at real field conditions. 87 heat pump systems were monitored for 3 heating periods. Many of the measurement data sets include records of the space heating demand and a few amount of data sets contain the DHW demand. 22 measurement data sets of 1 monitored year were provided by the responsible research team. Data mining was used to select correct data sets.

3.2.3 Data mining

Data mining is a metaphor for a systematic method to identify correct data sets in a big data pool of unknown quality according to Hastie, Tibshirani, and Friedman (2009). Automatically recorded data is often available with all the parameters and errors which occurred during the monitoring process. The aim of visual data mining is to include human beings in the data mining process by displaying and evaluating the initial data, the preliminary and final results. The most important and most commonly used data mining
techniques are classification, clustering, time series analysis and association rules. During the classification a set of training data is analysed and a model is derived, which meets the distinctive features of the classes. Clustering describes the analysis and identification of the data structures. A cluster is a set of data which shows a certain degree of similarity. The association aims to figure out connections and correlations between different attributes of big data sets. The attributes must be identified first and association rules are derived between the attributes afterwards.

For the space heating cross validation, 21 profiles with the data of space heating load were available. They were analysed visually with monthly average plots, average daily profiles, annual duration curves and heat maps. The visual data mining was used to sort out space heating profiles with measurement gaps, measurement errors and non-typical heating patterns. In addition, data sets with a night reduction for space heating are sorted out. The available data sets were classified into two groups, one for desired data sets and one for undesired data sets. One exemplary data set of each is visualised in Figure 3.1. Figure 3.1a shows a data set with a non-typical heating pattern. Space heating is only switched on during certain times of the day, in the morning and evening hours. It is blocked for the other hours of the day which does not match the expected heating pattern which is ambient temperature dependent.

![Exemplary profile with non-typical heating pattern](image1.png)  ![Exemplary profile with typical heating pattern](image2.png)

(a) Exemplary profile with non-typical heating pattern. (b) Exemplary profile with typical heating pattern.

Figure 3.1: Heat maps of space heating demand for visual data mining.

The heat map of a data set with a typical heat pattern is displayed in Figure 3.1b. The heat map shows high space heating demand during the night and low demand during the day, which is caused by the natural alteration of ambient temperatures. In summer, from day 160 to 260 or June to September respectively, days are mostly without space heating. The visual data mining yielded 15 desired and 6 undesired load profiles.

The computed statistical values of 5 exemplary data sets in Table 3.1 show the variety of different heating profiles. The annual sums of the data sets range from 6,500 to 28,700 kWh and the maximum hourly value from 2.5 to 7.5 kW. The correlation for the annual duration curves of the individual data sets with the mean of all data sets is strong and
shows that the profiles bear the correct characteristic demand curves. The correlation between the profiles varies between 0.54 and 0.83. These correlation values indicate a strong relationship between the data sets. Nonetheless the similarity of the data is not too strong. It can be seen from the annual peak value that the profile course of the mean data set is smoother than the individual data sets.

Table 3.1: Selected statistical data for space heating data mining

<table>
<thead>
<tr>
<th></th>
<th>Annual sum</th>
<th>Annual peak</th>
<th>Daily profile correlation</th>
<th>RMSE</th>
<th>Duration curve correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[kWh]</td>
<td>[kW]</td>
<td>[-]</td>
<td>[kW]</td>
<td>[-]</td>
</tr>
<tr>
<td>mean data set</td>
<td>13,569</td>
<td>3.8</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>data set 1</td>
<td>11,826</td>
<td>6.3</td>
<td>0.57</td>
<td>1.00</td>
<td>0.86</td>
</tr>
<tr>
<td>data set 2</td>
<td>28,669</td>
<td>5.1</td>
<td>0.72</td>
<td>1.09</td>
<td>0.98</td>
</tr>
<tr>
<td>data set 3</td>
<td>6,530</td>
<td>5.2</td>
<td>0.54</td>
<td>0.73</td>
<td>0.89</td>
</tr>
<tr>
<td>data set 4</td>
<td>17,846</td>
<td>2.5</td>
<td>0.78</td>
<td>1.36</td>
<td>0.97</td>
</tr>
<tr>
<td>data set 5</td>
<td>20,013</td>
<td>7.5</td>
<td>0.83</td>
<td>2.58</td>
<td>0.88</td>
</tr>
</tbody>
</table>

3.3 Cross validation

Many methodologies for model validation are known in statistical data mining. Cross-validation is a widely used and simple method for the estimation of prediction errors according to Hastie, Tibshirani, and Friedman (2009). For this validation method the observed data is split into two or more parts. The first part is used for model training, while the second part is used to compute the quality of the model prediction. Cross-validation was not used for the DHW model, since only 6 correct data sets were available. Instead, the DHW model was validated with reference load profiles as described in Appendix A (7f.).

The cross-validation is solely used for the space heating model. Therefore 5 of 15 space heating measurement data sets are randomly selected and used for the model training. Adjustments were made to improve the basic model, which consisted of physical and behavioural model parts. The other 10 measurement data sets of good quality are used for the validation of the model. The resulting plots and statistic values can be found in Appendix A (8ff.).
Chapter 4

Heat pump pool model

A verified and validated heat pump pool model is set up in this section. The five-step methodology to obtain a heat pump pool model is shown in Figure 4.1. The models for single heat pump systems are described first. Based on literature and manufacturer guidelines the recommended sizing of heat pump systems is explained. Then, the correct operation of the model is verified and two heat pump pools which are simulated with the recommended sizing procedure are validated. The validation shows the need of a randomised system sizing for the simulation of heat pump pools, which is introduced in the fourth step. Finally, the validation of a simulated pool with randomised system sizing is described.

![Figure 4.1: Methodology to set up an heat pump pool model.](image)

4.1 Heat pump system models

Two models were implemented to simulate the operation of heat pump systems. One simplified model for a 30 kW air source heat pump was set up during a Bachelor thesis (Scherer, 2014). This section aims to obtain two new representative models of air and ground source heat pumps. Space heating and domestic hot water (DHW) load profiles as presented in Chapter 3 are utilised. The major strength of the model is a quick configuration and the simulation of demand profiles not only for individual buildings but also for entire neighbourhoods or residential areas. The simplification allows fast simulation times, but show high accuracy as will be shown in Section 4.5.

The introduced heat pump systems consist of solely one electric heat pump or one heat pump with an electric backup heater, two separate storage tanks for DHW and space heating and a higher-level control system. A typical system diagram is shown in Figure 4.2. The system with two storage tanks in parallel is chosen with the help of a selection matrix,
which was developed during a research project regarding a step-by-step method for the design of small heat pump systems (Scherer, 2014, p. 36). Dependent on one or two heat sources the system model is called monovalent-parallel or bivalent-parallel. The models for heat pump, storages and the controller are introduced in the following sections.

4.1.1 Heat pumps

Many different heat pump technologies with compression, absorption and adsorption are available on the heat pump market. They are powered either by heat, gas or electricity and generate thermal power. Two heat pump models for electric compressor heat pumps were implemented by Scherer (2014, p. 39). Both are equipped with on-off compressors but have different heat sources (air and ground). Despite the similarity of the two models, some differences occur.

The characteristic values of the heat pumps are modelled with linear regressions based on manufacturer’s data. The performance is described as generated thermal power $\dot{Q}_{HP}$. The efficiency is expressed as the coefficient of performance ($COP$). Thermodynamically the $COP$ is the ratio between the generated thermal power and the consumed electric power $P_{HP}$ at one operation point and calculated as:

$$COP = \frac{\dot{Q}_{HP}}{P_{HP}}$$  \hspace{1cm} (4.1)

The regressions for the generated thermal power and $COP$ are temperature dependent. While the linear regression for the thermal power is dependent on the heat source temperature such as the ground source or the ambient temperatures, the quadratic regression for the $COP$ is directly influenced by the temperature difference $\Delta T$ between the heat source
and the supply side. The regression formulas are:

\[
\dot{Q}_{HP} = a_0 + a_1 T_{HP, src} \quad [\text{kW}] \quad (4.2a)
\]

\[
\Delta T = T_{HP, sup} - T_{HP, src} \quad [\text{K}] \quad (4.2b)
\]

\[
\text{COP} = b_0 + b_1 \Delta T + b_2 \Delta T^2 \quad [-] \quad (4.2c)
\]

where \(a_0, a_1, b_0, b_1\) and \(b_2\) are the coefficient letters of the linear and quadratic regressions, \(T_{HP, sup}\) is the supply water temperature of the heat pump and \(T_{HP, src}\) the heat source temperature.

The source temperature for the two heat pump models must be obtained. The ambient temperature for the air source heat pump model is given by the climate data that was used for the thermal load profile generation.

The ground source heat pump requires the temperature for the geothermal brine water or groundwater. As shown in Miara et al. (2014, 112ff.) the temperature varies during the year. Miara’s analysis of 33 systems with geothermal probes yielded a mean annual temperature \(\bar{T}_{probe}\) of about 4 °C. The average temperature amplitude \(\Delta T_{probe}\) is 4 K during one year and fluctuates sinusoidal. Thus a sinusoidal function was developed to model the ground source temperature. The minimum of the function is shifted to the day of the lowest ambient temperature \(n_{day(T_{min})}\), following the ground temperature determination methodology of Kusuda and Archenbach (1965, 12f.). The ground source temperature \(T_{HP, src}\) for each day of the year is calculated as:

\[
T_{HP, src}(day) = \bar{T}_{probe} - \Delta T_{probe} \cos \left( \frac{2\pi}{n_{days}} (day - n_{day(T_{min})}) \right) \quad [\text{°C}] \quad (4.3)
\]

where \(n_{days}\) is the number of days for the simulated year.

As described, the thermal power and performance of the heat pumps are based on linear regressions from Stiebel Eltron heat pumps. The linear regression curves for the air source heat pump (ASHP) are taken from the heat pump model WPL10AC (Stiebel Eltron, 2013, 150ff.) with 5.11 kW nominal heat power at A-7/W35 (air source (A) and supply water (W) temperature). The regression for the ground source heat pump (GSHP) is based on the model WPF10 (Stiebel Eltron, 2013, 244ff.) with 10.4 kW nominal heat power at B0/W35 (brine source (B) and supply water (W) temperature). The linear regression lines for the two heat pumps are shown in Figure 4.3. The thermal power regressions are shown in dependence of the source temperatures in Figure 4.3a, while Figure 4.3b presents the coefficient of performance dependent on the temperature difference \(\Delta T\) (see Equation 4.2). The parameters for the regression lines can be found in Table 4.1.
Chapter 4. Heat pump pool model

4.1.2 Storages

Thermal storages satisfy different tasks such as improving heat pump run-times, bridging blocking hours and reducing peak heat loads for space heating and DHW. The storage model is based on an energy balance described in Toral (2013, 41ff.). Two separate storages for space heating and DHW are assumed, thus detailed calculations of combined stratified storages can be neglected. The state-space representation is calculated as:

$$\dot{x} = Ax + Bu + Ez$$  \hspace{1cm} (4.4)

where the states $x$ represent the mean temperatures of the two storages, $u$ the thermal input powers of the storages and $z$ the thermal deviations through the DHW and space heating loads and the storage losses. The full numerical equation is:

$$
\begin{bmatrix}
T_{DHWS}(t) \\
T_{SHS}(t)
\end{bmatrix} =
\begin{bmatrix}
-\frac{\kappa_{SA_{DHWS}}}{C_{DHWS}} & 0 \\
0 & -\frac{\kappa_{ST_{SHS}}}{C_{SHS}}
\end{bmatrix}
\begin{bmatrix}
T_{DHWS}(t) \\
T_{SHS}(t)
\end{bmatrix}
$$

$$+
\begin{bmatrix}
-\frac{1}{C_{DHWS}} & 0 \\
0 & -\frac{1}{C_{SHS}}
\end{bmatrix}
\begin{bmatrix}
Q_{HP,DHW}(t) \\
Q_{HP,SH}(t) \\
Q_{BH,DHW}(t) \\
Q_{HP,SH}(t)
\end{bmatrix}
$$

$$+
\begin{bmatrix}
-\frac{1}{C_{DHWS}} & \frac{\kappa_{SA_{DHWS}}}{C_{DHWS}} \\
0 & \frac{\kappa_{SA_{SP}}}{C_{SHS}} - \frac{1}{C_{DHWS}}
\end{bmatrix}
\begin{bmatrix}
Q_{DHW}(t) \\
T_{env} \\
Q_{SH}(t)
\end{bmatrix}
$$

4.1.2 Storages

Thermal storages satisfy different tasks such as improving heat pump run-times, bridging blocking hours and reducing peak heat loads for space heating and DHW. The storage model is based on an energy balance described in Toral (2013, 41ff.). Two separate storages for space heating and DHW are assumed, thus detailed calculations of combined stratified storages can be neglected. The state-space representation is calculated as:

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$$
\begin{bmatrix}
T_{DHWS}(t) \\
T_{SHS}(t)
\end{bmatrix} =
\begin{bmatrix}
-\frac{\kappa_{SA_{DHWS}}}{C_{DHWS}} & 0 \\
0 & -\frac{\kappa_{ST_{SHS}}}{C_{SHS}}
\end{bmatrix}
\begin{bmatrix}
T_{DHWS}(t) \\
T_{SHS}(t)
\end{bmatrix}
$$

$$+
\begin{bmatrix}
-\frac{1}{C_{DHWS}} & 0 \\
0 & -\frac{1}{C_{SHS}}
\end{bmatrix}
\begin{bmatrix}
Q_{HP,DHW}(t) \\
Q_{HP,SH}(t) \\
Q_{BH,DHW}(t) \\
Q_{HP,SH}(t)
\end{bmatrix}
$$

$$+
\begin{bmatrix}
-\frac{1}{C_{DHWS}} & \frac{\kappa_{SA_{DHWS}}}{C_{DHWS}} \\
0 & \frac{\kappa_{SA_{SP}}}{C_{SHS}} - \frac{1}{C_{DHWS}}
\end{bmatrix}
\begin{bmatrix}
Q_{DHW}(t) \\
T_{env} \\
Q_{SH}(t)
\end{bmatrix}
$$

Figure 4.3: Linear regressions for air (ASHP) and ground source (GSHP) heat pumps.

Table 4.1: Parameters for linear heat pump regressions.

<table>
<thead>
<tr>
<th>HP type</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASHP</td>
<td>5.80</td>
<td>0.21</td>
<td>5.06</td>
<td>-0.05</td>
<td>0.00006</td>
</tr>
<tr>
<td>GSHP</td>
<td>9.37</td>
<td>0.30</td>
<td>10.18</td>
<td>-0.18</td>
<td>0.0008</td>
</tr>
</tbody>
</table>
where:

- \( T_{DHW_S}(t) / T_{SHS}(t) \): change of medium storage temperatures at time step (t) in K
- \( \kappa_S \): specific storage loss in kW m\(^{-2}\) K
- \( A_{DHW_S} / A_{SHS} \): surface area of the storages in m\(^2\)
- \( C_{DHW_S} / C_{SHS} \): heat capacity of the storages in kJ K
- \( T_{DHW_S}(t) / T_{SHS}(t) \): storage temperatures at time step (t) in K
- \( Q_{HP,DHW}(t) / Q_{HP,SH}(t) / Q_{BH,DHW}(t) / Q_{BH,SH}(t) \): thermal power of HP and BH at time step (t) in kW
- \( Q_{DHW}(t) / Q_{SH}(t) \): thermal loads at time step (t) in kW
- \( T_{env} \): temperature of the storage environment in K.

### 4.1.3 Controller

The controller of the heat pump is based on an unsteadily operating on-off controller. It compares the actual with the desired temperature and switches a device on or off. A hysteresis is introduced to avoid frequent switching. The heat pump is switched on by the lower boundary and switched off by the upper boundary of the storage temperatures.

The backup heater is controlled separately and is switched on when the heat pump power is not sufficient. It is usually blocked for ambient temperatures above the bivalence point (see Section 4.2.1). Apart from the storage charging algorithms the controller assures a minimal heat pump run-time of 6 minutes (Dimplex, 2015) and a minimal pause-time of 3 minutes. These are needed to guarantee a safe heat pump operation and to avoid damage to the compressor.

The temperature limits of the storages are determined as follows. The lower temperature boundary for the DHW storage is set by the DHW temperature analysis of Miara et al. (2014, p. 59). It yields mean DHW storage temperatures between 42.2 and 49.9 °C. The lower temperature boundary \( T_{DHW,lb} \) is set to 45 °C and a hysteresis of 7.5 Kelvin is chosen which sets the upper temperature boundary \( T_{DHW,ub} \).

The lower temperature boundary for the space heating storage \( T_{SH,lb} \) is set by heating curves which were defined during the GreenHP project and explained by Fischer et al. (2014a, p. 34). Heating curves are functions to calculate the supply temperature dependent on the ambient temperature. The storage hysteresis is set to 5 K in compliance with the analysis of Miara et al. (2014) and defines \( T_{SH,ub} \). The initial temperatures of the DHW and space heating storages are set to the respective mean values of the lower and upper temperature boundaries.

The backup heater control is prioritising the DHW storage charging over the space heating storage charging. At storage temperatures of 2 K below the lower temperature boundary,
the backup heater power $Q_{BH}$ is set to the maximum. If the storage temperature increases above the lower temperature boundary, $Q_{BH}$ is reduced to half of the maximum power. The backup heater is switched off above the upper storage temperature boundary.

An overall condition is that the backup heater is blocked for ambient temperatures above the bivalence point, except of two cases: parallel demand of the storages and storage temperatures that drop too low. The first case leads to rapidly decreasing storage temperatures, thus the $Q_{BH}$ is set to the maximum. In the latter case, the controller sets $Q_{BH}$ to the maximum for storage temperatures of 5 K below the lower temperature boundary.

A graphical overview of the backup heater algorithm can be found in Appendix B.

### 4.2 Recommended system sizing

The sizing of the heat pump system components is directly influencing characteristic values like seasonal performance factor ($SPF$), full load hours and average heat pump cycles per day. This section describes the recommended sizing for heat pump, backup heater and storages.

#### 4.2.1 Heat pumps

The correct sizing of the heat pumps is of major significance for an energy-efficient operation of the heating system. Some heat pump systems consist of the heat pump as the single heat source, thus it’s called a monovalent system. Other heat pump systems consist of the heat pump and an integrated or external electric backup heater for peak load supply. These systems reduce the size of heat pumps and are called bivalent or mono-energetic, since two different heating technologies with the same energy source are used. A mono-energetic system requires a careful sizing process.

For this thesis work, viable sizing procedures were derived from system design and installation manuals of German heat pump manufacturers. The sizing process for heat pump and backup heater is graphically shown in Figure 4.4 according to Buderus (2012), Stiebel Eltron (2013) and Viessmann (2011). The heat pump size is dependent on the heating loads of the building.

Figure 4.4 shows the determination of the heating load $\dot{Q}_{HL}$ for the sizing of mono-energetic or bivalent heat pumps. $\dot{Q}_{HL}$ is calculated as:

$$\dot{Q}_{HL,biv} = f_{\text{block}}(\dot{Q}_{SH}(T_{\text{biv}}) + \dot{Q}_{DHW,nom}) \quad [\text{kW}] \quad (4.6)$$

where $\dot{Q}_{SH}$ is the space heating load at nominal ambient temperature $T_{nom}$ or bivalence temperature $T_{\text{biv}}$, $\dot{Q}_{DHW,nom}$ the nominal domestic hot water load and $f_{\text{block}}$ the blocking hours factor. The nominal space heating load for the sizing of monovalent systems without
a backup heater is calculated as:

$$Q_{HL,nom} = f_{block}(Q_{SH}(T_{nom}) + Q_{DHW,nom}) \quad [\text{KW}] \quad (4.7)$$

The determination of the single parameters of Equations 4.6 and 4.7 is described in this section. The nominal ambient temperature is a standardised minimal temperature for a geographical location or climate region in Germany and defined in the annex of Deutsches Institut fuer Normung (2003). The standard also provides the calculation of the nominal space heating load $Q_{SH}(T_{nom})$ which is the heating load of a building at the nominal ambient temperature. The standardised calculation of the nominal space heating load follows Deutsches Institut fuer Normung (2003). Stiebel Eltron (2013) suggests a method for estimated space heating load determination by the specific heating load per m$^2$.

For sizing of monoenergetic heat pump systems the bivalence point or bivalence temperature $T_{biv}$ must be defined. It allows the operation of a heat pump with an electric backup heater. Above the bivalence temperature the heat pump is the only heating, while below that temperature the backup heater is switched on. The selection of higher bivalence temperatures results in a higher backup heater energy share of the annual heating demand. Different temperature ranges between -10 °C and -2 °C are shown in literature as summarized in Table 4.2. Buderus (2013, p. 48) suggests a bivalence temperature of -5 °C for good sizing and a heat pump energy share $\eta_{HP}$ of about 98%. Viessmann (2013a, p. 87) states that $\eta_{HP}$ share should not fall under 95%. For the calculation of the maximal heating load the nominal DHW demand $Q_{DHW,nom}$ must be considered to cover a possible double demand of space heating and DHW. The nominal DHW load is calculated by a specific DHW load in kW per person, defined as $q_{DHW}$. It ranges from 0.08 to 0.30 kW per person according to Viessmann (2013a, p. 87) and 0.2 kW/person is a mean value.
found in Buderus (2013, p. 41). The nominal DHW demand is then calculated as:

$$Q_{DHW,nom} = q_{DHW,n} \text{persons} \quad [\text{kW}] \quad (4.8)$$

where $n_{\text{persons}}$ are the number of occupants in the building. They can be given or calculated as:

$$n_{\text{persons}} = \frac{Q_{DHW}}{q_{DHW,p.a.}} \quad [-] \quad (4.9)$$

where $Q_{DHW}$ is the annual DHW demand in kW and $q_{DHW,p.a.}$ the annual DHW demand per person in kW. $q_{DHW,p.a.}$ ranges between 380 and 720 kWh per person in accordance with Verein Deutscher Ingenieure (2000, p. 10).

The factor $f_{\text{block}}$ is introduced to increase the heating load artificially for the compensation of heat pump blocking hours. They are a restriction of special electricity heat pump tariffs with lower prices per kWh. Heat pumps in Germany are usually fed with these tariffs, which allow electricity utilities and aggregators to switch off heat pumps up to 3 times a day for a maximum of two hours. The blocking hours factor is calculated with the number of blocking hours per day $n_{\text{block}}$ as:

$$f_{\text{block}} = \frac{24h}{24h - n_{\text{block}}} \quad [-] \quad (4.10)$$

Equation 4.6 and Equation 4.7 yield the heating load which needs to be covered by the heat pump. For mono-energetic systems, the power of the electric backup heater is determined as follows.

### 4.2.2 Backup heater

The nominal backup heater power $Q_{BH,nom}$ is determined by the difference between the nominal heating load of the building $Q_{HL,nom}$ and the heat pump power at the nominal ambient temperature $Q_{HP}(T_{nom})$ as shown in Figure 4.4 and expressed as:

$$Q_{BH,nom} = Q_{HL,nom} - Q_{HP}(T_{nom}) \quad [\text{kW}] \quad (4.11)$$
4.2.3 Storages

Two storages are implemented in the monovalent-parallel and bivalent-parallel models, one for DHW and one for space heating. The sizing procedures for the storages is different and is based on manufacturer’s system design guidelines and manuals as well as additional literature.

**Domestic hot water**

DHW storages provide hot water for the kitchen sink, washbasins, shower and other sanitary appliances in the building and are maintained at the set point temperature. The volume size of DHW storages is mainly influenced by the maximum hot water demand of the building, which is dependent on the number of occupants $n_{\text{persons}}$. If $n_{\text{persons}}$ is known, the storage volume can be calculated by two different methods. The first one is based on the average hot water demand $\dot{v}_{\text{DHW}}$ per person and day in litres. Gassel (1999, p. 44) provides measurement values, which range between 26 and 54 l/dperson. The German engineering association suggests values of $\dot{v}_{\text{DHW}}$ between 31 and 59 l/dperson (Verein Deutscher Ingenieure, 2000, p. 10), dependent on the hot water appliances of the household. The storage volume $V_{\text{DHW}}$ to cover the DHW demand theoretically for one day is then calculated as:

$$V_{\text{DHW}} = \dot{v}_{\text{DHW}} \cdot 1d \cdot n_{\text{persons}} \quad [\text{l}] \quad (4.12)$$

Another sizing procedure is based on a DHW storage sizing diagram in Recknagel, Sprenger, and Schramek (2010, p. 1559) which reduces the influence of increasing occupant numbers on the DHW storage size. The derived regression is calculated as:

$$V_{\text{DHW}} = S \cdot 64.972 \cdot \frac{l}{\text{person}}n_{\text{persons}}^{0.717} \quad [\text{l}] \quad (4.13)$$

where $S$ is the safety margin with values between 1.0 and 1.25 is introduced which is dependent on the number of building occupants. For 200 occupants a value of 1.0 is selected, while $S$ is increasing for less occupants.

**Space heating**

Three procedures for space heating storage sizing are introduced in this section. The first procedure aims to guarantee a stable heat pump operation. Viessmann (2011, p. 105) states that a minimum volume of 3 litres per kW is required in the system. It is possible to renounce the storage in floor heating systems due to the thermal inertia of the floor heating (Viessmann, 2013a, 89f.). In this case the system requires an overflow valve for minimum volume flow though.

The second procedure intends to optimize the heat pump run-times by prolonging them and reducing the number of on/off cycles. The space heating storage volume $V_{\text{SH}}$ is calculated
as:

$$V_{SH} = a_0 \dot{Q}_{HP, nom}$$ [l] (4.14)

where $\dot{Q}_{HP, nom}$ is the nominal heat pump power and $a_0$ is a specific storage volume. For runtime optimisation, $a_0$ is 20 to 25 litres per kW heat pump power (Viessmann, 2013a, 89f.).

The third procedure sizes space heating storages to cover the space heating demand during blocking hours. Two calculation methods are discussed here. The primary calculates the storage size by the heat energy which needs to be stored for the duration of blocking hours and the nominal space heating load as described in Viessmann (2013a, 89f.). Since this method yields comparably big storage sizes another sizing procedure was set up which takes the thermal inertia and the resulting decelerated cooling of the building into consideration. The space heating storage volume $V_{SH}$ is calculated as:

$$V_{SH} = a_0 \dot{Q}_{SH}(T_{nom})$$ [l] (4.15)

where $\dot{Q}_{SH}$ is between 60 and 80 litres per kW nominal space heating load in accordance with Viessmann (2013a, p. 90). Alternatively, linear regressions can be derived from storage sizes suggested in manufacturer guidelines. Stiebel Eltron recommends different sizes for radiator and floor heating systems (Stiebel Eltron, 2013). The storage volume is calculated as:

$$V_{SH} = a_0 \dot{Q}_{SH}(T_{nom}) + a_1$$ [l] (4.16)

where $a_0$ and $a_1$ are the coefficients of the regressions which are listed for radiator and floor heating systems in Table 4.3.

Table 4.3: Coefficients for linear regressions of the space heating storage volume.

<table>
<thead>
<tr>
<th>Heating system</th>
<th>$a_0$</th>
<th>$a_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor</td>
<td>28.2</td>
<td>86.9</td>
</tr>
<tr>
<td>Radiator</td>
<td>53.2</td>
<td>143.7</td>
</tr>
</tbody>
</table>

### 4.2.4 Implementation

In this section the implementation of the recommended system sizing is presented. Heat pumps, backup heater and storages are discussed.

#### Heat pumps

The determination of the nominal ambient temperature, the space heating loads and the nominal DHW load is done with synthetic thermal load profiles as discussed in Chapter 3. The load profiles provide the space heating and DHW load and the ambient temperature
during one simulation year.

The nominal ambient temperature $T_{nom}$ is determined by calculating the rounded six hour means of the ambient temperature and selecting the minimum. The respective space heating load is the nominal space heating load of the building $Q_{SH}(T_{nom})$. The space heating load at the bivalence temperature $Q_{SH}(T_{biv})$ is determined analogous. The bivalence temperature for the recommended sizing procedure is set to $-5 \, ^\circ C$ as presented in Section 4.2.1. The sizing of air source heat pumps is carried out for the heat load at the bivalence temperature, while the size of ground source heat pumps is determined for the heat load at the nominal ambient temperature.

The specific DHW load $q_{DHW}$ for the calculation of the nominal DHW load in Equation 4.8 is set to 0.2 kW per person. For the calculation of $n_{persons}$ in Equation 4.9 a mean DHW demand of 550 kWh per person is chosen.

The factor for the compensation of blocking hours in Equation 4.10 is calculated for 4 blocking hours which is a common value. In practice, 2 blocking hours can be disregarded due to the slow cooling of the building (Viessmann, 2013a, p. 86). Thus the factor $f_{block}$ is calculated and rounded to 1.1.

**Backup heater**

The electric backup heater for air source heat pump systems is sized according to Equation 4.11. Additionally, a minimum backup heater size is determined to compensate for undersized heat pumps. It is aligned with the backup heater energy share to the annual heat demand at a bivalence temperature of $-7 \, ^\circ C$ (Deutsches Institut fuer Normung, 2001, p. 73). The standard describes a backup heater size of 35 % share of the nominal heat load of the building which is implemented in the model.

**Storages**

For the determination of the DHW storage volume $V_{DHW}$, the advanced method in Equation 4.13 is selected because it avoids storage oversizing for buildings with many occupants. The safety margin $S$ in the model is dependent on the number of occupants and ranges between 1 and 1.25. The space heating storage volume is calculated by the procedure presented in Equation 4.16. It yields bigger storages for small heat pumps due to the coefficient $a_1$.

### 4.3 Model verification and validation with recommended system sizing

This section discusses at first the verification of the heat pump system model. Since this work aims for the flexibility assessment of a heat pump pool, repeated simulations
should match the characteristic values of monitored heat pump systems. The analysis of monitored systems is described and the results of the validation are presented.

4.3.1 Model verification

A single family house, build after 2002, with an air source heat pump was simulated for the exemplary verification of the model and the recommended sizing procedure. At first, the simulation yields the defined and calculated system parameters, which are displayed in Table 4.4. Heating curve index and bivalence temperature \( T_{biv} \) are set to the standard values, while the number of persons \( n_{\text{persons}} \) is calculated correctly to 4. The nominal thermal load of the system, determined from the nominal demand of space heating \( Q_{\text{SH,nom}} \) and DHW \( Q_{\text{DHW,nom}} \), is 7.2 kW. The heat pump system, sized at the nominal ambient temperature \( T_{\text{nom}} \) of -12.0 °C, provides a total thermal power of 8.6 kW at -7 °C. The share of heat pump energy from the total annual energy generation of the system is 99.3 % and shows that the sizing of heat pump and backup heater is carried out correctly. The storages show expected sizes of 53 l per person for DHW and 28.2 l per kW heat pump power for space heating with a floor heating system. The seasonal performance factor \( \text{SPF} \) is calculated to 3.5, which is expected for efficient air source heat pump systems.

Table 4.4: Characteristic data of an exemplary air source heat pump system.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating curve index</td>
<td>-</td>
<td>8</td>
</tr>
<tr>
<td>Space heating system</td>
<td>floor heating</td>
<td></td>
</tr>
<tr>
<td>( n_{\text{persons}} )</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td>( T_{biv} )</td>
<td>°C</td>
<td>-5.0</td>
</tr>
<tr>
<td>( T_{\text{nom}} )</td>
<td>°C</td>
<td>-12.0</td>
</tr>
<tr>
<td>( Q_{\text{SH,nom}} )</td>
<td>kW</td>
<td>6.4</td>
</tr>
<tr>
<td>( Q_{\text{DHW,nom}} )</td>
<td>kW</td>
<td>0.8</td>
</tr>
<tr>
<td>( Q_{\text{HP}} ) at A-7/W35</td>
<td>kW</td>
<td>5.7</td>
</tr>
<tr>
<td>( P_{\text{HP}} ) at A-7/W35</td>
<td>kW</td>
<td>1.9</td>
</tr>
<tr>
<td>( Q_{\text{BH}} )</td>
<td>kW</td>
<td>2.9</td>
</tr>
<tr>
<td>( V_{\text{SH}} )</td>
<td>l</td>
<td>180</td>
</tr>
<tr>
<td>( V_{\text{DHW}} )</td>
<td>l</td>
<td>210</td>
</tr>
<tr>
<td>( \text{SPF} )</td>
<td>-</td>
<td>3.5</td>
</tr>
<tr>
<td>( \eta_{\text{HP}} )</td>
<td>%</td>
<td>99.3</td>
</tr>
</tbody>
</table>

The simulation output provides the calculated storage temperatures, thermal power and electric demand of the heat sources. A profile extract of the simulated air source heat pump system is shown in Figure 4.5. The storage temperatures \( T_{\text{sto,DHW}} \) decreases due to DHW storage losses and irregular demand. The space heating storage temperature course \( T_{\text{sto,SH}} \) shows regular charging by the heat pump \( Q_{\text{HP,SH}} \) and discharging due to space heating demand. A deviation can be observed between 10:30 to 11:45. The priority of DHW storage charging \( Q_{\text{HP,DHW}} \) results in a \( T_{\text{sto,SH}} \) drop below the lower storage temperature boundary. The BH \( Q_{\text{BH,th}} \) switches on, when \( T_{\text{sto,SH}} \) is 5 K below the lower...
temperature boundary. The changing heat pump operation for DHW and space heating storage charging with DHW priority and additional backup heater control, shows that the controller is operating correctly.

![Heat pump control graph](image)

Figure 4.5: Example of simulated heat pump control.

### 4.3.2 Monitoring data and pool composition

The validation of the heat pump system pool is based on the analyses of Miara et al. (2014), carried out on monitored heat pump systems of the WP Monitor and WP Effizienz projects at the Fraunhofer ISE (see Section 3.2.2). 87 different heat pump systems were thoroughly investigated by the characteristic values a) seasonal performance factor \((SPF)\) which is the ratio of the annual thermal energy generation and the annual electric energy consumption, b) full load hours that describe the summed heat pump operation time in hours during one year, c) average number of heat pump cycles per day which represent how often a heat pump is switched on per day. Air and ground source heat pump systems are treated as two heat pump pools and analysed separately. The \(SPF\) is calculated as:

\[
SPF = \frac{Total\ heat\ energy\ output\ per\ annum\ [kWh]}{Total\ input\ electricity\ per\ annum\ [kWh]} \quad (4.17)
\]

Miara et al. (2014) provide the graphical distribution of the characteristic values as introduced above, but do not present the values of the individual heat pump systems. The mean and minimum/maximum values are quantified and further utilised in Section 4.3.3.

A pool of buildings with a heat pump system was defined which is based on the analysed heat pumps in Miara et al. (2014). The buildings represent the pool and were clustered by building type, 83% single family (SFH) and 17% terraced houses (TH), and the annual specific heat consumption \((ASHC)\). \(ASHC\) is calculated as:

\[
ASHC = \frac{Total\ heat\ energy\ output\ per\ annum}{A_{building}} \quad [kW h/m^2] \quad (4.18)
\]
where $A_{building}$ is the heated area of a building. Six building classes were selected for the simulation of thermal load profiles. Table 4.5 shows the three selected clusters and the chosen buildings of the thermal model with the means of the annual specific heat consumption $\text{ASHC}$.

Table 4.5: Selected buildings for the validation of heat pump pools.

<table>
<thead>
<tr>
<th>Data clustered by ASHC [$\text{kWh/m}^2\text{a}$]</th>
<th>Single Family Houses (SFH)</th>
<th>Terraced Houses (TH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity Class</td>
<td>ASHC</td>
<td>Quantity Class</td>
</tr>
<tr>
<td>30 to 70</td>
<td>SFH_6 55</td>
<td>TH_6 51</td>
</tr>
<tr>
<td>70 to 110</td>
<td>SFH_3 80</td>
<td>TH_3 74</td>
</tr>
<tr>
<td>110 to 200</td>
<td>SFH_2 144</td>
<td>TH_2 108</td>
</tr>
</tbody>
</table>

4.3.3 Pool validation with recommended sizing

The two pools with air and ground source heat pumps, as defined in Section 4.3.2, were simulated according to the recommended sizing in Section 4.2. The validation results are shown in Figure 4.6. The differences between the seasonal performance factors ($\text{SPF}$s) of air (ASHP) and ground source heat pumps (GSHP) in Figure 4.6a are significant. The $\text{SPF}$s of the GSHPs spread remarkably in comparison to the ASHPs. The average $\text{SPF}$s of the simulated pool in comparison with the monitored pool are 10.6 % higher for ASHPs and 17.4 % for GSHPs. It means that the heat pump $\text{COP}$s are lower and/or the heating curve index 8 and the corresponding supply temperature are underrated for real heat pump systems.

The full load hours in Figure 4.6b are mainly dependent on the correct heat pump size. Oversized heat pumps yield less while undersized heat pumps yield more full load hours. The mean ASHP full load hours are about 2,200 and match the monitored pool mean with -2.3 % deviation. The values of the simulated pool are distributed less than the compared data set for both ASHPs and GSHPs. The latter show a minor heat pump under-sizing.

The analysis of the average number of heat pump cycles per day in Figure 4.6c reveals significant inaccuracy with 50.7 % for ASHPs and 89.8 % for GSHPs. It is dependent on the storable energy in the building or the storage tanks. The observed deviation reflects undersized storages or small hystereses.

4.4 Randomised system sizing

The heat pump pool model requires the ability to simulate a variety of differently sized heat pump systems. A repeated simulation with the recommended system sizing yields optimally sized systems from a manufacturer point of view. However, they are not reflecting the observations made between monitored heat pump systems which show significant
Figure 4.6: Characteristic values for air (ASHP) and ground source (GSHP) heat pump pool simulated with recommended sizing (S: Simulated pool). Monitoring data (M) provide mean (long vertical lines) and minimum/maximum (short vertical lines) of the characteristic values.

differences in seasonal performance factor as well as heat pump, backup heater and storage sizes or supply and source temperatures. Thus, based on the addressed observations, the sizing procedure is complemented with a randomisation of heat pump system parameters as shown in Table 4.6.

Table 4.6a presents the uniform distribution of values for six parameters. Influences of the randomisation on the characteristic system values are discussed and sources for the value distribution are presented as follows:

- The state of charge (SOC) is the normed temperature level in % within the storage temperature boundaries. It is defined at the initial time step for the DHW and space heating storages and is varied to receive different conditions for first simulation steps.
- The heating curve index ranges between 5 and 8, dependent on the building age and the corresponding annual heating demand. Lower indices evoke lower SPF s.
Table 4.6: Randomisation settings for air (ASHP) and ground source heat pumps (GSHP) and standard values for the recommended system sizing (Std.).

(a) Uniform distribution with minimum (Min) and maximum (Max) of the defined value range.

<table>
<thead>
<tr>
<th>HP type</th>
<th>Parameter</th>
<th>Unit</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASHP &amp; GSHP</td>
<td>Initial SOC</td>
<td>%</td>
<td>50</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Heating curve index</td>
<td></td>
<td>8</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>ASHP</td>
<td>$T_{supply}$ offset</td>
<td>°C</td>
<td>1</td>
<td>0.99</td>
<td>1.01</td>
</tr>
<tr>
<td>GSHP</td>
<td>Storage sizes offset</td>
<td></td>
<td>1.0</td>
<td>0.7</td>
<td>1.1</td>
</tr>
</tbody>
</table>

(b) Normal distribution with mean value ($\mu$) and standard deviation ($\sigma$).

<table>
<thead>
<tr>
<th>HP type</th>
<th>Parameter</th>
<th>Unit</th>
<th>Std.</th>
<th>$\mu$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASHP &amp; GSHP</td>
<td>$Q_{HP}$ offset</td>
<td></td>
<td>1.0</td>
<td>1.1</td>
<td>0.2</td>
</tr>
<tr>
<td>ASHP</td>
<td>COP offset</td>
<td></td>
<td>1.0</td>
<td>1.0</td>
<td>0.09</td>
</tr>
<tr>
<td>GSHP</td>
<td>COP offset</td>
<td></td>
<td>1.0</td>
<td>1.0</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>$T_{ground}$ K</td>
<td></td>
<td>0.0</td>
<td>1.0</td>
<td></td>
</tr>
</tbody>
</table>

- The supply temperature $T_{supply}$ in K determined with the heating curve is scaled by a factor which causes a deviation of about 3 K. Higher values for $T_{supply}$ induce lower SPF's.
- An average range of the bivalence points ($T_{biv}$ in °C) in Table 4.2 is selected. Higher values evoke more full load hours for air source heat pumps.
- The storage size influences directly the number of cycles per day. Higher storage volume yield less heat pump cycles due to the increased storage capacity. Additionally, the heat pump runtimes are prolonged.

Table 4.6b shows the 4 parameters which are randomised by a normal distribution. Influences of the randomisation and sources for the value distribution are presented as follows:

- Thermal heat pump power $Q_{HP}$ is randomised normal to match the full load hour distribution of the monitoring data. Reduced power increases full load hours.
- The coefficient of performance (COP) influences the SPF directly. The normal COP randomisation is based on an analysis of all certified air and ground source heat pumps in Germany which are listed in BMWi (2016).
- The normal distribution of the ground temperature ($T_{ground}$) is derived from the analysis of heat pumps with geothermal probes in Miara et al. (2014). $T_{ground}$ influences the SPF of ground source heat pumps.


4.5 Model validation with randomised system sizing

The model validation of the pool with randomised system sizing was carried out with the monitored data described in Section 4.3.2. Figure 4.7 presents the validation results of the heat pump pool with randomised sizing (see Section 4.4). The three graphs show in general that the distribution of the characteristic values for air (ASHP) and ground source heat pumps (GSHP) increased remarkably. Thus, the randomisation of several parameters has the expected effects. The graphs show vertical lines of different lengths to indicate the values of the monitored data in comparison. Long lines indicate mean values and short lines present the lower and upper boundaries. The seasonal performance factor means in

![Graphs showing validation results for ASHP and GSHP](attachment:image.png)

(a) Seasonal performance factor.

(b) Full load hours.

(c) Average number of heat pump cycles per day.

(d) Accuracy of simulated means in % compared to the monitored means.

Figure 4.7a for simulated ASHPs and GSHPs differ from the monitored data means by 2.5 % and 5.3 % respectively. The minima and maxima are within the desired range as shown in the figure. Extreme SPF s are avoided because the number of monitored heat pumps with SPF s in the fringe area is not representative.
Full load hours are presented in Figure 4.7b. The mean of simulated ASHPs deviate from the monitored mean by 2.8 %, while the GSHP mean shows a deviation of 0.9 %. The extreme values are arranged within the values of monitored systems. The value distribution is not as wide as for the monitoring data to avoid unrepresentative unique extrema.

Finally, Figure 4.7c shows a broad value distribution of the average number of heat pump cycles per day. The simulated means for the ASHPs and GSHPs show deviations of 0.6 % and 1.7 %.
Chapter 5

Flexibility assessment

The steps taken to assess the flexibility of a heat pump pool are presented in Figure 5.1. At first a representative heat pump pool is chosen, then the appropriate signals are selected. The configurations for the building and heat pump pool simulations are presented. The characteristic parameters for flexibility are defined and their determination is described.

![Diagram](image)

Figure 5.1: General approach to determine flexibility of a heat pump pool.

5.1 Pool composition

The pool of heat pumps is defined by three characteristics: building type, building age and the heat pump source (see Section 2.1). The simulation of the buildings must be in accordance with the available building classes in the thermal model (Fischer et al., 2015, p.3) and the simulation of the heat pump systems must be in accordance with the heat pump pool model (see Section 4.1). Two building types were chosen, single family (SFH) and terraced houses (TH), while the multi family houses were neglected due to a minor share of only 2%. The information about age or energy standard of buildings with heat pumps was limited to "Renovated" and "New". Two building classes were selected for each: "1" (built before 1978) and "2" (built between 1978 and 2002) for the first, "3" (built after 2002) and "6" (built after 2002 with advanced energy standard) for the latter. Air and ground are the selected heat pump sources. The less common heat pumps with ground water are not presented in the pool.

284 building-heat pump combinations are defined for the pool and listed in Table 5.1. This pool is chosen to provide a minimum of 100 combinations for two different buildings types (SFH_3 and SFH_6). Thus an analysis of heat pump flexibility with two different representative pools is possible. Further, the table shows the mean of the annual specific
heat consumption $\overline{ASHC}$ for the building classes of the thermal model.

### Table 5.1: Composition of pool by building type and age/energy standard and heat pump source.

<table>
<thead>
<tr>
<th>Building definition</th>
<th>$ASHC$ [kW h/\text{m}^2\cdot\text{a}]</th>
<th>Quantity by HP source</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFH_1 before 1978</td>
<td>233</td>
<td>Air $19%$ Ground $6%$</td>
</tr>
<tr>
<td>SFH_2 1978 - 2002</td>
<td>144</td>
<td>Air $19%$ Ground $6%$</td>
</tr>
<tr>
<td>SFH_3 after 2002</td>
<td>81</td>
<td>Air $75%$ Ground $25%$</td>
</tr>
<tr>
<td>SFH_6 advanced</td>
<td>55</td>
<td>Air $75%$ Ground $25%$</td>
</tr>
<tr>
<td>TH_1 before 1978</td>
<td>166</td>
<td>Air $3%$ Ground $2%$</td>
</tr>
<tr>
<td>TH_2 1978 - 2002</td>
<td>108</td>
<td>Air $3%$ Ground $2%$</td>
</tr>
<tr>
<td>TH_3 after 2002</td>
<td>74</td>
<td>Air $9%$ Ground $3%$</td>
</tr>
<tr>
<td>TH_6 advanced</td>
<td>51</td>
<td>Air $9%$ Ground $3%$</td>
</tr>
</tbody>
</table>

The composition of the heat pump pool is graphically shown in Figure 5.2. The figures show the actual shares of building types, building ages and heat pump sources in the pool.

![Figure 5.2: Composition of the defined heat pump pool.](image)

### 5.2 Signal definition

Five signals are selected for the demand response during the simulation of the heat pump pool. They are listed and described in Table 5.2. The signals are derived from the SG Ready signals presented in Section 5.2 and manufacturer’s information about the SG Ready interface in heat pump controllers. These information were obtained by a questionnaire during the WP Smart project at the Fraunhofer ISE. The analysis of the questionnaire showed that 5 signals should be implemented to cover the 4 SG Ready signals and a variation of signal 4 with backup heater. It yielded that the hysteresis of the space heating storage is increased for signal 3 and the space heating storage temperature set to the maximal value for signal 4 and 5. An increased hysteresis of 10 K is chosen which is double...
the conventional hysteresis. The maximal storage temperature is set to 60 °C, because heat pumps usually stop operating at 60 to 65 °C supply temperature. The set temperature of the DHW storage is not changed, although some manufacturer’s allow an increased set point for signal 3, 4 and 5.

<table>
<thead>
<tr>
<th>Signals</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Off</td>
</tr>
<tr>
<td>2</td>
<td>Standard</td>
</tr>
<tr>
<td>3</td>
<td>On</td>
</tr>
<tr>
<td>4a</td>
<td>Superheat</td>
</tr>
<tr>
<td>4b</td>
<td>Superheat</td>
</tr>
</tbody>
</table>

Table 5.2: Signals for flexibility assessment.

The controller of the heat pump model for signal response is designed to receive a short signal impulse, which switches the heat pump on or off if possible and keeps - in case of response - the heat pump operating for one cycle according to the signal. This allows to evaluate the maximal response to a signal and avoids a variety of scenarios with different signal lengths. The length of the impulse signals is set to 1 minute which is the shortest time step available in the model.

Signals are received at every full hour and every day of the year. The space heating and DHW demand of buildings do not alter quickly, thus once every hour shall be sufficient for the assessment.

5.3 Configuration and simulation

The pool of 284 building/heat pump-combinations is simulated in two steps: the generation of thermal load profiles (see Chapter 3 for more information) and the simulation of heat pump systems (see Chapter 4 for more information). The buildings are simulated with the following configuration:

The generated thermal load profiles with space heating and DHW demand are used for the heat pump simulation. The air and ground source heat pump systems are automatically sized with the randomisation explained in Section 4.4. For each profile and signal 24 simulation runs are carried out, one for each hour of the day. Thus, the heat pump system has 24 hours to regenerate from the altered operation induced by the signal.
Table 5.3: Settings for randomised building simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation year</td>
<td>2015</td>
<td>Matches the German average climate. The Test Reference Year (TRY) is a representative mean climate year (Deutscher Wetterdienst, 2011).</td>
</tr>
<tr>
<td>Climate data</td>
<td>Potsdam</td>
<td></td>
</tr>
<tr>
<td>Time resolution</td>
<td>1 minute</td>
<td>Building orientation, room set temperature and heating limit.</td>
</tr>
<tr>
<td>Randomisation</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Night reduction</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Circulation losses</td>
<td>Yes</td>
<td>DHW circulation losses.</td>
</tr>
</tbody>
</table>

5.4 Flexibility determination

This section presents the analysis of an exemplary load deviation profile and the selected flexibility parameters. Figure 5.3 shows the signal response of the heat pump pool as simulated in Section 5.3. It shows the difference between the electric load of the pool responding to an On signal at time $t_0$ and the load of the conventionally operating pool (Standard signal).

![Figure 5.3: Exemplary determination of zero crossings. Electric load deviation in response to an On signal at time $t_0$.](image)

The rolling mean (orange curve) is introduced to smoothen the noise of the load deviation profile by calculating 5 minute means for each time step. The zero-crossings $t_1$ and $t_2$ are determined by disregarding intermediary zero-crossings due to side-peaks. The load deviation is highest in the few minutes after $t_0$, then some of the heat pumps switch off. It drops below the electric load of the conventionally operating pool at time $t_1$. $t_2$ describes the time when the pool is regenerated again and a similar state to the state in $t_0$ is reached. Three direct flexibility parameters and one derived parameter are defined as
shown in Figure 5.4a.

(a) Defined flexibility parameters and the derived value. (b) One extracted load response cycle and the selected parameters.

Figure 5.4: Definition of heat pump flexibility

Figure 5.4b shows the load response cycle of Figure 5.3 with the flexibility parameters. The full length of the cycle is divided into duration (Dur) and regeneration (Reg) in minutes. Dur is the length of the first positive or negative response of the pool in response to an on or off signal respectively. High Dur values indicate long-term flexibility which is useful for a constant flexibility need, low Dur values indicate short-term flexibility and are suited to cover short impulse-like flexibility need. Reg is the required time of the electric pool load to fully regenerate to the load of the conventional pool operation. High values of Reg signify that a high share of heat pumps is unavailable for signal reception for a long time. Low values are desired to quickly re-obtain an available heat pump pool after one given signal. Dur and Reg are calculated as:

\[ Dur = t_1 - t_0 \] [min] (5.1a)
\[ Reg = t_2 - t_1 \] [min] (5.1b)

The flexible power (FP) is the positive or negative load deviation of the pool between \( t_0 \) and \( t_1 \). FP is the main indicator for flexibility and alters over time. It usually maximises at \( t_0 \) and decreases to zero at \( t_1 \). Two more characteristic means are required to define FP properly. \( FP_{max} \) indicate the maximum FP and is dependent on the share of heat pumps (and backup heaters) responding to a signal. \( FP_{mean} \) is the mean flexible power during the duration time Dur. \( FP_{mean} \) indicates if the flexible power is constantly high or low during Dur.

The flexible energy (FE) in response to one signal, often referred to as shiftable load or energy in literature, is calculated as:

\[ FE = \frac{\sum_{t=t_0}^{t_0+\Delta t} FP(t)}{60 \text{min}} = Dur \cdot FP_{mean} \] [kWh] (5.2a)
where $FP$ is cumulated for the time period of $\Delta t$ and converted to kWh. The maximum flexible energy ($FE_{max}$) is calculated by cumulating $FP$ for $\Delta t = Dur$. $FE_{max}$ can be also calculated by $FP_{mean}$ and $Dur$ and indicates the full flexibility potential of a signal. It is suited to compare the flexibility of different signals.
Chapter 6

Results of flexibility assessment

This chapter shows the results of the flexibility assessment. The response of the heat pump pool to the selected signals is verified, a general comparison of the signals is presented and last, the pool flexibility is assessed generically.

6.1 Verification of signal response

As described in Section 1.2 this work aims to identify the flexibility of a defined heat pump pool. An exemplary extract of the pool operation is discussed in this section. Figure 6.1 shows two graphs with the electric load deviation of the pool in response to signals from the conventional operation and the absolute share of active heat pumps in the pool. The signals (see Section 5.2) for the exemplary pool operation were set at 12 pm on 5th of January. It is one of the coldest days of the simulated year and the ambient temperature at 12 pm is -2 °C.

The orange line in Figure 6.1a shows the share of active heat pumps in the pool for the conventional operation (Standard signal). About 45 % of the heat pumps are running at 12 pm. The share of active heat pumps is increasing during the afternoon and reaches almost 90% at 20 pm. This results from an increasing space heating and DHW demand due to lower ambient temperatures in the evening. The small load increase between 12:30 and 1 pm is caused by an higher amount of discharged DHW storages as a result of lunch cooking activities.

In Figure 6.1b the electric load deviations of the pool in response to the Off, On, Superheat (HP) and Superheat (HP+BH) signals are presented. Table 6.1 shows the corresponding flexibility parameters.

A few observations can be made for the pool responses. The On and the Superheat signals provoke to switch on more than 95 % of the heat pumps in the pool. Less than 5 % of the heat pump systems were operating until shortly before the signal and pause for the minimum pause-time of 3 minutes (see Section 4.1.3). The graph shows that the paused heatpumps switch on naturally at 12:30 pm for the Superheat signals. High shares of active heat pumps in the pool yield high electric load deviations. The On and Superheat (HP) signal provoke the similar maximal flexible power ($FP_{max}$) of about 150 kW but differ in
Chapter 6. Results of flexibility assessment

Dur (53 and 125 minutes respectively) for the reason of increased storage hystereses. The latter causes a difference of 16 k\textsuperscript{w} in mean flexible power ($FP_{\text{mean}}$). For the same increased storage hystereses the Superheat (HP+BH) signal response yields the highest $FP_{\text{max}}$ and $FP_{\text{mean}}$ which are about 2.5 to 3 times higher than for the other discussed signals. The comparably extreme values are induced by the electric load of the inefficient backup heater. The backup heater activation has another effect: the increased thermal power of the pool results in a reduced Dur of 97 minutes compared to 125 minutes for Superheat (HP). The combination of different Durs and FPs produce noticeable differences for the maximum flexible energy ($FE_{\text{max}}$). While 78 kWh are determined for On, the Superheat (HP) signal yield three times the energy and the backup heaters six times the energy.

The share of active heat pumps in response to the Off signal shows a different behaviour. The signal causes a reduction to about 15 % which cannot be switched off due to the minimum run-time of 6 minutes (see Section 4.1.3). Heat pumps are switching on quickly
Table 6.1: Characteristic parameters of the 4 signals for 12 pm at 5th January. Flexible energy (\(FE\)) and flexible power (\(FP\)) are presented for a pool of 100 heat pumps.

<table>
<thead>
<tr>
<th>Signals</th>
<th>(F_{E_{\text{max}}}) [kWh]</th>
<th>(F_{P_{\text{max}}}) [kW]</th>
<th>(F_{P_{\text{mean}}}) [kW]</th>
<th>(Dur) [min]</th>
<th>(Reg) [min]</th>
<th>(T_{\text{amb}}) [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off</td>
<td>-11</td>
<td>-87</td>
<td>-46</td>
<td>14</td>
<td>31</td>
<td>-2</td>
</tr>
<tr>
<td>On</td>
<td>78</td>
<td>151</td>
<td>89</td>
<td>53</td>
<td>126</td>
<td>-2</td>
</tr>
<tr>
<td>Superheat (HP)</td>
<td>219</td>
<td>157</td>
<td>105</td>
<td>125</td>
<td>195</td>
<td>-2</td>
</tr>
<tr>
<td>Superheat (HP+BH)</td>
<td>426</td>
<td>451</td>
<td>263</td>
<td>97</td>
<td>221</td>
<td>-2</td>
</tr>
</tbody>
</table>

After the signal set time and after one hour the pool is operating like the conventional pool again. This pool behaviour causes comparatively low negative \(F_{P_{\text{max}}}\) and \(F_{P_{\text{mean}}}\) values which are about half of the values for the \(On\) signal. \(Dur\) of 14 minutes is significantly shorter than for the other 3 signals. The short \(Dur\) in comparison to the other signals is caused by the small degree of freedom for the \(Off\) signals, which is the difference between the actual temperature and the lower temperature boundary of the storages. The short \(Dur\) and low \(FP\) yield a \(F_{E_{\text{max}}}\) of -30 kWh which is only 15% of the energy for the \(On\) signal.

6.2 Signal comparison

A comparison of the signals was carried out by calculating the averages of the maximum flexible energy. Values for the four signals are presented in Table 6.2. The \(On\) signal has an average of 61 kWh \(F_{E_{\text{max}}}\) per 100 heat pumps. The other signals are set in relation to the \(On\) signal. The comparison yields that the \(Superheat (HP+BH)\) signal has the highest \(F_{E_{\text{max}}}\) values, which are 5 times the value of the \(On\) signal. The \(Superheat (HP)\) signal has triple the value, while the \(Off\) signal provides 0.09 times the value. The latter has very low values due to the low probability to switch heat pumps off. Heat pumps are likely to not be in operation because of full load hours below 3000 or not be able to switch off due to the minimum runtime of 6 minutes. Since the \(On\) and \(Superheat\) signals increase the storage capacities by higher storage hystereses, they provide higher values of \(F_{E_{\text{max}}}\).

Table 6.2: Average of maximum flexible energy (\(F_{E_{\text{max}}}\)) for 100 heat pumps in response to signals.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Average (F_{E_{\text{max}}}) [kWh]</th>
<th>Compared [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off</td>
<td>-5</td>
<td>0.09</td>
</tr>
<tr>
<td>On</td>
<td>61</td>
<td>1.00</td>
</tr>
<tr>
<td>Superheat (HP)</td>
<td>182</td>
<td>2.97</td>
</tr>
<tr>
<td>Superheat (HP+BH)</td>
<td>306</td>
<td>5.00</td>
</tr>
</tbody>
</table>
6.3 Generic presentation

The assessment yielded, that the most generic approach to describe the flexibility of a heat pump pool takes the temperature-dependency into consideration. Three of the in Section 5.4 defined flexibility parameters are displayed in dependence of the ambient temperature in Figure 6.2. The maximum flexible energy ($FE_{max}$) in kWh per 100 heat pumps, $Dur$ and $Reg$ in minutes are presented for a temperature range between -10 and 29 °C. The coloured lines represent the mean values for the signals Off, On, Superheat (HP) and Superheat (HP+BH). Ambient temperatures with a unrepresentative number of data (less than 20 values) for the simulated year were removed from the figure. Quartiles shown as coloured shaded areas display the values between 25 % and 75 % of the data. The comparably large quartiles in a temperature range between 8 and 25 °C indicate that the space heating storage charging is switched off for an increasing part of the pool. The heating limit of a building defines if the space heating system is activated on a day of the simulated year and varies with the building type and a randomisation factor. The space heating heating systems of the entire pool are deactivated for ambient temperatures above 25 °C and the DHW systems are solely in operation. That reduces the flexibility substantially for the reason of only half of the available storages and static storage hystereses. For temperatures below 8 °C all the heat pump systems are charging both DHW and space heating storages. The graphs are complemented by the top graph with the share of active heat pumps in the pool for the conventional operation. The 3 lower plots show significant differences between the signals. In the following paragraphs the main findings are discussed and important connections between the flexibility parameters are pointed out.

6.3.1 Off signal

Off signals provoke negative $FE_{max}$ which increases for lower ambient temperatures and is almost zero above +7 °C. The increase is caused by longer Dur and a growing $FP$. Figure 6.3 shows three exemplary Off signal responses at different ambient temperatures. With a growing share of active heat pumps in the pool the potential to switch off heat pumps enlarges, thus the maximum of the load deviation $FF_{max}$ increases significantly for lower temperatures. The graph for the signal at -10 °C shows in addition that $Reg$ can be longer than 1.5 hours although the load deviation reaches values of conventional alteration after about 0.5 hours. At an ambient temperature of +10 °C a minor share of heat pumps switches off and provokes a load deviation, which hardly differs from the conventional load alteration. One reason for the low share of active heat pumps is the heating limit as explained above. A growing number of heat pump systems deactivates the space heating storage charging, thus flexibility can be neglected above +7 °C.
Figure 6.2: Characteristic flexibility parameters of the heat pump pool for the 4 defined signals. The graphs show mean values and quartiles which are normalised to 100 heat pumps. Temperature ranges with less than 20 flexibility values are removed.
$F_{E_{\text{max}}}$ induced by the Off signal is in general lower than the $F_{E_{\text{max}}}$ of the other three signals for two reasons:

1. The limited degree of freedom for switching off heat pumps. They can pause the operation until the space heating or DHW storages reaches the lower temperature boundary. The hysteresis for the space heating storages is set statically to 5 K, while other signals increase that value.

2. Heat pumps run between 1,500 and 3,000 hours during one year with 8,760 hours. Therefore, heat pumps are most likely not in operation at a certain time step and the chance to switching off is lower than for switching on.

The Off signal provides up to -33 kWh per 100 heat pumps at -10 °C with a $Dur$ of 21 minutes.

![Figure 6.3: Load deviation $\Delta P$ in kW and share of active heat pumps in % for the Off signal at different ambient temperatures.](image)

### 6.3.2 On signal

The On signal with an increased space heating storage hysteresis of 10 K yields a flat $F_{E_{\text{max}}}$ curve. At low ambient temperatures the flexibility is comparably low because the share of inactive heat pumps, which can be turned on, is small as can be seen in the upper graph of Figure 6.2. Therefore the potential $FP$ is low but the risen storage hysteresis has two positive effects: 1) the run-time of the individual heat pumps is prolonged, which leads to an extended and increasing $Dur$ down to -7 °C; 2) despite of lower $FP$ the increasing $Dur$ yields only a slight decline in $F_{E_{\text{max}}}$. For higher temperatures the $F_{E_{\text{max}}}$ increases up to +8 °C where some of the heat pump systems stop charging the space heating storage. Higher ambient temperatures signify a smaller share of active heat pumps caused by lower thermal demand. Less active heat pumps result in slowly discharging storages and a high potential to switch heat pumps on. Figure 6.4c shows that the maximal $FP$ is nearly doubled at +10 °C in comparison to 0 °C. The graphs as well show that $Dur$ at 0 °C is almost half as long as compared to +10 °C, that results in $F_{E_{\text{max}}}$ of 79 and 65 kWh per 100 heat pumps respectively. $F_{E_{\text{max}}}$ decreases to 50 kWh per 100 heat pumps at -10 °C. Figure 6.4a shows that the few responding heat pumps generate a considerably high $FP_{\text{max}}$. This is caused by the low heat pump efficiencies ($COP$) for low ambient and high supply temperatures.
Reg is longer than 2 hours for ambient temperatures above 0 °C and especially high for temperatures between 10 and 18 °C, where the space heating storage charging is activated for some of the systems. The space heating load of the buildings is low or zero and the space heating storages discharge slowly which results in long Reg. The latter decreases significantly below 0 °C and drops to about 30 minutes below -5 °C. This is explained in Figure 6.4a. A few heat pumps are still switching on but FP decreases quickly at first and then descend with a low gradient. At about 1.4 hours Reg begins but disappears immediately in the natural load alteration of the pool. Reg is therefore hardly noticeable and short.

Figure 6.4: Load deviation ΔP in kW and share of active heat pumps in % for the On signal at different ambient temperatures.

6.3.3 Superheat (HP) signal

The Superheat (HP) provokes heat pumps to switch on and to superheat the space heating storage to a upper temperature boundary of 60°C. Since the lower temperature boundary of the space heating storage is increasing with the heating supply temperature, the resulting storage hysteresis is decreasing for lower ambient temperatures. Even so, it is generally higher than the increased hysteresis of the On signal.

By comparing the Superheat (HP) to the On signal, the major difference are the significantly increased \( F_{E_{\text{max}}} \) and \( Dur \) in the entire temperature range. \( F_{E_{\text{max}}} \) maximises for higher ambient temperatures and days within the heating limit of the buildings. This combination yields high space heating storage hystereses which increase the storage capacities. The large quartiles at 13 °C show that more than 300 kWh per 100 heat pumps are feasible, but smaller quartiles and higher mean values at 6 °C indicate a reliable flexibility of 280 kWh per 100 heat pumps. Although \( Dur \) is doubled between +10 °C and -5 °C, \( F_{E_{\text{max}}} \) is decreasing for ambient temperatures below +5 °C. Figure 6.5a shows a similar pool behaviour at -10 °C like the On signal. The pool responses with a short intensive peak because of low heat pump efficiencies. It rapidly drops to 20 % of the peak value which results in low \( F_{E_{\text{max}}} \) and very short Reg (see Section 6.3.2).

The maximum Reg is found for ambient temperatures between +4 and +13 °C. It is as well the temperature range of the highest \( F_{E_{\text{max}}} \) values and demonstrates that storage charging up to 60 °C combined with low thermal loads lead to long Reg. \( F_{P_{\text{max}}} \) increases for higher ambient temperatures which is caused by less active heat pumps (see Figure 6.5c).
The heat pump run-times are reduced in comparison to the 0 °C plot in Figure 6.5b. This is caused by lower thermal loads and the resulting reduced storage discharging as well as higher thermal heat pump power. Below an ambient temperature of -2 °C the FE$_{max}$ quartiles start enlarging caused by activated backup heaters. Their activation or deactivation in the conventionally operating pool results in the enlarged quartiles.

![Graphs showing load deviation and active heat pumps at different ambient temperatures.]

(a) Signal at -10°C  (b) Signal at 0°C  (c) Signal at +10°C

Figure 6.5: Load deviation ΔP in kW and share of active heat pumps in % for the Superheat (HP) signal at different ambient temperatures.

6.3.4 Superheat (HP+BH) signal

The Superheat (HP+BH) signal is switching on the heat pumps and electric backup heaters of the pool and superheats the space heating storages to 60 °C. The signal shows the largest potential for FE$_{max}$ and yields reliable values above 400 kWh per 100 heat pumps for ambient temperatures below +9 °C, and for heating days even below +14 °C. Figure 6.6 shows three graphs for load deviation and active heat pumps at ambient temperatures of -10, 0 and +10 °C. FP$_{max}$ is the highest in the right graph due to less active heat pumps, while Dur is longest at -10 °C due to the highest thermal load and the resulting slow storage charging. The middle graph represents high FE$_{max}$ provoked by medium flexible power and Dur. FE$_{max}$ is constantly high for lower ambient temperatures because the electric load is increased by backup heaters which have a noticeable lower efficiency than the heat pumps.

Dur is lower than for the Superheat (HP) signal above -8 °C but higher for temperatures below -8 °C. This is caused by the accelerated storage charging due to the additional thermal power of the backup heater. The comparison of Figure 6.6a and Figure 6.5a yields that the additional backup heater power increases the electric load deviation of the pool substantially. The shape of the load deviation is visible clearer at low ambient temperatures.

The Reg of Superheat (HP+BH) shows similar values like Superheat (HP) for ambient temperatures above 2 °C. It stays constantly higher than 180 minutes for lower temperatures, but drops at fringe temperatures below -9 °C. However, it can be caused by the shape of the load deviation as can be seen in Figure 6.6a. The long and slowly reducing Dur results in a short regeneration time.
Figure 6.6: Load deviation $\Delta P$ in kW and share of active heat pumps in % for the Superheat ($HP+BH$) signal at different ambient temperatures.
Chapter 7

Conclusion

A three-step method for the flexibility assessment of a heat pump aggregation in terms of a representative pool was successfully developed in this work. It stretches from the generation of correct thermal load profiles and the simulation of heat pump pools to the analysis of heat pump flexibility.

The thermal models are suitable for the simulation of building pools. The underlying statistical data with socio-economic factors of 14 different occupant groups allows the generation of a variety of different DHW demand profiles. The correlation and typical values of the generated load profiles in comparison with DHWcalc, measurement and reference profiles show a realistic and consistent representation. The space heating model generates different load profiles with the combination of a physical and behavioural model. The physical model, based on a 5R1C-network, integrates 36 combinations of building types, energy standards and ages. The behavioural model adds occupant-dependent internal heat gains and a room set temperature adjustment, which account for deviations in the course of the daily space heating course. An additional randomisation of building orientation and comfort settings increase the variation of load profiles for the simulation of urban areas or pools. The validation shows correlations above 0.88 with a measured building pool and a higher accuracy than reference load profiles by VDI 4655.

The heat pump pool model based on a simplified heat pump system model and a parameter randomisation is able to generate diverse heat pump systems. The model simulates monovalent or mono-energetic air and ground source heat pumps systems. The sizing procedure recommended by heat pump manufacturers was applied on a heat pump pool and the validation was not matching the characteristics of a monitored pool. The introduced randomisation of heat pump system parameters such as heat pump COP, thermal power, bivalence point and storage sizes results in diverse systems. The validation of seasonal performance factors (SPFs), full load hours and average heat pump cycles yield correct results. It shows that the mean SPFs and full load hours are below 5 % deviation from the monitored pool and are within the variation range. The spreading of average heat pump cycles was correctly mapped while the mean values show a deviation of 10 % for air and 30 % for ground source heat pumps.

The response of a representative pool for 284 German building/heat pump-combinations
was simulated with five signals: a) Off with standard storage hysteresis, b) Standard with standard storage hysteresis, c) On with increased storage hysteresis, d) Superheat (HP) with maximal storage hysteresis and e) Superheat (HP+BH) with maximal storage hysteresis.

Flexibility is the electric load deviation of the pool in response to the signals and determined for: a) Flexible power, b) Flexible energy, c) Duration and d) Regeneration. The values are normalised to a pool of 100 heat pumps. The On signal yields an average flexible energy of 61 kWh, but the Superheat signals are significantly more effective and provide 3 times the energy for the sole heat pump response and 5 times for the response with an additional backup heater. The Off signal is less effective, which results in a tenth of the mentioned energy.

Most significant is the flexibility assessment dependent on the ambient temperature. On and Superheat (HP) signals provide the maximum values of flexible energy for high temperatures at heating days, 80 kWh and 300 kWh per signal respectively. A constant energy of more than 400 kWh is determined for Superheat (HP+BH) signals at heating days. The duration of the On and Superheat signals is in general longer for low ambient temperatures and high thermal demand of the buildings. Below -6 °C, the energy increases significantly for Superheat (HP+BH) and decreases for On and Superheat (HP) signals. The time for regeneration reduces at lower ambient temperatures. The Off signal induces up to -30 kWh and increasing regeneration at low ambient temperatures and a rather constant duration.

**Future work**

The flexibility assessment of heat pump pools can be extended. Additional signals could induce increased hystereses for the DHW storage. They could compensate for the low flexible energy at high ambient temperatures for some extent. That signals will be additionally assessed during the WPsmart project at Fraunhofer ISE.

The storage hystereses are the utilised degrees of freedom. Another degree can be added by increasing or reducing the room set temperature of the buildings. That requires a combined model for the thermal and heat pump load generation.

Additional analyses of the heat pump pool responding to signals are possible. The influence of the different signals on the performance in terms of COP or SPF is required for the economical assessment of flexibility business models. A more detailed analysis of flexibility could define clusters beside the ambient temperature, for instance daily ambient temperature courses or cloudiness. These clusters could allow an additional identification of patterns for increased or reduced heat pump pool flexibility.
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Appendix A

Scientific paper describing the domestic hot water and space heating models
A Stochastic Bottom-up Model for Space Heating and Domestic Hot Water Load Profiles for German Households

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Abstract

In 2013 83% of energy in the German residential sector is used for the preparation of domestic (13%) hot water and space heating (70\%\cite{1}]. Thermal demand profiles are essential to correctly determine operation and sizing of heating technologies. In this work a stochastic bottom-up approach for electric loads, domestic hot water (DHW) and heating demand for individual buildings and neighbourhoods is presented, validated and compared to currently used approaches. A behavioural model is used to determine DHW tappings, electric appliance use and temperature settings of the building. Building heat load is calculated using a simplified physical model, to allow for realistic energy demand profiles, efficient model parametrization and fast computation. A randomization approach for building heat load based on a clustered building typology, randomized building parameters and heating settings is presented which allows the simulation of larger quantities of similar buildings. Validation against measured data for German single family houses shows a correlation of the typical daily load profile for DHW consumption of 0.92 and a mean relative error of 3\% and for space heating 0.89 and 9\% respectively.

Keywords: Load Modelling, Demand Side Management, Load Profiles, Domestic Thermal Demand, Stochastic DHW Modelling

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Highlights

- High time resolution energy demand profiles for houses and neighbourhoods
- A stochastic bottom-up method for consistent electric, domestic hot water and space heating energy demand
- Combination of behavioural models, physical models and classes of reference buildings
- Comparison with measured data, VDI 4655 reference load profiles, DHWcalc and IEA Annex 42 profiles

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Preprint submitted to Elsevier December 23, 2015
1. Introduction

In 2013 the demand of the residential sector made up 28% of Germany’s total final energy consumption. Changes in energy supply concepts of the residential sector thus have a strong impact on national energy demand. 17% of residential energy demand was caused by electric appliances, 13% by the preparation of domestic hot water (DHW) and 70% by space heating [1]. In the context of the German “Energiewende” and the introduction of stricter efficiency regulations for buildings the energy supply concepts of neighbourhoods and buildings will change considerably. A change in heat generation technology from gas boilers towards thermal-electric systems like heat pumps and micro CHP units leads to altered electric demand profiles which are closely linked to thermal demand [2; 3]. Renewable heat and electricity generation sources such as solar thermal collectors and PV systems will lead to further changes in domestic energy consumption patterns as perceived by the utility, grid operator or district heating system operator. In this context consistent demand profiles of electricity and thermal demand are important to correctly plan and evaluate energy supply and management concepts for buildings and neighbourhoods.

For the design and simulation of energy supply concepts for neighbourhoods and residential areas a high number of load profiles is needed. Also for design and simulation of distribution grids or district heating networks a high number of different buildings have to be considered. In this case the diversity of the load profiles has to be respected to avoid aggregation of peaks and capture smoothing effects [4]. Currently applied methods rely on standardized load profiles, reference load profiles or detailed physical models and have the shortcomings of not accounting for diversity, not being interconnected or requiring a high modelling effort. The methods are discussed in Section 1.1. In this paper an efficient method to model and simulate the entire buildings and residential areas is presented.

User behaviour plays a key role in when and how energy is used in buildings. Correctly representing user characteristics is one of the remaining modelling challenges in residential energy models. The combination of behavioural and physical models to generate energy demand profiles is presented in 2 and is one possible solution to this challenge. Its potential is demonstrated in section 3, by comparing simulation results to measured data and commonly used load profiles.

With the introduced approach it is possible to model electricity, space heating (see Section 2.3) and DHW demand (see Section 2.2) of entire living areas with reasonable effort and time. The presented method is extending the synPRO model for electric appliances, which is introduced and validated in [5]. This work focuses on the part of thermal demand.

1.1. Thermal load modelling

In the following two sections selected approaches to determine the thermal demand for domestic hot water (DHW) and space heating are discussed.

1.1.1. Space heating

Standardized load profiles method: In this approach an average load profile (sometimes referred to as synthetic load profile) is derived from measurements, usually linked with outdoor temperature and scaled to a specific yearly energy demand. Those profiles are often provided by gas and electricity distribution companies and are easy to obtain. Since the method is based on a vast number of datasets, which are averaged, resulting profiles can be seen as valid. The drawback of using standardized load profiles is, that those profiles are usually smooth and do only partly reflect individualities in the building due to different physical building properties or the inclusion of solar gains. [6] uses a scaled version of the Dutch standardized load profile to calculate the demand and the daily load profiles for houses in an electric distribution grid simulation. For German applications [7] uses an average load profile for heating gas provided by a gas distribution company as heat load profile for German households.

Reference load profiles method: A representative load profile is selected from measurements, representative days are extracted from this profiles and recombined in accordance to the wanted climate data. One example are the VDI 4655 reference profiles for DHW, space heating and electricity demand [8; 9] created to simulate cogeneration units in buildings. In that case 12 representative days are extracted from measured values, depending on the weather conditions, weekday and outdoor temperature. From those 12 days one year with custom weather data can be sampled and scaled to the right yearly energy demand. The disadvantage of using VDI 4655 reference load profiles is that only limited numbers of reference buildings and days are provided. For the same climate data and building type the resulting load profiles are of identical shape.

Statistical methods: A statistical model is built based on measured data. Purely data driven methods to determine building heat load can be found in [10] and [11], where regression methods are used. The resulting profiles show good accuracy in predicting known buildings, but suffer from predicting new buildings or respecting building dynamics.

Physical modelling: A model of the building based on lumped energy balance equations and physical building properties is used to calculate heat loads. Depending on the level of detail required, the elements of the building are modelled individually respecting their physical properties. Whereas those models show good accuracy in correctly predicting thermal load, they often suffer from correctly reflected user behaviour. The strength of physical models is in investigating the influence of building material and control strategies on thermal comfort and energy use. Also dynamic effects and solar gains are taken into account. The weakness of those bottom-up models is that often a lot of information needs to be known to be able to run a simulation. Further computation time increases with model complexity and the number of thermal nodes.

RC-Network models: Physical models with a reduced complexity. A number of simplified RC-Network representation models have been proposed to decrease engineering effort and computation time. [12] concludes that with a 2R5C-Model...
the accuracy of representing thermal load is similar to those of a more complex model. The DIN EN 13790 [13] is a widely used calculation procedure for hourly heat loads where a 5R1C-Network representation of the building is chosen. This approach offers the possibility of efficiently calculating thermal building loads with comparable accuracy to more detailed model, which was shown in [14].

A challenge in all physical models is to correctly reflect user behaviour, which has been shown in [15] to significantly influence building energy performance.

1.1.2. Domestic hot water

The methods for DHW consumption modelling are similar to those applied for space heating demand. Reference load profiles are suggested in VDI 4655. Using reference or standardized load profiles has the drawback of not capturing stochasticity and smoothing effects that appear when many households are simulated together. In IEA Annex 42 [16] a set of two representative synthetic DHW load profiles is suggested, generated with a stochastic approach.

The importance of stochastic load profiles has been realized by Jordan and Vajen [17; 18] who, motivated by observations of measured data, derive a set of 4 tapping classes - short tapping, medium tapping, bathing, showering. For those tappings a probability distribution for the daily time of occurrence has been constructed. From that distribution daily tappings with a fixed length are sampled. During the course of the year this probability is adjusted, depending on the day of the week, season, day of the year and holiday. Their method has been implemented in the software tool DWHcalc.

A stochastic bottom-up approach for DHW based on a behavioural model using Markov chains was presented in [19]. In this work a tapping schedule is derived for different DHW activities in a households and linked to a specific energy demand.

1.2. Value added by this work

The presented approaches provide valuable ideas and inputs to what is presented in this work. But yet for the modelling of neighbourhoods the three main shortcomings of the existing approaches are the lacking link of heat load, DHW demand and electric demand, a lack of representing diversity, especially when a high number of load profiles are needed, and the missing possibility of investigating a change in occupant type or building physics without high implementation effort. Among the new ideas and solutions presented in this work are:

1. The combination of physical and behavioural models.
2. Respecting different user types by including socio-economic factors.
3. The use of a building model to calculate thermal demand, with respect to building physics and the activity of the occupant.
4. Coupling electric, DHW and space heating demand, based on behavioural data.
5. The use of clustered building types combined with a randomization approach to efficiently model neighbourhoods.
6. The use of stochastic bottom-up approaches to increase load profile variability and allow for aggregation.

2. The synPRO model for DHW and space heating load

The aim of developing this model is to create consistent, realistic energy use profiles for electric and thermal energy demand in residential buildings and neighbourhoods. Focus is set on reduced modelling effort and computing time while respecting the diversity of buildings, occupants’ daily routines and comfort settings. The model is based on the synPRO model for electric loads [5], which is extended in this work to capture thermal demand. Figure 1 shows the resulting model structure.

The model is based on a combination of a physical model with a behavioural model. This approach has been successfully applied for the generation of electricity demand profiles for households in [5] and is now extended to thermal demand. This enables a generation of interlinked, consistent load profiles for space heating load, DHW and electric demand in buildings and residential areas. The behavioural approach allows to account for group specific behaviour of building occupants which are distinguished by their socio-economic factors such as age, working pattern or housing situation.

2.1. Time of use data as model foundation

The data set used for calibrating the behavioural model is the German version of the European harmonized time of use survey [20]. For this study people were asked to fill in a diary for three days. For each ten minutes activities based on a predefined list were reported. The survey resulted in a set of 32,000 diary days from 7,200 households [21]. Socio-economic factors such as age, working pattern and housing situation were noted.

The dataset was analysed and information of daily activities such as their starting time and duration combined with socio-economic factors were extracted and built the foundation of the behavioural model. The following activity categories are used in the presented thermal part of the model: The occupants’ presence at home as well as the sleeping, hygiene and cooking activity. For the adjusted space heating settings the presence at
home and sleeping are used. Hygiene and cooking activities are used to model DHW consumption.

2.2. Domestic hot water model

Domestic hot water consumption is heavily influenced by user behaviour. Time of use, duration and temperature depend on the individual likings. The energy needed to heat up the tapped water $\dot{Q}_{\text{dhw}}(t)$ needed at time $t$ for the preparation of DWH depends on the tapped mass flow $\dot{m}$, the temperature of the hot water at the tapping point $T_{w,h}$ and the nominal incoming water temperature $T_{w,c,0}$ which is set to 10 °C [22]. A loss term $\dot{Q}_{\text{losses}}$ accounting for circulation losses is added, if this applies to the building. The resulting energy balance is:

$$\dot{Q}_{\text{dhw}}(t) = f_{\text{season}}(t) \cdot [\dot{Q}_{\text{losses}}(t) + \dot{m}(t) \cdot c_w \cdot (T_{w,h}(t) - T_{w,c,0})] \text{ [W]} \quad (1)$$

Where $f_{\text{season}}$ is a factor correcting for cold water temperature as explained in Section 2.2.4 and $c_w$ is the specific heating capacity of water.

2.2.1. Behavioural model

The schedule for the activities cooking, hand washing, shower and bathing is created and linked with specific tapping profiles to create a DHW demand profile for each household. In this schedule the time and duration of the activities are noted on a ten second base and then mapped to a specific energy consumption. The distribution differs for each user group and a distinction is made between weekdays, Saturdays and Sundays. Thus the model accounts for group specific behavioural patterns and the change during the course of a week. Three main steps are done for the generation of an activity schedule.

1. Determination of the number of starts:
The first step in the generation of a DHW load profile is to determine how often DHW consuming activities take place for each day. From an evaluation of the time of use survey data a probability distribution of the daily frequency for each activity is derived. From this distribution the number of starts is sampled. In Figure 2(a) the distribution for the number of starts is shown for the hygiene activity.

2. Determination of the time of tapping:
When knowing how often an activity is performed during the course of the day the start time is sampled. For this purpose a second probability distribution is used. This distribution is shown in Figure 2(b) for hygiene activities.

3. Determination of the duration:
The duration of a certain activity is dependent on the time an activity is started. To account for this the duration is sampled from a joint probability distribution and is conditional on the start time. The joint probability distribution for hygiene activities is shown in Figure 2(c) for weekdays.

Figure 2: Used probability distributions for hygiene activities for a household with 2 full-time working occupants.
To link the hygiene information which is given in the TUS data to a specific hygiene activity like hand washing, showering or taking a bath the duration of each activity is used. Depending on the duration of the hygiene activity the likelihood of showering or taking a bath is determined. The values are provided in Table 1. Hygiene activities below 10 minutes are set to hand-washing, while for an activity length between 10 and 25 minutes either hand-washing or shower is selected. For a duration of more than 20 minutes either shower, bathtub or hand-washing is possible. It is also possible that a hygiene activity is performed without considerable tapping, like brushing teeth, this is accounted for by introducing a "Nothing" activity.

2.2.2. Mapping of activities to energy

For each specific activity a tapping profile is constructed. One tapping is characterised by the temperature, volume flow rate and total tapped volume and is generated by sampling from uniform distributions. The value range for temperature, volume flow rate and total tapped volume is based on VDI 2067 and presented in Table 2 and [22]. Equation 1 is used to calculate the resulting energy demand for each tapping.

With the described steps it is possible to calculate the mass flow rates and tapping temperatures for each point of the day and year.

2.2.3. Circulation losses

In addition to the energy needed to directly heat the water for tapping, losses in the piping system due to the constant circulation of hot water are taken into account. If the DHW system of a building is designed with a circulation pump, circulation losses can add a considerable share to the DHW demand. Based on measurement results and the discussion presented in [23] a loss value of 9-14 kWh/m² for each square meter living space is added to the DHW demand. The chosen value is depended on the building energy class used for the calculation of the space heating load.

2.2.4. Seasonal effects

The cold water temperature of the city water entering the system impacts DHW energy demand [24]. The incoming water needs to be heated to the desired temperature. The inflow temperature of the water depends on the season. Based on [24] the following equation is used to determine the input temperature depending on the mean yearly ambient temperature $T_{amb}$:

$$T_{w,c}(n_{day}) = T_{amb} - 3K \cdot \cos\left(\frac{2\pi}{365} \cdot (n_{day} - n_{days,offset})\right)$$  \hspace{1cm} [K] (2)

Table 1: Mapping of duration to probabilities for hygiene activities.

<table>
<thead>
<tr>
<th>Duration Minutes</th>
<th>Probability [%]</th>
<th>Handwash</th>
<th>Shower</th>
<th>Bath</th>
<th>Nothing</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 10</td>
<td>75</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>25</td>
</tr>
<tr>
<td>10 - 25</td>
<td>30</td>
<td>20</td>
<td>0</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>&gt; 25</td>
<td>30</td>
<td>30</td>
<td>15</td>
<td>15</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Most important tapping points and corresponding volume flow rates, temperatures and volume per tapping based on [22].

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Handwash</td>
<td>3-8</td>
<td>0.25-1.5</td>
<td>38-42</td>
</tr>
<tr>
<td>Shower</td>
<td>9-11</td>
<td>12-60</td>
<td>38-42</td>
</tr>
<tr>
<td>Bathtub</td>
<td>9-11</td>
<td>100-130</td>
<td>38-42</td>
</tr>
<tr>
<td>Cooking</td>
<td>3-8</td>
<td>0.25-10</td>
<td>48-52</td>
</tr>
</tbody>
</table>

Figure 3: Course of the cold water temperature over the year

Where the offset $n_{days,offset}$ is included, based on the coldest day of the year and on the temperature change delay due to the depth of water piping. This method is based on the ground temperature calculation of [25] and meets the cold water seasonality as described in [23]. In Figure 3 the cold water temperature over the course of the year is shown. The energy demand for DHW and circulation losses, calculated with a nominal cold water temperature of 10 °C in Equation 1, is adjusted using the seasonal factor $f_{season}$.

$$f_{season}(n_{day}) = 1 + \frac{T_{w,c,nominal} - T_{w,c}(n_{day})}{\Delta T_{w,0}}$$  \hspace{1cm} [-] (3)

where:
- $f_{season}$: the seasonal effect of the cold water temperature on the DHW demand
- $T_{w,c,nominal}$: Nominal cold water temperature
- $\Delta T_{w,0}$: Nominal temperature difference between cold and hot water

Thus the influence of the cold water temperature is taken into account for the circulation losses of the DHW piping.

2.3. Space heating model

The target of model development is the ability to model and simulate an entire residential area, of which the most important factors should be captured, but still keep model complexity low. For modelling space heating load it is assumed that the heating load of a building is mainly dependent on two factors:

1. The building’s physics. It influences heat losses, solar gains and dynamics.
2. The behaviour of the building’s occupants. This effects set-points for indoor temperature, ventilating and internal loads.
Energy demand for space heating is calculated using a dynamic building model and a behavioural model.

2.3.1. Behavioural model

User behaviour influences temperature settings and internal gains of the building. Internal gains through the physical presence of persons and the use of electric appliances is calculated with:

\[ \dot{Q}_{g,\text{int}}(t) = P_{el}(t) + n_{\text{pers}}(t) \cdot 65.0 \quad [W] \quad (4) \]

For each present person \( n_{\text{pers}} \) in the building an internal gain of 65 W is assumed. The electricity consumption \( P_{el} \) of appliance use is added. To determine the presence at home the behavioural model explained in Section 2.2 and [26] is used.

[15] shows that occupants’ presence in the building has a significant impact on heat demand and increases the building’s space heating consumption. This is due to ventilation and increased comfort requirements. To account for that the temperature set point of the building model is made dependent on the time of day and the presence of people in the house.

\[ T_{\text{room, set}}(t) = T_{\text{setpoint}}(t) + \Delta T_{\text{user}}(t) \cdot n_{\text{pers, active}}(t) \quad [K] \quad (5) \]

The temperature set point of the room heating \( T_{\text{setpoint}}(t) \) is increased by \( \Delta T_{\text{user}} \) for each person \( n_{\text{pers, active}} \) that is at home and not sleeping. It is assumed that temperature comfort requirements depend on the time of day and the duration of presence. The temperature set point is increased depending on the time of day and number of people present: Before 8 a.m. by \( 0.1 \frac{K}{\text{person}} \), until 4 a.m. by \( 0.2 \frac{K}{\text{person}} \) and by \( 0.4 \frac{K}{\text{person}} \) in the evening.

Electricity, DHW and space heating demand are implicitly connected by using the same behavioural model and data set.

2.3.2. Building model

Space heating demand is modelled using a 5R1C-Network representation, which is based on the simplified hourly method as described in DIN EN ISO 13790 [13]. Figure 4 shows a schema of the model. The model inputs are the building’s physical properties, ambient temperature, irradiation, temperature set points and internal gains. For calculation three temperature nodes are taken into account. The air node of the room, a node for the interior wall surfaces and a mass node.

The energy balance of the building is the sum of the supplied heat from the space heating \( \dot{Q}_{sh} \), transmission losses \( \dot{Q}_{l,\text{trans}} \), ventilation losses \( \dot{Q}_{l,\text{vent}} \) and the heat used for temperature change of the building mass \( C_m \) in each time step.

\[ \dot{Q}_{sh} = \dot{Q}_{l,\text{vent}} + \dot{Q}_{l,\text{trans}} - \dot{Q}_{g,\text{sol}} - \dot{Q}_{g,\text{int}} - C_m \frac{\Delta T_m}{\Delta t} \quad [W] \quad (6) \]

The resulting node temperatures for a given heat load at each time step are directly calculated solving the equations for the RC-Network as described in [13]. The needed heat for keeping the wanted room temperature is calculated iteratively by numerically solving the energy balance and the node temperature equations.

2.3.3. Stochastic modelling of residential areas

When modelling residential areas the main challenge is to derive representative space heating and DHW load profiles for a great variety of buildings and occupants. The generation of DHW and electric load profiles for a great number of living units is straightforward using the presented stochastic bottom-up approach. The calculation of space heating loads is more labour-intensive since the building properties, areas and orientation have to be considered. Access to information about the most important building parameters can be hard. For simulation studies detailed building properties and it’s orientation are frequently unknown. Aggregation of existing measured data or models of few entities can lead to unwanted effects, such as peak summation or high simultaneity and lacking variation in the load profiles. The simple reuse of a single (or a set) of parametrized building models will lead to a set of identical heat load profiles. This leads to a summation of load profiles without correctly accounting for building diversity.

This is why the stochastic bottom up approach is combined with a database of representative buildings and a randomization approach. The key component is a set of 36 representative buildings. Based on the building stock and physical data provided in [27] representative classes have been extracted and are distinguished by:

- Building Type: Single family house, terraced house, small and large multi family house
- Energy standard: Normal, refurbished, advanced refurbishment

For each class the model parameters for the 5R1C are implemented. By using the described buildings an entire residential area can be approximately modelled with limited time.
Within each building class the heat load profiles differ since the internal gains and users’ comfort settings are generated using the behavioural model (section 2.3.1). Further diversity in load profiles is reached by a randomization of:

- Heating set-points,
- Activation time, duration and set-point temperatures for day and night program,
- The mean temperature limit when the heating system is taken into and out of operation,
- Building orientation to modify the hour and amount of solar gains.

In addition the area of windows and outside walls are linked to the living space, allowing for a further variation of heat demand by varying living area.

3. Validation

Model validation is done by comparing simulated load profiles to measured data. The data used is obtained from the research project WPmonitor [28]. In this field trial the operation of heat pump systems in over 100 single family and terraced houses was measured from the beginning of 2011 until the end of 2013 with a time resolution of one minute. From this dataset 10 single family houses constructed after 1978 and located in different places in Germany were selected for validation according to data quality and available data points.

For each measured household 10 synthetic load profiles (synPRO profiles) were generated with a 15 minute time resolution using the corresponding building and occupant class. Test reference year climate dataset for the location of Potsdam (TRY04) was chosen to obtain ambient temperatures and solar irradiation. For each measured load profile the synthetic load profile with the smallest summed deviation in monthly energy consumption over the year was selected. The generated profile is scaled to match the yearly energy sum of the measured data.

Focus in validation is the representation of load characteristics by means of the annual duration curve, the correct representation of seasonal fluctuation and the representation of the characteristic daily load profile, since the aim of model development is generating realistic load profiles, rather than exactly representing a given entity.

The key performance indicators used for the comparison of two profiles are Peak Value, Root Mean Square Error (RMSE) and Pearson’s correlation coefficient. All indicators are computed on 15 minutes time resolution.

3.1. Domestic hot water model

For validation the generated domestic hot water profiles are compared to the measured profiles. In a second step the synthetic load profiles are compared to measured data, VDI 4655 (Single Family House), IEA Annex 42 (1 minute data 100 l per day) and DHWcalc load profiles.

3.1.1. Annual duration curve

The distribution of values on an annual base is shown in the annual duration curve depicted in Figure 5. The annual sum of the profiles is 1400 kWh. The peak value for the mean curve of the measured data is 16.3 kW and 19.7 kW for the synthetic profiles. The correlation coefficient between the mean duration curves is 0.99. The RMSE is 0.1 kW. In the hours with medium and high load the synthetic values are considerably higher than the measurements. The absolute values shown in Table 4 indicate that the mean peak value of the synthetic profile is 47% higher than in the measured data. This indicates that the values [22] used for maximum temperature and volume of the bathtub shown in Table 2 are in this case higher than measured. The overall variation in the synthetic data matches the observed variation in the measured demands.

3.1.2. Daily load profile

A comparison of the mean daily load profiles for the whole year is shown in Figure 6. It shows that the range of synthetic load profiles fits well within the range of measured profiles. The morning and the evening peaks are captured. It shows that the synthetic profiles have higher values in the 0.75 quantile during early evening hours. Correlation coefficient between the mean daily profiles is 0.92. The RMSE between the mean profiles is 40 W. From hour 5 to 10 the distribution of values between measured and synthetic shows a high consistency. During the late morning hours demand and variation of the measured values is between 5% and 45% higher than in the synthetic data. During early evening hours the synthetic DHW demand profile shows a wider spread of values and a 60% higher demand.

3.1.3. Seasonal fluctuation

To analyse the seasonal fluctuation, the standard deviation of the mean daily energy demand is plotted on a monthly base in Figure 7. Days with no DHW tappings in the measured data were removed from the synthetic load profiles to correct for holidays. It shows that the seasonal fluctuation of the DHW energy demand is captured by the model with a correlation of 0.94. The day to day variation, showed as the standard deviation in the plot, is similar for the measured and the synthetic data.
3.1.4. Impact of socioeconomic factor and circulation losses

To demonstrate the impact of user groups on the DHW model the yearly energy sums per person for the different socioeconomic factors are listed in Table 3. It can be seen, that with increased number of persons the specific energy demand is reduced. This is due to reduced demand for cooking, which is a shared activity, and shorter durations of the hygiene activity for more people in the household. Table 3 shows further that specific DHW consumption varies up to 37\% between the groups. Retired people consume the most and full time workers the least.

The mean DHW consumption, when a mix of all socioeconomic factors is selected is 576 kWh per person and year, which lies well within the range of 380-720 kWh per person and year stated in [29].

Table 3: Simulated energy demand for DHW without circulation losses in kWh/p/a.

<table>
<thead>
<tr>
<th>Occupants</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family</td>
<td>x</td>
<td>x</td>
<td>563</td>
<td>521</td>
<td>542</td>
</tr>
<tr>
<td>Fulltime Workers</td>
<td>500</td>
<td>492</td>
<td>476</td>
<td>411</td>
<td>470</td>
</tr>
<tr>
<td>Fulltime Partime</td>
<td>571</td>
<td>518</td>
<td>533</td>
<td>497</td>
<td>530</td>
</tr>
<tr>
<td>Retired</td>
<td>692</td>
<td>598</td>
<td>x</td>
<td>x</td>
<td>645</td>
</tr>
<tr>
<td>All groups</td>
<td>603</td>
<td>587</td>
<td>557</td>
<td>557</td>
<td>576</td>
</tr>
</tbody>
</table>

3.1.5. Comparison with available load profiles

For the simulation of residential areas and district heating networks aggregation properties of the load profiles are important. In the following aggregation properties of the synPRO profiles are demonstrated and compared with measured data, the IEA Task 42, VDI 4655 and DHWcalc load profiles described in Section 1. For each measured household a load profiles has been generated with the mentioned methods and scaled to match the demand of the measurements. The profiles have then been aggregated. The main results are shown in Table 4. A comparison of the mean daily load profiles is shown in Figure 8. The typical daily profiles correlate between 0.59 and 0.92 with the measured data. Differences appear when the distribution of values is investigated using the annual duration curve as shown in 9. The peak values of the different methods differ up to factor 6.1.

3.2. Space heating model

For each measured household a corresponding building class was selected and 10 synthetic profiles were simulated. The synthetic load profile with the smallest summed deviation in monthly energy consumption over the year was selected for the corresponding measured houses. The measured space heating demand profiles are compared to the synthetic profiles in the following.
### Table 4: Characteristic values and correlation of synthetic and measured data for DHW profiles with an annual sum of 1400 kWh.

<table>
<thead>
<tr>
<th></th>
<th>Annual Peak [kW]</th>
<th>Daily Profile Correlation</th>
<th>Duration Curve RMSE [kW]</th>
<th>RMSE [kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured</td>
<td>4.2</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>synPRO</td>
<td>6.2</td>
<td>0.92</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>DHWcalc</td>
<td>18.6</td>
<td>0.92</td>
<td>0.03</td>
<td>0.19</td>
</tr>
<tr>
<td>VDI</td>
<td>12.5</td>
<td>0.59</td>
<td>0.08</td>
<td>0.12</td>
</tr>
<tr>
<td>IEA</td>
<td>26.9</td>
<td>0.86</td>
<td>0.04</td>
<td>0.30</td>
</tr>
</tbody>
</table>

**Figure 10:** Duration curves for space heating.

#### 3.2.1. Annual duration curve

Figure 10 shows the distribution of the annual heating load for the set of measured and synthetic load profiles. The peak value of the mean profile is 8.8 kW for the measured single family houses and 7.4 kW for the synPRO data. RMSE is 200 W. The spread of values of the synthetic profiles matches well with the measured profiles. During the hours of high heat demand the measured values show higher loads. Between hour 2500 and 4000 the synthetic load profiles show higher variability than observed.

#### 3.2.2. Daily load profile

The mean daily load profiles for the whole year, winter and changing season are shown in Figure 11. It can be seen that the synPRO model catches the typical characteristics of the measurements. The correlation between the measured and the synthetic profiles are 0.9 for the whole year, 0.91 for winter days and 0.88 for days in the changing seasons. RMSE is 240 W for the mean daily profile of the whole year. During evening hours the simulated heating demand is 14% below the measured values and during late night and early morning is 16% higher. The effects of the inhabitants on temperature settings can be observed around hour 6 and 19 especially during winter days and is more extreme in the 0.75 quartile of the measured data than in the the synthetic profiles. During changing season the variation in measured values corresponds well with the simulated values, whereas during winter the measured values especially during afternoon hours show a lower variation than the synthetic data.

**Figure 11:** Daily space heating load profiles, mean value and quartiles.
3.2.3. Comparison with VDI 4655 profile

In Figure 12 the mean hourly space heating demand for the houses are shown for the measured data, the synPRO data and data generated with VDI 4655. The annual peak values are 5.5 kW for the measured, 6.8 kW for the synPRO and 4.2 kW for the VDI 4655 profiles. For the synPRO data and the measurements solar gains are leading to lower heat loads during the day. This can not be observed at the VDI profiles. The effect of seasons is also clearly visible. The difference in TRY data to the measured data leads to a different time of the year with maximum heat load. The variation in heat load depending on radiation and ambient temperature is captured more realistic in the synPRO model than when using the VDI reference load profiles. This is especially true during late spring time, when heat load is low. The RMSE for the mean daily profile of VDI 4655 and synPRO to the measurements is 0.25 kW and 0.11 kW respectively. For that case Pearson’s correlation coefficient is -0.11 for the VDI 4655 profiles and 0.94 for the synPRO data.

4. Conclusion

For the design and simulation of energy concepts for residential buildings and areas, simple and consistent methods to generate demand profiles for electricity, space heating and domestic hot water demand are needed. Time-dependent characteristics of residential energy demand are strongly dependent on user behaviour, which needs to be accounted for. The presented modelling approach is based on the coupling of behavioural and energy balance models and stochastic modelling. This allows modelling and computation time efficient generation of realistic and consistent load profiles for space heating, domestic hot water and electricity for buildings and residential areas. The model for electric appliance use presented in [5] has been extended in this work to include thermal demand.

It has been shown that the typical hourly, daily and yearly characteristics of the domestic hot water profile are correctly captured by the synthetic load profile. The advantage of the presented stochastic load profiles is that smoothing effects are accounted for when aggregating more than one housing unit. This has been shown by comparison with measured data, VDI 4655, IEA Annex 42 and DHWcalc load profiles.

For space heating the presented method generates approximate but realistic heat load profiles for living areas even with limited data available. The model is based on a combination of the simplified hourly method [13] with a behavioural model, a set of standardized buildings and randomization of control parameters and building properties. A comparison to measured data of single family houses showed a correlation between 0.88 and 0.91 for the typical daily and monthly characteristics. During the late night hours and early morning hours the calculated heat demand exceeds the measured demand which might indicate a potential weakness of the SR1C representation and should be addressed in further research. A comparison with VDI 4655 reference load profile shows that the seasonal and daily characteristics and stochasticity are better represented by the developed model. The possibility of randomization of building types and parameters, occupant types and comfort settings allows simulating neighbourhoods with reasonable modelling effort.
The model will be used for the design of energy supply concepts for houses and neighbourhoods and for investigation of the impact of different heating technologies on the electric distribution network.

Acknowledgements

The research leading to these results was developed within the "WPsmart im Bestand" project financed by the German Ministry of Economics and Energy (BMWi). We thank Andreas Härtl for the work put in the synPRO model.

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Appendix B

Backup heater control algorithm
Figure B.1: Backup heater control algorithm.