Potential of a Long-Term Predictive Controller for Managing Energy Storages to Reduce the Electric Grid-Load of an Air-Source Heat Pump

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ABSTRACT

Electrifying the domestic heating sector is mandatory to decarbonize the buildings sector but leads to additional peak loads in the public grid. Air-source heat pumps the mostly used technology in this regard even though, they suffer from lower efficiency during times of high heat demands. The usage of energy storages and predictive controllers enables operation shifting and hence offers potential to decrease the peak loads in the electric grid. This potential can be increased by using a longer prediction horizon as extended operation shifting can be performed. In this contribution, a methodology to derive the theoretical potential on the grid peak load reduction of such a long-term predictive controller is introduced. The electric load profile of an air-source heat pump in a typical German single-family home was generated based on different weather data scenarios for the city of Ingolstadt. Based on the profile the dependency between peak load reduction and required storage capacity was identified. In the case study a reduction of the peak load from 21 – 31 % for an unrenovated building was achieved using a 500 litres buffer storage. Further investigation needs to be done to derive a more realistic potential for renovated or new buildings.

Keywords: *Storage Management, Peak Shaving, Predictive Control, Air-Source Heat Pump*

1. INTRODUCTION

As the largest contributor to the EU's greenhouse gas emissions, Germany must change its energy system to reach carbon neutrality by 2045 [1]. Up until today, 78% of the provided energy in the German building sector is used for space heating and domestic hot water preparation [2]. At the same time, 80% of the German buildings are supplied by fossil-based heat generators [3]. Thus, supplying renewable heat to German households is required to reach its climate goals.

Ongoing research investigates different pathways for Germany how to reach carbon neutrality. Considering different scenarios, the heat pump (HP) technology is one key technology for the transition within the building sector [4]. According to the authors, 6 Mio. HPs must be installed by 2030, which is an increase of 260% considering the current number of installed HPs.

HPs acquire energy from an ambient energy source on a low temperature level and use electrical energy to provide thermal energy to a heat sink on a higher temperature level. In some cases, the electrical energy is covered by a decentral PV-system on the rooftop of a building. However, during winter times when there is less or no sunshine the HP mainly depends on the supply from the public electricity grid. Thus, the load on the public electricity grid will increase to reach the national climate goals.

The effect of an increasing load on the public electricity grid due to a higher HP penetration in a city district has been investigated in a simulative study [5]. The authors show that the grid faces critical situations when its components reach the design limit with a penetration level of only 11%. This happens due to clustering effects within the district and the resulting peak loads during winter times, when the space heating demand is high.

The most sold HP-type in Germany is with 87% the Air-Source HP (ASHP) [6]. This has different reasons, for example simple easy installation, or low requirements

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on installation site. As the name indicates, ASHPs acquire the ambient thermal energy on a low temperature level from the ambient air. For ASHPs the impact of peak loads on the public electricity grid is higher compared to other HP types acquiring energy from the ground or water. This is because of the lower COP of ASHPs during winter times when the space heating demand is high. Thus, the expansion of the HPs are likely to be slowed down due to limitations of the electricity grid and endanger the fulfilment of national climate goals.

One possibility to tackle this issue is to apply peak shaving techniques. Peak shaving describes the shift of demand from times of peak demand towards times of lower demand. This can be realised by the integration of an energy storage to decouple demand and supply in time. The flexibility potential offered by an energy storage of any type (electrical, thermal, …) depends on its specifications (e.g. capacity, losses, charging power, …). While seasonal storages would offer a high flexibility potential, they also require long installation times and low economic benefits. Decentral storages like a water-based buffer storage or a battery are easy to install and are already widely used in buildings but have limited storage capacity. However, cutting peak loads does not require large storage capacities hence decentral storages offer a great potential to reduce the electric peak loads of an ASHP.

First insights are given in a simulative study, in which the peak shaving potential was investigated for a district of 100 buildings [7]. Each building was equipped with an energy storage of 10 kWh capacity and a heat pump. The authors were able to reduce the peak load of the district by 25% considering the heat load profile of one day.

However, the question remains to which extent decentral storage capacities can reduce the electric peak load over a longer period (e.g. complete year) and under different weather conditions. This will be investigated in the given contribution. Due to its wide application and larger storage capacity compared to a battery in domestic application, a water-based buffer storage will be focus of this study. The results are also discussed regarding further extension of the flexibility by considering other available decentral storage capacities such as thermal building mass activation or a domestic battery.

2. METHODOLOGY

This research followed four steps which are shown in Figure 1. The first step was the generation of a heat load profile for a domestic building, in this case a single-family-home (SFH). Based on the heat load profile, an electric load profile was derived using the efficiency map of an ASHP. For a building without a PV-System this represents the grid load of one building to heat the house. Thus, the periods of electric peak loads can be identified based on this profile in a third step. This was done by introducing a maximum electric power limit. This limit can be interpreted as an undersized heat pump, which is not able to cover the complete heat demand of the building. Instead, the storage covers the remaining heat demand and acts as a second "heat generator" during peak times. The last step is then to evaluate each identified peak load period and calculate the required storage capacity to cover the demand during each period. The four steps are described more detailed in the following.

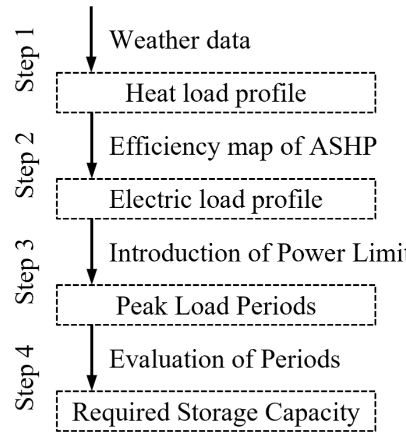

Figure 1 Methodology of the given simulative study.

Step 1: Within dynamic building simulations the heat load profile for space heating of an exemplary building was generated. The simulation environment of MATLAB Simulink including the CARNOT Toolbox [8] Version 7.3 was used. Based on weather data and internal gain profiles for occupancy and electrical gains, the heat load profile was calculated using the predefined model blocks of the library. In the IEA SHC Task 44, reference building models on different insulation levels along with standardized internal gain profiles were defined and are provided within the Toolbox [9]. Using publicly available weather data with an hourly resolution [10], the heat load was calculated within the simulation.

Step 2: The resulting space heat load profile was translated into an electric load profile by using the efficiency map of an exemplary ASHP. The efficiency of an ASHP depends on the source and sink temperature. Considering a constant supply flow temperature to the building, the electrical power consumption was calculated based on the ambient air temperature and the required heat load of the building. In some applications, the supply temperature to the building would change (e.g. when a heat curve is applied). This is the case when no buffer storage is used between the heating system and the HP. In this investigation, a water-based buffer storage was considered. Thus, a constant sink temperature was assumed.

Step 3: The electric load profile was used to identify periods of peak loads which should be cut. An electric power limit was introduced which cuts the load profile into loads above and below the limit, see Figure 2. Integrating the area between the electric load profile and the defined power limit results in the amount of energy which either will be drawn from or fed into an energy storage. To take the storage duration into account, constant storage losses were considered. Since the energy storage can only provide enough energy if it has been charged before, the cumulated energy for discharging including losses must be smaller than the cumulated energy for charging, see inequality (1). Based on this procedure, the start and end time of a period was identified when the storage will be used for cutting the electric peak load.

$$E_{charge} \geq E_{discharge} + E_{loss} \tag{1}$$

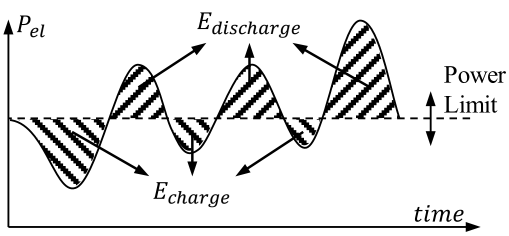

Figure 2 Schematic methodology of identifying periods of peak loads which need to be covered by an energy storage for a defined power limit.

Step 4: The required storage capacity was calculated for each identified peak period. This is done by summing up each charged and discharged energy stepwise resulting in a profile of the currently stored energy $E_{st}(t)$, see Figure **3**.

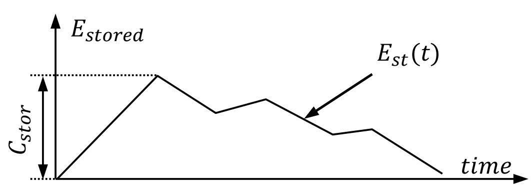

Figure 3 Calculated energy amount stored in the energy storage for each charge and discharge step during a peak period.

Based on this profile the required storage capacity is calculated by taking the difference between the maximum and minimum of the profile, see Equation (2).

$$Capacity = max(E_{st}(t)) - min\ (E_{st}(t),0) \tag{2}$$

2.1 SETUP OF SIMULATED CASE STUDY

In this study two different building models from the CARNOT Toolbox were used: 'SFH45' which represents a renovated building, and 'SFH100' which represents an existing non renovated building. The heating system of both models are equally parametrized to represent a floor heating system. In the building model, the change of the room temperature is set to zero, meaning that for each time step in the simulation the exact energy demand for heating or cooling was calculated to ensure a constant room temperature. Thus, dynamics of a heating controller are not considered. On the one side, this has the benefit of preventing non-realistic peak loads due to bad controller parametrization (e.g. too long reaction times). On the other side, keeping the room temperature constant induces also higher peak loads because no temperature variation is allowed. In this study the approach of a constant room temperature is chosen, because of its high reproducibility of the results for different building standards under different weather conditions. However, the difference between a variable and a constant room temperature will be investigated in an upcoming study.

As weather data the publicly available database from the German Weather Service (DWD) was used [10]. The DWD provides for a grid with a resolution of 1 km² different weather data sets. The test reference year (TRY) summarizes the weather data from 1995 until 2012 resulting in an average but typical weather progression for each of the locations on the grid. Also, the weather data for an extreme cold winter and extreme hot summer of the location is provided for each grid point. In both extreme scenarios, the weather data refers to one actual year which has been within the considered years. The selection procedure of the year representing an extremely hot summer and an extremely cold winter followed multiple statistical criteria [11]. In this study, the weather data for the city of Ingolstadt of a typical year and an extremely cold winter was used.

In this study, water-based buffer storages were considered as decentral energy storage capacity. The heat losses were assumed to be constantly at 100 W. To calculate the storage capacity a temperature difference from 40 to 60 °C was considered. As floor heating system usually require supply flow temperatures around 35 °C, the storage would be able to supply the thermal energy at sufficiently high supply temperatures every time it is discharged. Also, to charge the water storage, the ASHP needs to provide water at a certain temperature level. Most of the market available ASHP are able to reach 60 °C. Based on a temperature difference of 20 °C, the storage capacity for different water volumes could be calculated.

The power limit was varied stepwise to find the dependency between peak power reduction and required storage capacity. The maximum occurring electric load as reduced by equally sized steps of 100 W. The lowest power limit was set to 3 kW below the maximum electric load resulting in 30 iterations for each scenario.

The described setup of the case study resulted in 4 simulations to calculate the heat load profile of each scenario consisting of building model corresponding weather data and 120 evaluations to calculate the required storage capacity for each power limit. This is summarised in Table 1.

Table 1. Overview of considered scenarios in the case study

Heating system	Floor Heating Max. supply flow temperature 35°C	
Air-Source Heat Pump	Efficiency map of model *Hoval Belaria Pro 8* Constant sink temperature: 60°C	
Energy Storage	Water-based buffer storage Constant heat losses: 100 W	
Building Model	Renovated Building (SFH 45)	Unrenovated Building (SFH 100)
Weather data	TRY / Cold winter	TRY / Cold winter
Power limit	$P_{max} - 100W \cdot i$ i: 0 – 30 (iteration)	$P_{max} - 100W \cdot i$ i: 0 – 30 (iteration)

3. RESULTS AND DISCUSSION

In Figure 4 the dependency between required storage capacity and acquired absolute peak load reduction for the unrenovated building model are shown. In both weather scenarios, the required storage capacity to decrease the peak load by up to 1 kW is below 8 kWh. From this point onwards, the trend of the plotted line increases significantly. This behaviour can be expected due to two reasons: First, the areas which are between the introduced power limit and the load curve change non-linearly with the power limit due to the shape of a peak (c.f. $E_{discharge}$ and E_{charge} in Figure 2). Second, when reducing the power limit also the inequality (1) has to be fulfilled which leads to longer storage durations and hence larger storage losses. To meet both requirements the required storage capacity increases non-linearly with the reduced peak load.

For the unrenovated building the different weather conditions lead to difference in required storage capacity. While in the beginning until 1 kW peak load reduction both curves progress in a similar way, the required storage capacity differs in both cases for higher peak load reductions. However, the difference is with its highest value of 2.8 kWh at a peak load reduction of 2.8 kW rather small compared to the required storage capacity of 84 kWh in the cold winter scenario and 113 kWh in the typical year scenario.

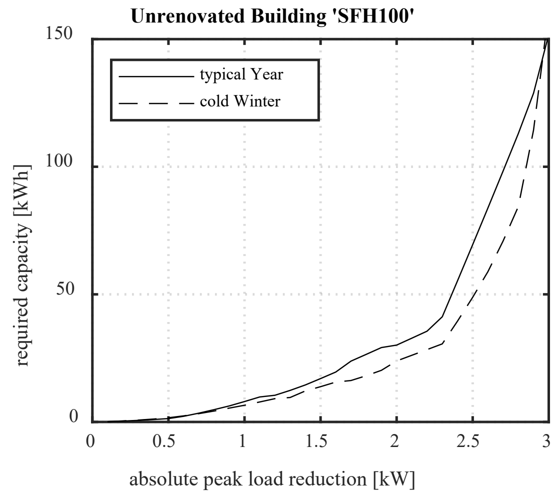

Figure 4 Dependency between required storage capacity and absolute peak load reduction of an unrenovated building during a typical and a cold year in Ingolstadt.

Considering typical volumes for water-based buffer storage in domestic applications of 500 and 1000 litres a storage capacity of 11.6 kWh and 22.3 kWh can be provided respectively using the temperature difference of 20°C as mentioned in chapter 2.1. Using the calculated dependency between storage capacity and peak power reduction the potential of both water-based buffer storages can be determined, which are summarized in Table 2.

Table 2. Peak load reduction potential of a 500 and 1000 litres water-based buffer storages for an unrenovated building

SFH100	Cold Winter	Typical Year
500 litres	1.4 kW (21 %)	1.3 kW (21%)
1000 litres	2.0 kW (31 %)	1.7 kW (28 %)

In Figure 5 the dependency between required storage capacity and acquired absolute peak load reduction for the renovated building model are shown. As for the unrenovated building, the required storage capacity increases non-linearly with the peak load reduction. This is expected because the same arguments are true for both building models.

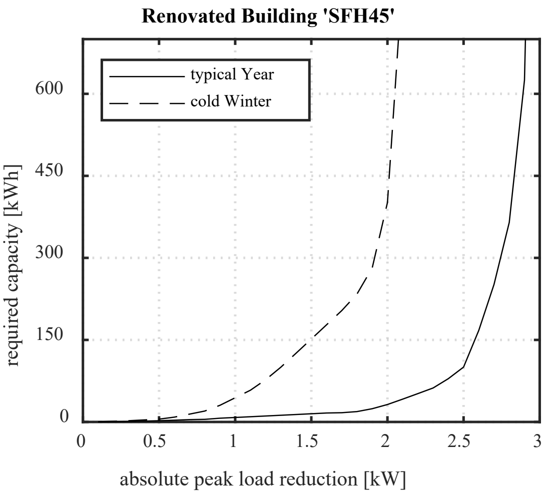

Figure 5 Calculated required storage capacity of a renovated building during a typical and a cold year in Ingolstadt.

In contrast to the results for the unrenovated building, the impact of the weather conditions on the dependency curves for the renovated building is significantly larger. While the curves for both weather scenarios show in general a similar progression, the absolute values differ significantly from each other. This can be quantified using the same the sizes of water-based buffer storages of 500 and 1000 litres. The results of the evaluation are shown in Table 3.

Table 3. Peak load reduction potential of a 500 and 1000 litres water-based buffer storages for an unrenovated building

SFH45	Cold Winter	Typical Year
500 litres	0.6 kW (0.3 %)	1.3 kW (40 %)
1000 litres	0.8 kW (0.4 %)	1.9 kW (61 %)

Possible reasons for the differences in the sensitivity to varying weather conditions between both building models are the assumptions made within this theoretical study. The steps three and four (c.f. Figure 1) to determine the dependency between peak load reduction and required storage capacity are the same for each scenario. Hence, the difference must be based on the methodological steps one and two. Three assumptions were made within these two steps: Constant storage losses, constant sink temperature of the ASHP and constant room temperature. All three assumptions have an impact on the calculated electric load profile of the building.

The sink temperature of the ASHP was set to the maximum required temperature level to charge the storage, in this case it was set to 60 °C. The efficiency of the ASHP is decreased compared to a variable sink temperature. The calculated electric load profile of the building will change and have less or lower peaks. But the effect on the profile is the same for both buildings and both weather scenarios. Thus, it is not expected that this assumption leads to the observed difference.

Constant heat losses of 100 W for water-based buffer storages are assumed to take longer storage durations into account. In reality, the heat storage losses of thermal storages depend on its mean temperature which changes with the state of charge. The impact of this assumption on the results of the study lies in step three and four, in which the periods of peak load and the required storage capacity are determined. An increase of the storage losses leads to a longer period as more energy is required to be fed to the energy storage. Based on longer periods, the required storage capacity can increase also. But since this depends on the maximum and minimum value (see Equation (2)) this does not have to be the case for all periods. The considered heat losses of 100 W are typical but in the upper segment comparing the data sheets of different thermal storages. Hence, variable storage losses will lead to a lower average value compared to the value considered in this study. Based on the discussion above, the impact of constant storage losses on the results are not easy to understand. Further investigations would need to be done e.g. by changing the storage losses to different values and see, how it affects the results. Also, a function could be formulated to make the storage losses dependent on its state of charge.

The last assumption taken in this study is considering constant room temperature. This assumption is expected to have the most significant effect on the results which is based on the following aspects. When no variations in the room temperature are allowed and the losses (transmission, ventilation, …) of the building are higher than the gains (solar, electric, occupancy, …), the difference between both values will be considered as the heat load. During times, when the gains are higher than the losses, the difference will be considered as a cooling load. Thus, the thermal inertia of the building is not considered in the calculated heat load profile. This leads to higher peaks in the heat load profile, which will not exist in reality due to the thermal inertia of the building. How large the impact of this assumption on the calculated heat load profile is depends on both the thermal inertia of the building and its heat load. In this study both building models have the same thermal inertia as the models were parametrized using the same building materials. The difference lies in the heat load based on different heat loss coefficients. In the considered cases the average heat load over the complete year of the unrenovated building is in comparison to the renovated building by 520 to 530 % higher depending on the weather scenario. This means that the ratio between heat load to thermal inertia of the unrenovated building is higher compared to the renovated building. The unrenovated building “reacts” faster to changes in the boundary conditions (e.g. ambient air temperature, solar gains, …) because the thermal inertia has a lower decoupling effect. Hence, the assumption of a constant room temperature shows a lower impact on the resulting heat load profile of the building. To quantify this hypothesis, further simulations allowing a variable room temperature including a heating controller need to be done, as stated in chapter 2.

4. CONCLUSION AND OUTLOOK

In this study, the potential of decentral storage capacities was quantified. The discussion makes it clear that more investigations need to be performed before the theoretical potential of a long-term predictive controller can be determined reliably based this methodology. However, the results for the unrenovated building are expected to be in a realistic range as the assumptions taken within this study are considered to be of lower impact. In this case, the electric peak load could be reduced by 21-31% using water-based buffer storages of 500 and 1000 litres. This is in the same range compared to the value of 25 % which was given in the literature [7]. Based on this, it was shown that decentral storage capacities can have a significant impact on reducing the electrical peak load of an ASHP.

The focus of this study was the peak load reduction of ASHP in domestic applications. However, the described approach to manage decentral energy storages influences also other aspects of ASHP systems, e.g. the system efficiency, operational costs, share of renewable energies during the consumption, or the self-consumption of decentral supplied renewable energies. Since a variety of aspects is important but single quantities and effects stand in contrast to each other, an optimal compromise for all aspects must be found. This requires the formulation of an optimisation problem and a well-defined cost-function which covers all necessary aspects to find solutions for this compromise. The knowledge to which extent managing decentral storage capacities offer a potential for the different aspects of the optimization, helps researchers and developers of control algorithms to focus their work. For example, the theoretical potential can be used as a benchmark during the development process to quantify the difference between the performance of a control algorithm and the optimal case. Furthermore, use cases can be defined under which climatic conditions and for which building standards the management of decentral storages makes most sense. Suggestions can be formulated based on large parameter studies to point out the most promising scenarios. This helps to bring predictive control algorithms more into practice within domestic applications.

AUTHORS' CONTRIBUTIONS

Conceptualization and methodology: David Schmitt (DS), Tobias Reum (TR), Tobias Schrag (TS); Analysis, Data Curation and Writing: DS; Reviewing Thorsten Summ (TSu), TS; Funding Acquisition TR, TS, Christoph Trinkl (CT). All authors have read and agreed to the published version of the manuscript.

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