SimBuild 2024

Eleventh National Conference of IBPSA-USA
Denver, Colorado
May 21 – 23, 2024

Assessing Energy Flexibility Potential via Statistical Analysis of Building Mass Using Rule- and Schedule-Based Control

Joscha Reber*, Xenia Kirschstein, Nadja Bishara
Technical University of Darmstadt, Department of Civil and Environmental Engineering,
Institute of Structural Mechanics and Design, Darmstadt, Germany
corresponding author: reber@ismd.tu-darmstadt.de

Abstract

With the increasing integration of volatile renewable energy sources into the power grid, the focus is shifting from power generation to demand side management (DSM), especially in the energy-intensive building sector. There are various methods to evaluate building mass as an energy flexible thermal storage, similar to an efficiency label. While previous studies have investigated factors that affect the derived storage capacity, none have statistically quantified the effective storage capacity over a whole year, particularly comparing the results for rule-based and schedule-based control. In this study, we found that in our use case the rule-based control assigns approximately 40% less effective storage capacity to the building mass than the schedule-based control, despite the same average duration. This should be considered when using standardized KPIs for evaluating the energy flexible building mass.

Introduction

The accelerated expansion of renewable energy, and thus volatile power sources such as wind and solar radiation, requires a shift in consumption (Denholm and Hand 2011)(Morales et al. 2014). To meet the demand at all times and to stabilize the grid, storage technologies are already being used (Hu et al. 2017). In the future, however, it will be necessary to balance surpluses and shortages in the energy supply by means of an adapted demand side (Lund and Münster 2006)(O'Malley et al. 2016). The building sector in particular offers great potential for this energy flexibility (Zafar et al. 2018), accounting for 40% of total energy consumption worldwide (Nejat et al. 2015). The 2018 revision of the European Energy Performance of Buildings Directive (EPBD) already highlights the importance of energy flexibility in buildings and introduces the Smart Readiness Indicator (SRI). This is designed to assess a building's ability to adapt its operation to the needs of its occupants and the demands of the grid (European Parliament 2018).

Demand side management

Within the domain of electricity consumption, demand side management (DSM) encompasses various techniques, including load reduction, load increase, and load rescheduling (Lund et al. 2015)(Gellings and Smith 1989). All measures can be categorized as either energy efficiency, which is a permanent reduction in energy demand, or demand response (DR), which is a temporary change in energy demand (Morales-España, Martínez-Gordón, and Sijm 2022). Based on this, active demand response (ADR) describes short-term load changes, e.g. on an hourly basis, which can be adjusted daily by external signals (Lauro et al. 2015). In Germany, the Act for Digitizing the Energy Transition, effective from May 2023, mandates the integration of dynamic pricing by 2025 (Bundesministerium der Justiz 2023), which paves the way for more flexible energy applications in Germany and encourages consumer participation, as described by Lauro et al. (2015), Arteconi et al. (2014), Arteconi and Polonara (2018), de Coninck and Helsen (2016) and Luc et al. (2020). Common household appliances suitable for ADR include washing machines, dishwashers, boilers and heat pumps (Callaway and Hiskens 2011). Heat pumps in particular can contribute to short- to medium-term load shifting through thermally activated building structures (TABS) such as floor heating systems and the thermal inertia of the building mass (Reynders, Nuytten, and Saelens 2013)(Arteconi, Hewitt, and Polonara 2012), without compromising thermal comfort (Arteconi et al. 2014).

Key performance indicators

A key challenge for recognizing the role of building energy flexibility in future energy grids is to develop a methodology to assess and quantify the building mass potential (Airò Farulla et al. 2021). The five most popular key performance indicators (KPIs), according to Li et al. (2021), are peak power reduction (Cetin 2016), flexibility factor (Le Dréau and Heiselberg 2016), self-supply and self-consumption (Vanhoudt et al. 2014), ADR capacity and efficiency (Reynders, Saelens, and

Diriken 2015), and flexibility index (Vigna et al. 2019). The method of Reynders, Saelens, and Diriken (2015) focuses on quantifying the storage capacity, rather than directly considering the monetary savings resulting from optimized DSM. With this approach, the setpoint room temperature is increased temporarily and the thermal energy stored in the activated building is evaluated (Luc et al. 2020)(Le Dréau and Heiselberg 2016)(Foteinaki et al. 2018). The setpoint temperature adjustment can be controlled by a fixed schedule or by rule-based responses to an external signal, such as electricity market prices (Arteconi and Polonara 2018)(Luc et al. 2020)(Arteconi, Mugnini, and Polonara 2019)(Foteinaki et al. 2020). The factors affecting thermal capacity and efficiency in terms of ADR have been the subject of numerous studies, including a comparison of buildings of different ages and insulation thicknesses by Vivian et al. (2020). In a previous study, we have already examined one rule- and one schedule-based control strategies through a one-year simulation to quantify the effective storage capacity of the building mass (Reber, Kirschstein, and Bishara 2023).

Research Aim

In this study, we quantify the energy flexibility of the building mass using the storage capacity, as presented in Reynders, Saelens, and Diriken (2015). We consider two control strategies, rule-based and schedule-based, through a dynamic building energy simulation. To eliminate the influences of different boundary conditions and to generalize the results of Reber, Kirschstein, and Bishara (2023), two schedules are examined. The novelty lies in the impact of different control strategies on the statistical evaluation of the effective storage capacity of the building mass over the period of one year. The results are intended to show a possible difference in the resulting effective storage capacity due to the choice of control strategy and thus underlying the need for standardized key performance indicators for the energy-flexible use of TABS.

Methodology

The objective of the study is to demonstrate the discrepancy of different control strategies in quantifying the flexibility potential of the building mass. It is based on a building energy simulation of a new residential district and the storage capacity metric introduced by Reynders, Saelens, and Diriken (2015). To receive representative results for thermally activated building structures (TABS), the investigations are performed statistically on data obtained from the simulation of a whole year.

Building energy simulation (grey box model)

To implement the investigated control strategies for energy flexibility a grey-box model of a new residential district planned in Darmstadt, Germany, consisting of 140 apartments in 8 buildings, is used. The model is developed using the simulation software Trnsys, which is a graphical software environment for simulating the behavior of transient systems (TRNSYS 2023). The floors are grouped into thermal zones, which is a good compromise between simulation speed and accuracy (David Bewersdorff 2021). In this study, only the results of one zone are presented for the sake of clarity, as highlighted in figure 1. The buildings themselves are designed with a high standard of insulation, i.e. U-values of 0.118 - 0.151 $W \cdot m^{-2} \cdot K^{-1}$ for the exterior walls, 0.078 - 0.104 $W \cdot m^{-2} \cdot K^{-1}$ for the roof and 0.78 $W \cdot m^{-2} \cdot K^{-1}$ for the windows. The total floor area is 9827 m^2, of which about 75% is thermally activated by floor heating with a supply temperature of 40 °C in a 0.065 m-thick screed. The floor heating system is implemented using the heat exchanger effectiveness approach as described by Kirschstein et al. (2023). For the simulation over one year with time steps of one minute, the minimum air exchange rate of 0.44 h^{-1} and the internal heat gains of 90 $Wh \cdot m^{-2} \cdot d^{-1}$ are used according to DIN V 18599. The room setpoint temperature during the heating season (September 30 - April 30) is set to 20.5 °C. For the comparison of the control strategies, the weather data of the test reference year 2015 of the German Meteorological Service is selected, which represents an average and typical year for Darmstadt. No explicit days or weeks (cold, moderate, warm) are deliberately chosen, because the focus is on comparing effective storage capacities as they might occur in real operation. The annual heat demand results in 23.22 $kWh \cdot m^{-2} \cdot a^{-1}$.

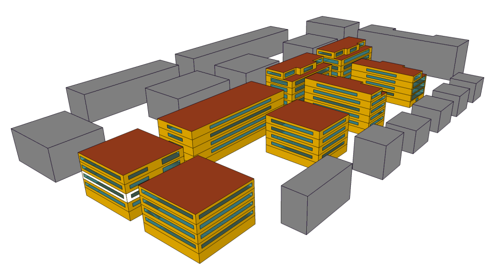

Figure 1: N-W-view of the modeled district section. The presented study is limited to the white marked floor.

Active demand response (up event)

Several measures are possible to implement active demand response (ADR) strategies within demand side management (DSM). To use the building mass as a flexible thermal storage, TABS can be controlled via the room setpoint temperature. Temporary limited temperature increases are used to exploit the so called upward flexibility and temperature decreases for the so called downward flexibility. Since we expect the temperature increase to be more acceptable to users, only upward events are considered in this study, denoted as up events. In the overall optimization of flexibility potential, down events should also be considered, especially during the heating season, to temporarily minimize the electrical load on the grid. Within a defined comfort band of T_{low} = 20.5 °C and T_{up} = 22 °C, consistent with other publications such as Arteconi, Mugnini, and Polonara (2019), the setpoint temperature is raised to T_{up} during an up event, resulting in three phases: In the charge phase, there is an additional heat demand compared to a reference control without increasing the setpoint temperature. The activated building mass is charged with heat. Once the setpoint temperature T_{up} is reached, a slightly increased heat demand remains to compensate for the increased transmission heat losses. This phase is called steady state. As soon as the set temperature is reduced to T_{low}, the discharge phase begins, in which the additional heat stored in the activated building mass is used. Compared to the reference control, energy is now saved until the room temperature reaches the setpoint temperature T_{low} again. The concept of an up event is shown in figure 2.

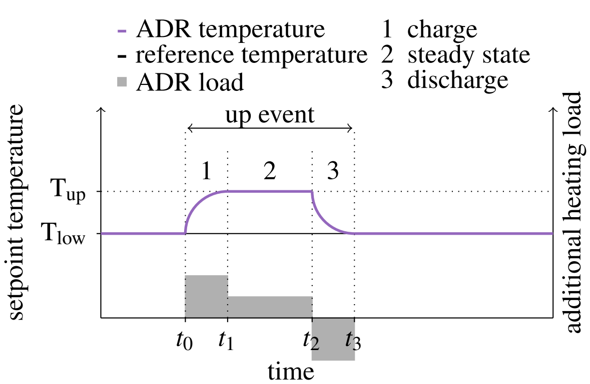

Figure 2: Scheme of an up event with its three typical phases.

In order to characterize the up events that occur in a year, the duration t, the additional heat demand Q and the additional averaged heating load P, compared to a reference control with constant set point temperature T_{low}, are used in this study and are calculated as follows:

$$t_{\text{charge}} = t_1 - t_0 \tag{1}$$

$$t_{\text{steady state}} = t_2 - t_1 \tag{2}$$

$$t_{\text{discharge}} = t_3 - t_2 \tag{3}$$

$$Q_{\text{charge}} = \int_{t_0}^{t_1} (P_{\text{up}} - P_{\text{ref}})\, \mathrm{d}t \tag{4}$$

$$Q_{\text{steady state}} = \int_{t_1}^{t_2} (P_{\text{up}} - P_{\text{ref}})\, \mathrm{d}t \tag{5}$$

$$Q_{\text{discharge}} = \int_{t_2}^{t_3} (P_{\text{up}} - P_{\text{ref}})\, \mathrm{d}t \tag{6}$$

$$P_{\text{charge}} = \frac{Q_{\text{charge}}}{t_{\text{charge}}} \tag{7}$$

$$P_{\text{steady state}} = \frac{Q_{\text{steady state}}}{t_{\text{steady state}}} \tag{8}$$

$$P_{\text{discharge}} = \frac{Q_{\text{discharge}}}{t_{\text{discharge}}} \tag{9}$$

According to the definition of Reynders, Saelens, and Diriken (2015), the additional heat demand in a charge phase is the storage capacity of the building mass activated by the ADR strategy (eq. 10). However, since there are always different boundary conditions per up event in this study, especially the real room temperature influenced by solar gains etc., the storage capacity is averaged over all events and defined here as the effective storage capacity (eq. 11). The reduced heat demand in the discharge phase can be additionally used to determine the efficiency of the charge and discharge phase (eq. 12) or of an total up event (eq. 13).

$$C_{\text{ADR}} = Q_{\text{charge}} \tag{10}$$

$$C_{\text{eff}} = \overline{C_{\text{ADR}}} = \frac{1}{n} \sum_{i=1}^{n} Q_{\text{charge},i} \tag{11}$$

$$\eta_{\text{charge/discharge}} = \frac{|Q_{\text{discharge}}|}{Q_{\text{charge}}} \tag{12}$$

$$\eta_{\text{up}} = \frac{|Q_{\text{discharge}}|}{Q_{\text{charge}} + Q_{\text{steady state}}} \tag{13}$$

To correctly identify the respective phases (charge, steady state, discharge) in the individual up events of the annual simulations, the algorithms presented and verified by Reber, Kirschstein, and Bishara (2023) are used.

Control strategies for an up event

Various control strategies can be used to implement ADR strategies, such as up events. Depending on the chosen strategy, different frequencies and durations of the individual events result. In this study, a rule-based control is compared with two different schedule-based controls. In all variants, the setpoint temperature is raised from T_{low} = 20.5 °C to T_{up} = 22 °C. The rule-based control uses the German electricity market prices for the year 2021 (Bundesnetzagentur 2023) as an external signal, which are available with a resolution of 15 minutes. Adapted from Foteinaki et al. (2020), the lower quartile of the electricity prices is calculated monthly and defined as a threshold value p_{th}. When the electricity price falls below the threshold, the set temperature is increased to T_{up}. If the electricity price rises above the threshold, the set temperature is lowered again. Accordingly, different durations of the up events are possible and new charge phases can occur without the previous discharge phase having ended. Since the corresponding additional heat demand of the charge phase is strongly dependent on the duration (Foteinaki et al. 2018), the average value of all charge phases over one year in the rule-based control (2.5 h) is used as a fixed duration for the two schedule-based controls to ensure comparability. Since the schedules have fixed start and run times, two simulations with different schedules are examined to identify a possible influence of the time of day. The first starts at 10:00 am and ends at 12:30 pm. The second is intended to provide a preheating so that tenants or owners find a heated home in the evening after work. It starts in the afternoon at 2:00 pm and ends at 4:30 pm. The concept of rule-based and schedule-based control is illustrated in figure 3.

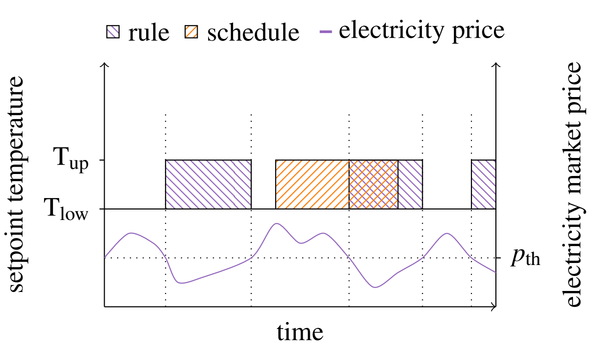

Figure 3: Comparison of the two control strategies (fixed schedule and electricity price-based rule).

Statistical analysis and data visualization

To obtain representative values for quantifying storage capacity, the simulated time period is one year and all up events are included in the evaluation. Since the generation and evaluation of data is time-consuming, the time period to be studied and the temporal resolution of the simulation models should not be arbitrarily large. However, the reliability of statements about a measured variable increases with the amount of data obtained. In particular, if several data sets are to be compared with each other, there must be a high probability that the existing distributions will not lead to different results in further measurements. Transferred to the field of building energy simulations and energy flexible control of TABS, this raises the question of how many heating periods must be simulated in order to obtain representative values for quantifying the storage capacity in the different control strategies. In this study, one heating period is simulated and the results for the different control strategies are statistically evaluated using the Brunner-Munzel test (Brunner and Munzel 2000). Based on the assumption that the obtained data sets are only a snapshot of the real distribution of the data, the Brunner-Munzel test checks the stochastic difference between two non-normally distributed data sets. The tested statement, called null hypothesis, is that both data sets are based on an identical stochastic distribution and a possible difference is therefore not significant. With a probability of $p \leq 0.05$, the null hypothesis is rejected and any difference that occurs, e.g., between the means of the two data sets being compared, can be considered significant and therefore comparable. At a higher probability of $p > 0.05$, either the available data sets are not large enough to detect a significant difference, or the data sets are indeed similar. The following notation is used in the results:

- $p > 0.05$: ns (not significant)
- $p \leq 0.05$: * (significant)
- $p \leq 0.01$: ** (significant)
- $p \leq 0.001$: *** (significant)
- $p \leq 0.0001$: **** (significant)

Since the data sets do not fit any statistical distribution model, such as the normal distribution, characterization by simple metrics is also limited. For this reason, the results are presented using box plots, which provide a brief visual summary of the variability of the values in the data sets. The median, mean, upper and lower quartiles, and

5% and 95% whiskers are shown. However, to reduce complexity, the mean is chosen in the description.

Results & Discussion

In this section the results of the distribution of each phase in all up events over one year for the different control strategies are presented, statistically analyzed and discussed. The duration, the additional heat demand and the additional heating load are used for the evaluation. From this, the average used storage capacity is derived, which is referred to as the effective storage capacity. An up event is defined by the temporary increase of the setpoint temperature from 20.5 to 22 °C. The schedule-based control is examined in two simulations: a morning schedule from 10:00 am to 12:30 pm and an afternoon schedule from 2:00 pm to 4:30 pm. The fixed duration is derived from the previously determined average duration of all rule-based up events. The statistical difference between the data sets is evaluated using the Brunner-Munzel test. The abbreviation n.s. (not significant) means that the data sets to be compared are similar and that an identical distribution is likely if the data set is enlarged through further simulations. Since there is no normal distribution of the data sets, the median, which is less sensitive to outliers, is shown in the graphs in addition to the mean. However, for ease of reading, only the mean is reported in the text. Unless otherwise noted, mean values are listed as follows: (mean: rule / schedule 1 / schedule 2).

Duration of the three phases in up events

In figure 4 the duration of all phases of the individual up events using the three control strategies (rule and two schedules) are shown. The number of phases is indicated above the upper whisker in each case, e.g. n = 163 for the charging phases in the rule-based control for one year. The mean duration of the charge phase of the three control strategies (mean: 2.18 / 2.00 / 2.09 h) differ less than 10% from each other, which is advantageous and intended for the comparability of the additional heat demand.

Also the evaluation according to Brunner-Munzel is to be regarded as positive in this case. Since the up events in the rule-based control do not have a time limit, the steady state phases are comparatively longer (mean: 1.72 / 0.74 / 0.65 h). The schedule-based controls do not exceed 2.5 hours in the charge and steady state phases, as these were previously defined as max. duration. For all control strategies, the discharge phases are significantly

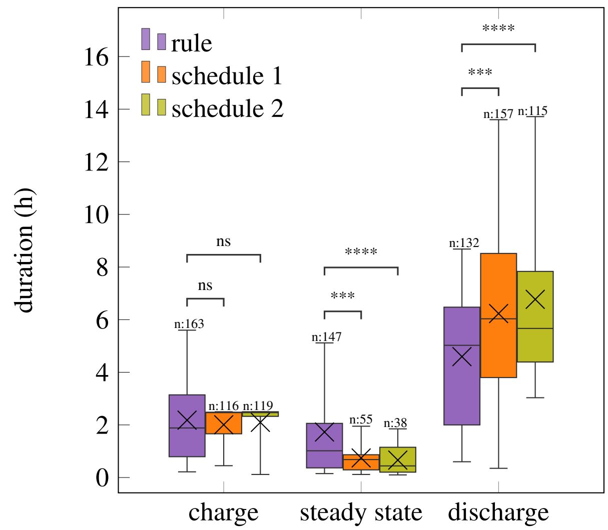

*Figure 4: Comparison of the duration in the three control strategies, separated into the individual phases of the up events. p-values indicate statistical significance (***$p \leq 0.001$, ****$p \leq 0.0001$).*

larger than the charging phases (mean: 4.60 / 6.24 / 6.77 h). This is due to the high energy standard of the considered buildings, which results in low transmission heat losses. Unlike the schedule-based variant, the rule-based variant may initiate a next up event before the discharge phase is completed, resulting in shorter duration. Together with short periods of low energy prices, this is one of the reasons why not all available storage capacity can be used during the charge phase. Therefore, in addition to the use of electricity prices, further constraints should be introduced for a reasonable operation of rule-based control.

Additional heat demand

The additional heat demand compared to a reference control with no up event is shown in figure 5. In the charge phase, the rule-based control stores on average 40% less additional heat in the building mass per up event than the schedule-based control (mean: 28.4 / 49.3 / 48.6 Wh·m^{-2}). The two schedule-based controls, on the other hand, differ only slightly. As described in the methodology, the additional heat can be understood as the effective storage capacity of the thermally activated building mass. In the steady state phase, the upper setpoint temperature is reached and only the increased transmission heat losses compared to the reference control without up events are compensated (mean: 5.9 / 4.7 / 4.1 Wh·m^{-2}). The longer duration in the rule-based control are reflected in this case.

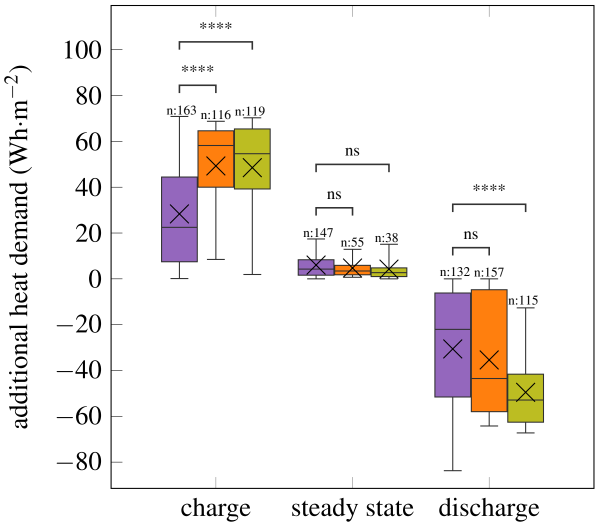

*Figure 5: Comparison of the additional heat demand in the three control strategies, separated into the individual phases of the up events. p-values indicate statistical significance (****$p \leq 0.0001$).*

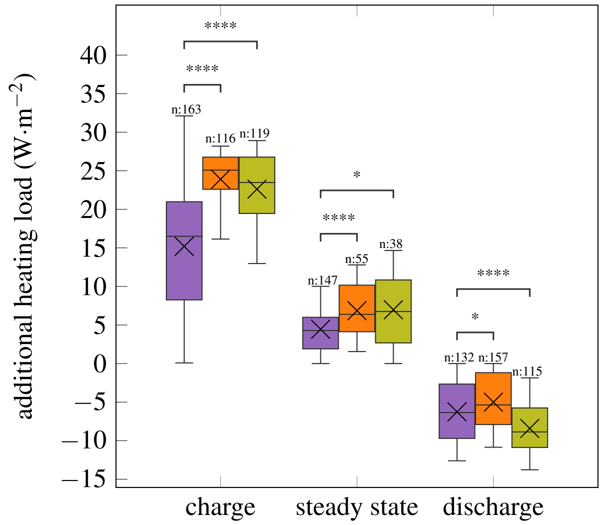

Figure 6: Comparison of the additional heating load in the three control strategies, separated into the individual phases of the up events. p-values indicate statistical significance ($p \leq 0.05$, ****$p \leq 0.0001$).*

The efficiency of the thermal storage can be determined from the ratio of the additional heat demand in the charge and discharge phases, but requires a clear assignment of the individual phases. This is particularly complex in rule-based control, since new up events can occur even before the previous discharge phase is complete. However, if the quotient of the cumulative energy of all discharge phases and the cumulative energy of all charge phases is formed, the following values are obtained for the three controls: 93% / 94% / 96%.

Additional heating load

From the duration and the additional heat demand of the individual phases, the average additional heating load can be derived, as shown in figure 6. Similar to the heat demand, it can be seen that the rule-based control reaches approx. 33% lower values in the charge phase than the variants with the schedule-based control (mean: 15.2 / 23.8 / 22.6 $W{\cdot}m^{-2}$). Thus, the discrepancy in heat demand cannot be explained by duration dependence. Similar behavior is observed in the steady state phase, where especially higher transmission heat losses have to be compensated, compared to the reference variant (mean: 4.5 / 6.8 / 7.0 $W{\cdot}m^{-2}$). Reasons for this behavior may include the occurrence of up events at different times of the day, in particular ambient temperature and solar gains, which were not investigated further.

Limitations

Grouping the floors into zones is a good compromise between simulation speed and accuracy, but also leads to a change in temperature dynamics within a simulated day. The different solar gains per side of the building throughout the day are assigned equally to a zone rather than to specific rooms. However, assuming that the rooms are heated equally, the difference in heating loads of the individual rooms should be averaged over the floor. A more accurate statement can only be made by simulating both variants. Since the focus of this work is on the comparison between the control strategies, no further investigations were carried out in this regard for the time being.

The temporary increase of the room setpoint temperature is used to exploit the upward flexibility and the resulting reduced load on the power grid, as well as to save electricity costs on the consumer side. However, the higher room temperature is associated with higher heat transmission losses and therefore higher final energy demand. Nevertheless, the calculation of the annual electricity costs related to the provision of heat is not included in this paper. In order to make a well-founded statement about the most cost-effective control strategy, an individually optimized operation and optimization of the individual constraints is required. For example, in the rule-based control strategy, the lower quartile for the electricity price limit is selected based on literature, but no parameter variation or sensitivity analysis was additionally performed, since the focus was on the quantification of the effective storage capacity under comparable boundary conditions, here the average charge duration. The electricity costs associated with the results would therefore not be universally valid.

Conclusion

In this study, the influence of active demand response (ADR) strategies for thermal activated building structures (TABS) was investigated using building energy simulation over one year for a new residential district. The focus was on the impact of different control strategies on the quantification of the effective storage capacity. For this purpose a rule-based control system was used, which increases the setpoint temperature depending on electricity market prices, as well as two independent, schedule-based controls (10:00 am to 12:30 pm and 2:00 pm to 4:30 pm). Despite comparable duration in the different control strategies, the rule-based control results in an average of 40% less effective storage capacity across all up events than the two schedule-based controls. The same applies to the additional heating load, which has about 30% lower mean value in the rule-based control. The following general observations can be made:

- The schedule-based control leads to a higher use of the flexible storage capacity then the rule-based control under comparable boundary conditions.
- The associated average heating load is correspondingly lower in the rule-based control than in the schedule-based control.
- Optimal use of flexible storage capacity in rule-based control requires further constraints to ensure reasonable operation in addition to the simple use of electricity market prices. This could include a minimum run time or minimum available storage capacity based on the current room temperature.
- The efficiency of the thermal storage, calculated from the ratio between the charge phases and the discharge phases, is greater than 90% in all control systems (taking into account the high energy standard).
- Assigning efficiencies to individual charge phases is particularly challenging in rule-based control because new charge phases may occur before the previous discharge phase is complete.

These results emphasize the need to consider control strategies when creating standardized KPIs for the energy-flexible use of TABS. In particular, building owners can obtain a realistic value for the cost-benefit ratio of the effective storage capacity during the design phase. The construction of the activated components can thus be optimized accordingly.

It was not within the scope of this study to investigate the reasons for the difference in effective storage capacity between the control strategies. However, we excluded the influence of duration by ensuring the same average duration for the charging phases in both control strategies. In particular, solar gains and ambient temperatures are likely to have an important influence. In addition to the boundary conditions, future work could also investigate the differences in quantifying downward events to temporarily minimize the electrical load on the grid, especially during the heating season.

Nomenclature

DSM	Demand side management
DR	Demand response
ADR	Active demand response
KPI	Key performance indicator
TABS	Thermally activated building structures
TES	Thermal energy storage
ns	Not significant

References

Airò Farulla, Girolama, Giovanni Tumminia, Francesco Sergi, Davide Aloisio, Maurizio Cellura, Vincenzo Antonucci, and Marco Ferraro. 2021. "A Review of Key Performance Indicators for Building Flexibility Quantification to Support the Clean Energy Transition." *Energies* 14 (18): 5676.

Arteconi, A., D. Costola, P. Hoes, and J.L.M. Hensen. 2014. "Analysis of control strategies for thermally activated building systems under demand side management mechanisms." *Energy and Buildings* 80:384–393.

Arteconi, A., N. J. Hewitt, and F. Polonara. 2012. "State of the art of thermal storage for demand-side management." *Applied Energy* 93:371–389.

Arteconi, A., A. Mugnini, and F. Polonara. 2019. "Energy flexible buildings: A methodology for rating the flexibility performance of buildings with electric heating and cooling systems." *Applied Energy* 251:113387.

Arteconi, A., and F. Polonara. 2018. "Assessing the Demand Side Management Potential and the Energy Flexibility of Heat Pumps in Buildings." *Energies* 11 (7): 1846.

Brunner, Edgar, and Ullrich Munzel. 2000. "The Nonparametric Behrens-Fisher Problem: Asymptotic Theory and a Small-Sample Approximation." *Biometrical Journal* 42 (1): 17–25.

Bundesministerium der Justiz. 22.05.2023. *Gesetz zum Neustart der Digitalisierung der Energiewende*. Volume 2023.

Bundesnetzagentur. 2023. SMARD — Download market data. Available online: `https://www.smard.de/en/downloadcenter/download-market-data/` (accessed on: 16 October 2023).

Callaway, D. S., and I. A. Hiskens. 2011. "Achieving Controllability of Electric Loads." *Proceedings of the IEEE* 99 (1): 184–199.

Cetin, Kristen S. 2016. "Characterizing large residential appliance peak load reduction potential utilizing a probabilistic approach." *Science and Technology for the Built Environment* 22 (6): 720–732.

David Bewersdorff. 2021. *HYGGiency: Raumhygiene und Behaglichkeit durch energetische Sanierung im Quartier = HYGGiency - Room hygiene and comfort through energetic refurbishment in district*. Volume Band 61 of *Mechanik, Werkstoffe und Konstruktion im Bauwesen*. Wiesbaden: Springer Vieweg.

de Coninck, Roel, and Lieve Helsen. 2016. "Quantification of flexibility in buildings by cost curves – Methodology and application." *Applied Energy* 162:653–665.

Denholm, Paul, and Maureen Hand. 2011. "Grid flexibility and storage required to achieve very high penetration of variable renewable electricity." *Energy Policy* 39 (3): 1817–1830.

European Parliament. 2018. Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency (Text with EEA relevance).

Foteinaki, Kyriaki, Rongling Li, Alfred Heller, and Carsten Rode. 2018. "Heating system energy flexibility of low-energy residential buildings." *Energy and Buildings* 180:95–108.

Foteinaki, Kyriaki, Rongling Li, Thibault Péan, Carsten Rode, and Jaume Salom. 2020. "Evaluation of energy flexibility of low-energy residential buildings connected to district heating." *Energy and Buildings* 213:109804.

Gellings, C. W., and W. M. Smith. 1989. "Integrating demand-side management into utility planning." *Proceedings of the IEEE* 77 (6): 908–918.

Hu, Xiaosong, Changfu Zou, Caiping Zhang, and Yang Li. 2017. "Technological Developments in Batteries: A Survey of Principal Roles, Types, and Management Needs." *IEEE Power and Energy Magazine* 15 (5): 20–31.

Kirschstein, Xenia, Joscha Reber, Rouven Zeus, Miriam Schuster, and Nadja Bishara. 2023. "Modelling of Floor Heating and Cooling in Residential Districts." *Energies* 16:5850.

Lauro, Fiorella, Fabio Moretti, Alfonso Capozzoli, and Stefano Panzieri. 2015. "Model Predictive Control for Building Active Demand Response Systems." *7th International Conference (Energy Procedia) SEB-15, 1st-3rd July 2015, Lisbon, Portugal*, Volume 83. 494–503.

Le Dréau, J., and P. Heiselberg. 2016. "Energy flexibility of residential buildings using short term heat storage in the thermal mass." *Energy* 111:991–1002.

Li, Han, Zhe Wang, Tianzhen Hong, and Mary Ann Piette. 2021. "Energy flexibility of residential buildings: A systematic review of characterization and quantification methods and applications." *Advances in Applied Energy* 3:100054.

Luc, Katarzyna M., Rongling Li, Luyi Xu, Toke R. Nielsen, and Jan L.M. Hensen. 2020. "Energy flexibility potential of a small district connected to a district heating system." *Energy and Buildings* 225:110074.

Lund, Henrik, and Ebbe Münster. 2006. "Integrated energy systems and local energy markets." *Energy Policy* 34 (10): 1152–1160.

Lund, Peter D., Juuso Lindgren, Jani Mikkola, and Jyri Salpakari. 2015. "Review of energy system flexibility measures to enable high levels of variable renewable electricity." *Renewable and Sustainable Energy Reviews* 45:785–807.

Morales, Juan M., Antonio J. Conejo, Henrik Madsen, Pierre Pinson, and Marco Zugno. 2014. *Integrating*

Renewables in Electricity Markets. Springer New York, NY.

Morales-España, Germán, Rafael Martínez-Gordón, and Jos Sijm. 2022. "Classifying and modelling demand response in power systems." *Energy* 242:122544.

Nejat, Payam, Fatemeh Jomehzadeh, Mohammad Mahdi Taheri, Mohammad Gohari, and Muhd Zaimi Abd. Majid. 2015. "A global review of energy consumption, CO 2 emissions and policy in the residential sector (with an overview of the top ten CO 2 emitting countries)." *Renewable and Sustainable Energy Reviews* 43:843–862.

O'Malley, Mark, Benjamin Kroposki, Bryan Hannegan, Henrik Madsen, Mattias Andersson, William D'haeseleer, Mark F. McGranaghan, Chris Dent, Goran Strbac, Suresh Baskaran, and Michael Rinker. 2016. *Energy Systems Integration. Defining and Describing the Value Proposition*. Office of Scientific and Technical Information (OSTI).

Reber, Joscha, Xenia Kirschstein, and Nadja Bishara. 2023. "Evaluation of Building Mass Characterization for Energy Flexibility through Rule- and Schedule-Based Control: A Statistical Approach." *Energies* 16:6878.

Reynders, G., T. Nuytten, and D. Saelens. 2013. "Potential of structural thermal mass for demand-side management in dwellings." *Building and Environment* 64:187–199.

Reynders, Glenn, Dirk Saelens, and Jan Diriken. 2015. "A generic quantification method for the active demand response potential of structural storage in buildings." *14th Conference of International Building Performance Simulation Association, Dec. 7-9 2015, Hyderbad, India*. 1986–1993.

TRNSYS. 2023. Transient System Simulation Tool. Available online: `https://www.trnsys.com/` (accessed on: 28 July 2023).

Vanhoudt, D., D. Geysen, B. Claessens, F. Leemans, L. Jespers, and J. van Bael. 2014. "An actively controlled residential heat pump: Potential on peak shaving and maximization of self-consumption of renewable energy." *Renewable Energy* 63:531–543.

Vigna, Ilaria, Ina de Jaeger, Dirk Saelens, Marco Lovati, Roberto Lollini, and Roberta Pernetti. 2019. "Evaluating Energy and Flexibility Performance of Building Clusters." *16th IBPSA International Conference and Exhibition, 2-4 Sept 2019, Rome*. 3326–3333.

Vivian, Jacopo, Umberto Chiodarelli, Giuseppe Emmi, and Angelo Zarrella. 2020. "A sensitivity analysis on the heating and cooling energy flexibility of residential buildings." *Sustainable Cities and Society* 52:101815.

Zafar, Rehman, Anzar Mahmood, Sohail Razzaq, Wamiq Ali, Usman Naeem, and Khurram Shehzad. 2018. "Prosumer based energy management and sharing in smart grid." *Renewable and Sustainable Energy Reviews* 82:1675–1684.