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Assessing Energy Flexibility using a Building's Thermal Mass as Heat Storage

a case study on demand response in office buildings retrofitted with a heat pump

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A Thesis in the Field of Building Physics and Services for the Degree of Master of Architecture, Building and Planning

Assessing Energy Flexibility using a Building's Thermal Mass as Heat Storage

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Abstract

Intermittent and stochastic behaviour of renewable energy sources (RES) comes with technical challenges in the energy transition. According to the 'Klimaatakoord', 70% of the energy mix must come from RES. Due to the loss of inertia in the power system provided by traditional power plants, other forms of energy flexibility will be required to maintain grid stability and balance. Buildings have been proven to have intrinsic properties to provide flexibility through demand response, where end-uses that may be controlled such as heating, ventilation and air-conditioning (HVAC) systems, on-site photovoltaic (PV) systems and white good appliances. Furthermore, aggregation of a cluster of buildings becomes possible through intermediary actors of the electricity market allowing buildings to participate in spot and ancillary service markets. In this paper, energy flexibility will be explored based on dynamic building energy simulations, using the thermal mass of a case study office building as the storage component. A parametric study, where downward set-point regulations, starting times and duration of demand response events (DREs) are varied to quantify the energy flexibility. An aggregation of energy flexibility of the case study building onto the whole building compound is implemented to determine the feasibility of electricity market participation solely through heat pumps as opposed to the need for a larger pool of heat pumps or other systems in the compound. Finally, historical effects are examined in the same representative week to have an initial understanding of charging and discharging characteristics of the thermal mass and determining requirements for a prediction model that will allow buildings to bid in the intraday or day-ahead markets. Results of the parametric study found an upper limit the amount of energy flexibility that may be provided. Associated net earnings were obtained based on energy costs, however, further research is required to determine the cost of providing flexibility such as operational or maintenance costs. It was found that historical effects may reduce the energy flexibility by up to %37 and the earnings by up to %73. The higher drop in earnings are due to increased energy consumption. Lastly, a 'discharging effect' of the thermal mass was observed through a steady decrease in the average floor surface temperature, when historical effects are taken into account. This may explain the increased energy consumption due to previous DREs discharging the thermal mass. Such uncertainties in the amount of energy flexibility may be detrimental to grid service providers, since lack of commitment may be penalised in electricity markets. As a result, model-based controllers may be necessary when performing DREs and bidding into the electricity market.

Contents

1 Introduction

The 'klimaatakkoord' (Climate Agreement) of the Netherlands, based on the EU 2050 clean energy package, is an agreement which aims, by 2030, to reduce greenhouse gas emissions by 49% relative to that of 1990. To achieve this, 70% of all electricity must come from renewable energy sources (RES), with the primary alternatives being solar PV and on/offshore wind power [1]. Furthermore, electrification of the demand in the built environment must take place, including the transition from gas-fired boilers to thermally or electrically powered heaters for building space and domestic water heating. The 'klimaatakkoord' states that, by 2050, the current building stock consisting of 7.74 million homes and 570,000 commercial buildings must become "gas-free", meaning the building systems must be either non-combustible thermal or electric. As a milestone, the agreement sets a target in which 1.5 million homes must become "gas-free" by 2030.

The energy transition from centralised, fossil fuel-based sources to de-centralised, RES comes with new challenges in the electrical infrastructure of the built environment. Wind and solar energy have an intermittent and stochastic power output due to their dependence on weather conditions. The result is a large variability and peaks in the residual power load in the low and medium voltage level. Furthermore, there is an uncertainty factor due to 'forecasting errors', which becomes significant with the expected increase in wind power capacity until 2050 [1]. These characteristics, as a result, require the Dutch power system to have power reserves and sources of flexibility [1, 2].

Power reserves are a responsibility of the power generating units, however flexibility is an opportunity for prosumers (e.g. building owners with large demands or PV capacity) to participate in services of the power system. Such opportunities may be further argued due to the fact that solar PV and on/offshore wind power are mainly integrated into the medium- and low-voltage network [3]. The aforementioned services may include trading electricity in spot markets, congestion management to avoid overloading of transformers or feeders, and ancillary services such as local balancing [2].

Balancing electricity supply and demand is necessary to maintain grid stability. To ensure this balance, a paradigm shift in the energy network from supply-response to demand-response is essential. There exist many alternatives to tackle flexibility and power reserves including grid reinforcement, distributed or large-scale energy storage and fast-response generating units. Most or all of the aforementioned alternatives may be necessary in the energy transition and the comparison between them is out of the scope of this paper. However, it has been shown that demand response (DR) is a cost-effective measure to accommodate for variable RES integration. Benefits include lower system operation costs and reduced grid-reinforcement and generation capacity requirements [4, 5].

Various sources of demand-side flexibility exist, including buildings, electric vehicles, electrical or thermal storage and industrial end-uses. In order for any to be of potential, large-scale implementation is necessary due to the low power density of one unit such as an industrial or home battery system. Currently, natural gas plants provide flexibility, where the levelised cost of energy (LCOE) is around ≈€100/MWh [6]. The cost of other storage technologies such as NiCd batteries, which can have a mean LCOE of €421/MWh when used for bulk energy storage and a mean LCOE €337/MWh if used for transmission and distribution services [7], show that electrochemical batteries are yet to constitute a competitive alternative as a source of flexibility. On the other hand, a building's existing structural mass as a 'heat battery', requires a negligible amount of investment and, in aggregation, may provide the energy flexibility necessary through demand response events (DREs), where heating, ventilation, and air-conditioning (HVAC) systems or other end-uses are controlled [4, 8].

Previous studies have already shown the potential of buildings to be sources of flexibility through DREs, including valley filling, peak clipping, conservation, flexible load (load-following), load building or load shifting as shown in Figure 1 [8–15]. Buildings, however, have an important requirement of maintaining occupants' comfort. This is due to a strong correlation between occupant comfort and health and productivity [16].

Demand-side energy flexibility in buildings has been studied extensively by utilising various end-uses such as white goods (washing machines, dishwashers, etc.), building systems (HVAC, domestic water heating, lighting, etc.) within economic, technological or techno-economic models [5,17,18]. An important note is that the term "Energy Flexibility" was not commonly utilised in papers prior to [19]. Examples of terminologies that have been utilised include demand side management or demand response, where the same concept is utilised in a same or different context.

Most studies in literature model the system to be grid-connected and therefore follow demand response (DR) programs to interact with the grid. Due to the vast domain of model development to investigate DR potential of different resources, Boßmann and Eser [17] conducted an extensive and comprehensive literature review followed by categorising properties, which are summarised as follows:

- spatial properties: international, national, regional and local
- temporal properties: ex-post, ex-ante and within each the time-resolution (hours, minutes, seconds)
- methodological properties: model perspective, model approach, mathematical method
- technological properties: industrial, residential, tertiary and transport sectors
- practical properties: DR activity type and DR programmes

The sub-categories within each category are extensive [17]. Therefore, only relevant sub-categories are addressed and discussed within this paper.

One of the challenges is to define practical properties in DR models. The unknown future of the EU electricity market structure and policy changes supporting the integration of distributed energy resources hampers the ability of determining the feasibility without assumptions. Currently in the Netherlands, zonal pricing is used in the electricity market and is based on full-hour contracts, where fossil-fuel powered plants are used for flexibility. This becomes problematic in an energy transition to RES, when in comparison to natural gas plants, energy storage needed for RES such as electrochemical storage, hydrogen storage or hydro-storage have very high investment costs [7, 20].

In the US, demand response (DR) (Figure 1) through aggregations and atypical pricing schemes have been widely applied such as in the PJM American market. DR support schemes in the PJM are setup such that end-users can participate through "Curtailment Service Providers", which serve as intermediary agents or in more recent terms, through "aggregators" [21]. Most countries, however, utilise time-of-use (TOU) pricing schemes and therefore consider buildings to be passive actors in the market [15]. Studies currently show potential for end-uses to be actively participating in the markets such as in balancing and ancillary services market [22].

Required tasks within balancing markets include, trading electricity either in the day-ahead or intraday markets

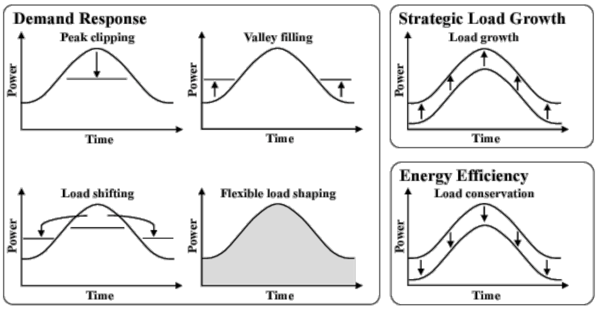


Figure 1: Demand response methods [23]

to ensure a continuous balance between electricity supply and demand. The day-ahead and intraday markets are traded on the spot markets where the platform used in the Netherlands is the EPEX SPOT exchange. This market is also shared between multiple EU countries, therefore allowing cross-border trading. The prices are determined based on production costs of generation units as well as electricity costs, which is obtained from the supply and demand bids as legislated by the European Commission [24].

While for ancillary services, frequency containment regulation (FCR) and restoration reserve (FRR) are assigned to parties that are qualified and have a minimum capacity reserve. The services are traded on the intraday market and are activated in scales between near real-time up to 30 minutes. Due to the constraints of heat pumps' minimum run- and pause-times and this case study building's system size, primary (FCR) and secondary (part of FRR) control reserves can be neglected, which must must respond in less than 15 minutes. However, tertiary control reserves (part of FRR) may still be an opportunity in the event of aggregations.

The potential electrical energy flexibility using the building's thermal mass as heat storage is shown to be one of many promising solutions to stabilise the grid in renewable energy-based grid. Swati et al. [13] focused on quantifying and analysing the energy flexibility in the context of a smart energy network by implementing demand response events (DRE) using set-point changes of an ideal heating system. In this paper, the same objective is set, however, the difference is the change of heating system to a heat pump. The retrofit to a heat pump is important considering the targets set by the Netherlands and the EU to eliminate the use of natural gas, specifically in the 'klimaatakkoord' agreement [25], where a 50% reduction in carbon emissions is set as a target for 2030 and 100% by 2050 compared to levels in 1990 [26].

The main research objective is to *assess the energy flexibility provided by a heat pump system when utilising the thermal mass as the heat storage medium.* Indicators are chosen so as grid operators or aggregators can obtain knowledge on the building's heating system capabilities in a future scenario, where buildings will provide services in stabilising the surrounding energy network.

The research question can be specified as follows including sub-questions that will aid in the main answer:

- How much energy flexibility can BAM's office building offer with a heat pump system through its thermal mass?

  1. How much energy flexibility do climate control schemes provide during heating season?
  2. Is it currently feasible for BAM to use its building compound to solely participate in the electricity market?
  3. How does thermal mass perform with historical demand response event effects?

In this paper, a building energy simulation model-based assessment of the energy flexibility of a case study building retrofitted with a heat pump is performed. The thermal mass of the case study building is used as heat storage, and in the context of the Dutch power system and climate. The structure of this paper is as follows, this sections outlines the scope of this paper including the purpose, objectives, and research questions. Section 2 will be a review of previous papers in this field, where the focus will be on papers using DR when investigating energy flexibility in buildings. Section 3 includes how the model is developed and utilised to assess energy flexibility in order to answer the research questions. This is followed by section 4 and 5, with the results and discussion. Finally, sections 6 and 7 include the conclusions and any further research needed to improve our understanding in energy flexibility in the future energy system.

2 Literature Review

In literature, demand-side flexibility is studied through various models, and in the context of electricity markets, may be categorised according to demand response (DR) properties as aforementioned. From a spatial properties perspective, most studies refer to local, regional and national scale and therefore stay within borders of individual countries [17]. Within the temporal properties, most studies analyse system performance on hourly to annual scales however, the resolution of most models do not exceed one hour [17]. Recently, studies such as [27–29] are beginning to implement high time-resolution models, i.e. sub-hourly, to aid the electricity system and market actors in gaining knowledge on response capabilities and characteristics of different end-uses for ancillary or balancing services. This is an important step in a trend of diminishing system inertia and non-fossil fuel-powered flexible generators in the power system. Moreover, current market conditions still deem large-scale implementation of energy storage technologies such as electrochemical batteries and hydrogen-based technologies as costly. As for the technological properties, the residential sector has a high focus in comparison to the industrial and commercial sector [15]. More research is needed in other sectors that can offer significant sources of flexibility. As can be expected in the methodological approach, the model perspectives are limited to end-uses or distributed generators such as PV and battery systems due to the nature of buildings. However, from the mathematical models aspect in the methodological properties, authors utilised either of two alternatives: rule-based control (RBC) or model predictive control (MPC) controllers that manage the building systems [30] to perform energy flexibility-related strategies. Both types of control have their advantages, however, it was shown that MPC outperforms RBC in accounting for the stochastic profile of wind and solar power by pre-heating or pre-cooling a building to exploit power generation peaks, therefore being proactive versus reactive as compared to RBC.

In general there has been an evolution in research with respect to utilising and evaluating energy flexibility in buildings, which falls under the methodological properties category. Initially, authors set an objective of maximising self consumption with on-site RES [31–42], without giving specific attention to indicators pertaining to electricity market services. The main discussion included the performance of on-site energy matching and system efficiency, while aiming to reduce or eliminate grid interaction. Moreover, costs were taken into account through peak shaving or load shifting based on TOU or RTP pricing.

On the other hand, more recent papers such as [29] focus on using DR as the key to participate in aggregations or, if large enough, solely to participate in electricity markets i.e. to provide balancing services to the grid.

The performance indicators differ between the aforementioned approaches due to the different objectives. The self consumption objective utilises indicators such on-site energy matching (OEM) and on-site energy fraction (OEF) [36]. Whereas, studies focussing on DR aim to minimise energy costs by using TOU or RTP pricing [43–45], or quantify the potential for supporting the grid in balancing services using more recent energy flexibility indicators [2, 46]. In both cases however, CO_2 emissions may be accounted for as an additional indicator.

One note is some of recent papers still utilise self consumption and this could be due to other objectives such as saving costs for building owners in current scenarios. Some authors such as [45, 47–50] stood out due to their respective early publishing dates and use of flexibility indicators in addition to energy costs.

CO_2 emissions, self consumption and energy cost indicators are directly comprehensible, however, energy flexibility indicators are developing, where the the IEA has created "Annex 67" in order to improve our understanding in how much different types of buildings and their end-use systems may offer flexibility to the future energy system [19]. The purpose of the annex is to prepare for a smart grid scenario, where buildings can serve as an actor in the energy system. Figure 2 depicts the scenario in which heat pumps may aid a 0.4 kV feeder in avoiding overload by peak shaving and load shifting.

Hurtado et al. [2] have compiled a group of indicators that take into account flexibility indicators including ramp rate, capacity and energy values as shown in Figure 7 in section 3. Note that thermal comfort was integrated in order to not sacrifice occupant comfort, health and productivity. The importance of such indicators presents itself when grid operators and distributed resources owners such as PV or wind farms or industrial, commercial and residential end-users are collaborating to instantaneously balance the electricity supply and demand. The nature of electricity networks requires accurate prediction in both supply and demand in order to anticipate imbalances and reduce or activate supply or demand resources. Furthermore, when specifically focussing on buildings as an actor in balancing electricity, one must account for stakeholders including building owners or occupants that have cost and comfort requirements that serve as constraints or objectives depending on the perspective it is observed from. Based on all these requirements are indicators to be established and utilised as criteria for evaluating any energy flexibility measure.

In order for buildings to be flexible, a storage component is essential that allows for the load to shift or reduce. In buildings that may come in many forms, however, most buildings utilise insulated water tanks, thermal inertia of a building's structure, or electrochemical batteries. Furthermore, other alternatives to provide demand-side flexibility exist, such as grid batteries or electric vehicles. The comparison to the latter alternatives are out of the scope of this paper, however, as aforementioned in section 1, large scale implementation of grid batteries still remains costly due to the high capital cost required. On the other hand, when comparing storage tanks to thermal mass, it was shown in a Danish case study of the detached house building stock that thermal mass is more cost effective due to higher initial investment costs of storage tanks in comparison to lower energy costs savings [19, 51, 52].

Building energy simulation (BES) models are considered a white-box approach, which may simulate demand response events (DREs). They provide the ability to predict a building's potential energy flexibility and physical insights into the energy storage responses such as that of the structural thermal mass. Such an approach is advantageous when, for example, a building is still in the design

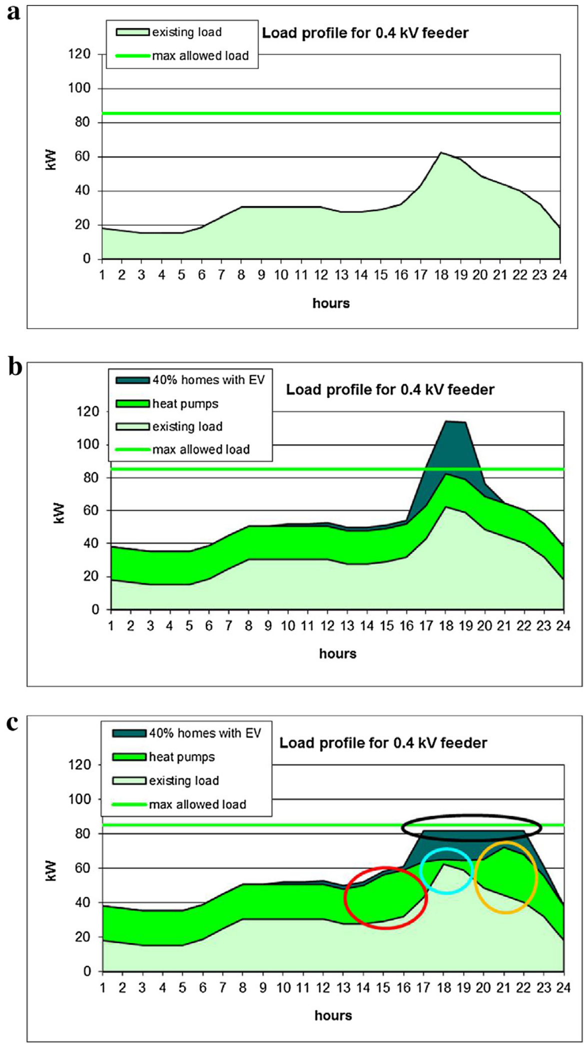


Figure 2: (a) Current scenario with peaks occurring in evening hours due to cooking appliances. (b) future scenario showing heat pumps and electric vehicles will cause an overload to the current system. (c) a smart grid solution where buildings are pre-heated prior to cooking peak, therefore shifting the load to avoid a peak [19]

stage and the operational aspects need to be investigated. This may also apply if a building is in a retrofit design stage.

BES models always include a representative thermodynamic and heat transfer model of the building including resistance, capacitance, and all energy gains and losses. Other components that are part of the building energy system such as HVAC or PV systems may or may not be dynamically modelled including the approach to which they are controlled. Building systems control is a significant aspect since it defines the capabilities when performing demand response event (DREs). The approaches were previously mentioned in the methodological properties as either model-predictive control (MPC) or rule-based control (RBC).

In general, authors focus on the economic aspect for building owners or energy service companies (ESCOs) when performing demand response [31, 50], particularly if authors choose MPC as a control strategy [52]. For example, Liu and Heiselberg [53] focus on shifting heating and cooling loads of an office building in Denmark using RBC. The control strategy depends on price levels, which are categorised into low, medium and high values. The RBC aims to avoid consumption in high price levels and shifting such loads to medium or low price level periods. Even though economic incentives were set as the main objective, other indicators were reported such as power decrease for grid operators to have insights required for ancillary and balancing services. It was found that the energy consumption increases compared to a reference comfort-based control strategy. However, there was a distinct difference between the different RBC strategies, where a simple strategy of shifting loads from high to low price levels increased energy consumption by around 41% and after adding a weather-predictive controller, the increase was limited to 4%. The BES model included a convective heating and cooling system supplied by a heat pump and chiller respectively and historical electricity market prices from 2015.

Authors that use MPC have shown the improved capabilities in minimising energy costs due to improved scheduling of heating or cooling system operation to time periods with lower energy prices. In summary, MPC provides optimal performance, whereas RBC yields sub-optimal results due to a lack in capability from the latter in anticipating future states and conditions [30]. However, MPC comes with challenges such as increased computational times, complexity and therefore increased costs and risk of modelling or prediction errors [52].

There is a lack of a detailed overview on expectations of energy flexibility provided by the thermal mass. Similarly to this case study, most office buildings comprise of concrete structures that are considered heavyweight in terms of thermal mass [54]. The International Energy Agency (IEA) Annex 67 characterises a building's thermal mass energy flexibility with the exclusion of historical effects, weather and occupancy changes. The latter two have a stochastic nature, which provides uncertainty in the amount of available energy flexibility due to the thermal mass's charging and discharging characteristics. For example, a sunny day will charge the thermal mass and may be used the following day when it is overcast. Similarly, a day where occupants have the windows open may cool the building causing the thermal mass to dissipate it's heat to the outside, thereby temporarily reducing its energy flexibility capacity until recharged.

Historical demand response events must be taken into account in building energy simulations when assessing the current energy flexibility that may be provided. Most papers address this using MPC, where heuristic or analytical optimisations are performed to determine the schedule for end-uses such as HVAC systems and appliances [46]. When using HVAC systems, the medium through which flexibility is provided may be either passive using the thermal mass or active through storage tanks. Due to the autonomous nature of model-predictive controllers, the analysis of historical effects are often neglected in such studies. Therefore, there is a lack of reporting in order to build reliability and close the gap between research and grid operators to utilise building thermal mass a heat storage or 'power-to-heat'.

Most of literature perform seasonal or annual analyses by setting thermal comfort constraints to ensure applicability. An analogy of this, could be with the state of charge of electrochemical batteries. Grid operators or building owners have an indicator of the current ability to perform a demand response event. However, unless a building has a model-based controller, estimating the instantaneous amount of flexibility due to thermal mass may bring a level of uncertainty. Such uncertainties may impose penalties on aggregators or building owners if they fail to meet the bid/contract agreed with the electricity market.

3 Methodology

The approach taken in this study is utilising a computational building performance simulation model to simulate demand response (DR) programs. The energy and comfort performance, due to changes in indoor air temperature set-points, are investigated. As a result, a theoretical upper limit of the energy flexibility potential is determined. The most important factors in the model are therefore the building and the heating and ventilation system, which govern the amount of flexibility a building can provide.

Future outcomes are uncertain for electricity market prices, therefore the focus in this paper relies on dynamic building energy simulations to quantify energy flexibility using current real-time pricing (RTP) of ancillary and balancing markets. Using RTP, either through aggregators or directly with the electricity market, buildings may offer balancing services. The markets in which this paper assumes the case study building and compound to participate in, are the balancing markets, which have a 24-hour cycle with a 15-minute time step as shown in Figure 3.

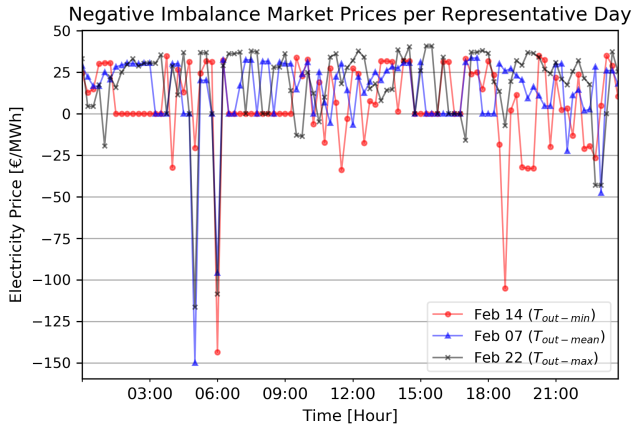


Figure 3: Real-time (imbalance) electricity prices in the Netherlands for each representative day chosen

To address the *first and second part of the research question* in quantifying the energy flexibility that may be provided by the heating system, demand response events (DREs) are simulated using the building energy model. DREs were limited to downward regulations, i.e. reducing the set-points. Findings from the previous study of the same case study building [13] showed that upward regulation of the set-point increased overall energy consumption in relation to the total energy shifted, leading to a loss for the building owner or aggregator. A parametric study is conducted to simulate DREs as will be discussed in section 3.4.

Previous research has already shown that frequency of charging and discharging thermal mass with heat may conflict in more than 24-hour periods. Therefore, this impacts the participation in demand response (DR) due to thermal comfort constraints and as a result an understanding of the historical effects of demand response events (DREs) is needed. This aids the electricity market actor responsible for bids to predict the extent of flexibility the building is able to provide. To understand such dynamics and address the *third part of the research question*, the difference in behaviour between two cases, one including- and the other excluding historical DRE effects, gives an indication on the degree of impact and dependency between two or more DREs.

Multiple stakeholders are involved in this study such as occupants of the building in which their comfort must not be compromised, building owners or energy service contracting organisations (ESCOs) in which maximising profits is important to protect their business value stream, electricity system operators (SOs) in which must maintain the the system's adequacy and security to all consumers. Therefore a feasible solution is one which satisfies all requirements from different stakeholders. The key performance indicators (KPIs) were chosen to reflect these requirements, where the objective is to maximise energy flexibility to the grid and maximise net earnings to the building owners, ESCOs or aggregators.

In summary, the parametric analysis is evaluated based on whether it is feasible from a comfort perspective followed by choosing the DRE with highest energy flexibility for each representative day. Subsequently, the aggregated energy flexibility of the building compound may be obtained, where it can be known whether it is feasible, using heat pumps, to solely participate in electricity markets. The main requirement is the 1 MW minimum reserve, as aforementioned in section 1, to be able to provide balancing services. Otherwise, an 'aggregator' would be required to gather a larger pool to trade on behalf of BAM.

3.1 Case Study Building and Retrofit Design

The case study, referred to as building "D", is an office building located in the city of Bunnik, Netherlands, which will be investigated for the potential electrical energy flexibility using the building's thermal mass as heat storage. Currently, the building is heated using three central gas-fired boilers. In response to a need for an alternative heating source, a heat pump is added as a retrofit to the building in place of the current gas-fired boilers. The choice of a heat pump is due to its capabilities of responding promptly to control signals (≈15min) and higher energy efficiency compared to gas boilers. The building characteristics are summarised in Table 1.

Table 1: Case study building D characteristics

Elements	Amount	Unit	Remarks
Area	3	Floors	1284 m^2
Age	2002	Year	-
Occupancy	74	People	-
Ventilation	4	ACH	Balanced
Heating	3x65	kW	Gas Boilers

Built in 2002, the building (Figure 4a) is part of a larger building compound consisting of eight office buildings as shown in Figure 4b. The total floor area of the compound is approximately 17000 m^2. Each building in the compound is nearly identical to one another from a typological, structural and architectural perspective. Therefore, it was assumed the case study building may be a representative building of the compound. It should be noted however, building orientations vary therefore heating demand profiles may vary between each individual building due to different solar gain profiles.

In total there are three storeys in the building, each having mostly an open-plan layout. The orientation as seen in Figure 4b is East-west in the longitudinal direction, therefore the larger areas of the façade are facing North and South.

3.1.1 Building Enclosure

The system used for most of the external components including walls, floors and roofs is precast concrete insulated sandwich panels. The fenestration system consists of double-glazed windows with aluminum frames. A summary of the thermal characteristics and window-to-wall ratios are presented in a previous study [13].

(a) Southeast view of building D

(b) Building Compound of Case Study

Figure 4: Case study building shown in top from a Southeast perspective. The bottom figure shows BAM's building compound comprising of 8 buildings.

3.1.2 Heating and Ventilation System

As aforementioned, the building uses three natural gas boilers as the heat source. As a medium, hot water is distributed for space heating, whereas domestic hot water is provided using separate electric resistance boilers.

The hydronic distribution is split between a radiator terminal system and heating coils of an air handling unit system as shown in Figure 9.

The air handling unit (AHU) contains a sensible heat recovery wheel with a 75% effectiveness ratio. As a result, the heating demand of the AHU is significantly reduced, leaving the majority of the heating demand with the radiator system, where the heating coil requirements may be considered negligible.

3.1.3 Heating system retrofit and design

The heat pump system serves as a retrofit to the case study building by replacing the current central gas-fired boilers. Based on this system architecture, the heat pump(s) were sized to meet the full heating demand requirements of the building.

Sub-hourly building energy simulations were utilised based on a validated building model [13]. A load duration curve of the annual heating demand (Figure 5) was predicted using TRNSYS. The load duration curve and thermal comfort constraints, based on Dutch indoor climate standards, were utilised for sizing the heat pumps. An air-source heat pump was chosen as the retrofitted system type based on a discounted payback analysis, where the results may be seen in Figure 6. Results for the HVAC sizing may be found in Appendix B.

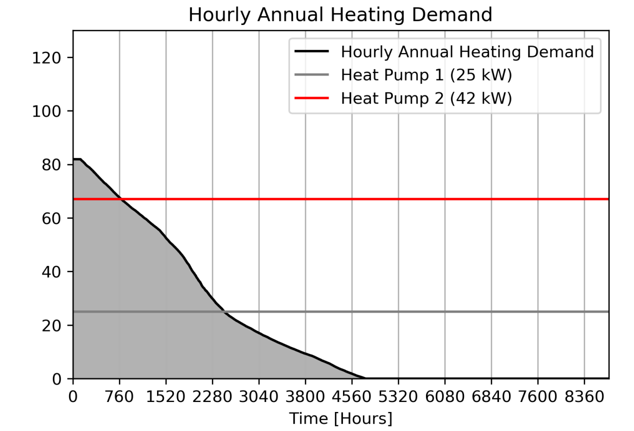


Figure 5: Predicted load duration curve of annual heating demand of building D simulated in TRNSYS

3.2 Energy flexibility using thermal mass

The total energy consumed by the HVAC system including the heat pumps, circulation pumps and air handling unit fans are utilised when calculating the energy flexibility-related indicators.

3.2.1 Key performance indicators

As aforementioned, key performance indicators (KPIs) were chosen carefully to account for relevant stakeholders including building owners, ESCOs, aggregators and grid operators.

Hurtado et al. [2] developed a graphical representation highlighting the main performance indicators when conducting a demand response event (DRE) as shown in Figure 7. Grid operators pay attention to the energy side such as peak clipping ($\pi^{+/-}$), load shifting or conservation ($\epsilon^{+/-}$) and duration of time of each (t). Whereas, building owners and ESCOs focus on costs incurred on the building including energy costs and thermal comfort. Equation 1 and 2 show how these indicators are calculated.

$$\pi^{+/-} = P_{flexible}(t) - P_{reference}(t) \tag{1}$$

$$\epsilon^{+/-} = \int_{t_{DREStart}}^{t_{DREEnd}} \pi^{+/-}_{flexible}(t) - \pi^{+/-}_{reference}(t)dt \tag{2}$$

where $P_{flexible}(t)$ is the total energy consumed by the HVAC system including the heat pumps, circulation pumps, and air handling unit fans when a DRE is performed in kW, $P_{reference}(t)$ is the same as $P_{flexible}(t)$ but without any DRE performed, $t_{DRE\,Start}$ is the starting time of the DRE event and t_{DREEnd} is the ending time of the DRE event.

To quantify the energy flexibility on an aggregated level of BAM's building compound and address the *second part of the research question*, the 'energy flexibility intensity', formulated in Equation 3 is used to calculate the total energy flexibility that can be provided by the compound.

$$E^{-}\ or\ \Pi^{-} = \frac{\epsilon^{-}\ or\ \pi^{-}}{A_{casestudy}} \times A_{compound} \tag{3}$$

where, E^{-} is the energy capacity shifted or partially conserved of the whole compound in kWh, Π^{-} is the power capacity clipped in kW, $A_{casestudy}$ is the floor area of the case study building in m^2 and $A_{compound}$ is the floor area of all buildings aggregated in the compound in m^2.

Thermal comfort may be characterised using indoor operative temperature, where the range must be bound within the upper and lower limits. Linden et al. [55] investigated the adoption of adaptive comfort limits in the Netherlands. It was stated that during heating season, where mean outdoor temperatures are below 11-12°C, type 'Beta' operative indoor temperature limits apply. To take the best-case scenario in providing flexibility to the grid, the 65% acceptability limits were taken into account that ranges between 18 and 19°C for lower limits, depending on outdoor temperatures.

As for the economic indicators, the service of providing flexibility is assumed to be incentivised in the electricity market context through demand response (DR), in line with the ambitions of the EU including the Netherlands [25]. Furthermore, to ensure a current best-case scenario, the maximum imbalance market price excluding any outliers is taken into account for each representative day as shown in Table 2. The market data set also includes ancillary services. Depending on the capacity of the energy flexibility, buildings may take part in either directly- or scheduled-activated frequency restoration reserve (mFRRda or mFRRsa). An aggregated amount of 20 MW is required by the former (mFRRda), whereas the latter is not specified therefore a minimum of 1 MW is assumed (as per market regulations) [56].

It should be noted however, that the economic analysis uses the flexibility service costs as a revenue due to the building owner (BAM) perspective, whereas the energy imported from the grid is taken as a cost. Therefore, the cost KPI is formulated as in Equation 6.

$$R = \epsilon^{-}\ C_{max}(t_0) \tag{4}$$

$$\Delta C_{imports} = \sum_{t_0}^{t_7} C_{flexible}(t) - \sum_{t_0}^{t_7} C_{reference} \tag{5}$$

$$P = R - \Delta C_{imports} \tag{6}$$

where, P are the net earnings in €, R is the revenue generated from performing a demand response event (DRE) in €, $\Delta\, C_{imports}$ is the difference between the total electricity importing costs of the reference case ($C_{reference}(t)$) with no DRE and the electricity import costs of the flexible case ($C_{flexible}(t)$) with DRE, in €, t_0 is the representative day, and t_7 is the day, one week subsequent to the representative day. By taking into account the energy consumption one week subsequent to the DRE, the "rebound effect" is included, in case the overall energy consumption may increase, remain the same or decrease.

3.2.2 Scenarios

To provide a clear context in which this research is investigated in and due to the shear amount of possible scenarios that exist, assumptions are made with the objective of using the best-case scenario in order to determine whether buildings' thermal masses are a feasible source of flexibility.

Electricity market prices were based on a single year's profile of the EU-NL wholesale market. This data is openly available and provided by Tennet through its ENTSO-e transparency platform. The year chosen was 2018 as it is the most up-to-date complete annual data set. However, to simplify and choose a best-case scenario, the maximum price of each day is used excluding any outliers as summarised in Table 2.

Based on preliminary simulations, it was found that February provided the highest energy flexibility due to the highest heating demand and lowest COP. Therefore, February was chosen as a representative month for a best-case

Capital Cost* (€)	Discount rate (%)	Lifespan (yrs)	Salvage (%)	Natural Gas (€/GJ)	Electricity (€/kWh)
8050 (ASHP) / 24100 (GSHP)	3	15	0	21.4	0.1

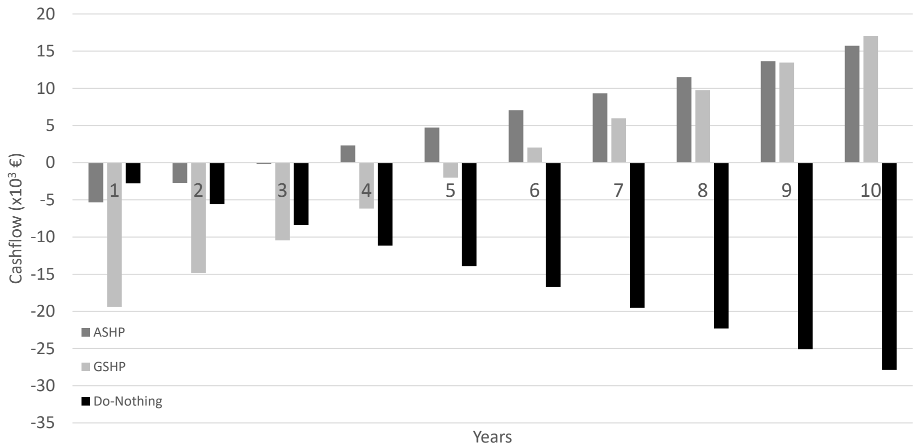


Figure 6: Discounted payback period for two retrofitting alternatives based on building performance simulations, air-source heat pump (ASHP) and ground-source heat pump (GSHP), compared to a "Do-Nothing" case.

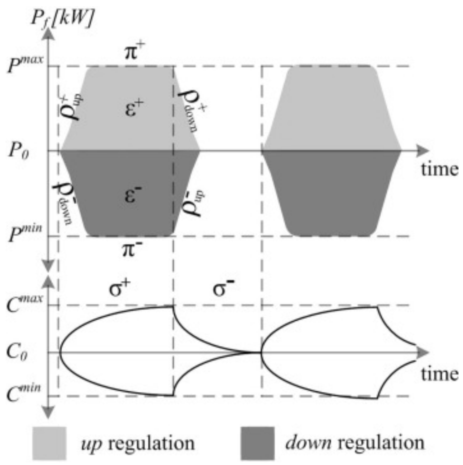


Figure 7: Energy flexibility key performance indicators [2]

scenario. Within February, the minimum, mean and maximum outdoor temperature days were chosen to simulate all DREs as summarised in Table 2.

3.3 Building Energy Model

3.3.1 Building

Due to the open-plan layout of the office building and exclusion of a cooling system, each floor was simplified as one heating zone as shown in Figure 8. Nair et al. [13] validated the building model based on utility bills. All relevant window and building characteristics are presented in Appendix B and may be found in [13].

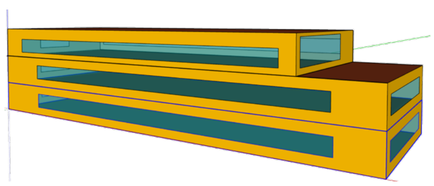


Figure 8: Geometrical model of case study in TRNSYS

3.3.2 Heating and Ventilation

Based on the object-oriented modelling methodology, the model was developed using various components from the TRNSYS and TESS libraries. Figure 9 depicts the architecture of the HVAC system modelled. In total two air-source heat pumps were sized and modelled based on load duration curves, to minimise on-off cycles (partial load conditions). It must be noted however, that a heat storage buffer tank was excluded in order to isolate the thermal mass and indoor air as the only sources of flexibility, providing a better understanding of how thermal mass performs.

The circulation pumps and fans are modelled as variable speed, where the performance curves were derived from the manufacturers' documentation due to the existing distribution system of the building and may be found in Appendix B.

As for the controls, a simple real-time three-stage on/off thermostat was utilised for each floor, where if one floor requires heat, the heat pumps are switched on with a 15-min time delay per stage. It must be noted however, that the circulation pump works on partial load if not all floors require heating. The first two stages are for both heat pumps and the third stage is for an auxiliary heater if the outdoor ambient temperature are below design conditions.

3.4 Simulation setup

The setup of the model allows to run simulations throughout the entire heating season, which provides an estimate on how much the case study building can offer to help balancing the electricity supply and demand in a renewable-energy based grid. Parametric runs are utilised in determining daily sub-optimal demand response events, with the objective of maximising energy flexibility ($\epsilon^{+/-}$) and determining the associated net earnings, while satisfying thermal comfort constraints. Table 3 summarises the input parameters used and the list of possible values.

As a result, a total of 120 control strategies per representative day (Table 2) are simulated, where the energy flexibility is calculated. It must be noted however, that an annual simulation without any demand response event (DRE) is used as a *reference case* when calculating the energy and cost KPIs.

The second part of the simulations involves a parametric study to investigate the historical effects of DREs. In this case only one input parameter was chosen, DRE starting

Table 2: Days chosen in representative month of February

Description	Statistic	Day	$T_{ambient-average}$ [°C]	Electricity $Price_{max}$ [€/MWh]
$T_{out-min}$	Minimum	Feb 14	2.3	57.2
$T_{out-mean}$	Mean	Feb 07	7.6	46.9
$T_{out-max}$	Maximum	Feb 22	10.9	60.5

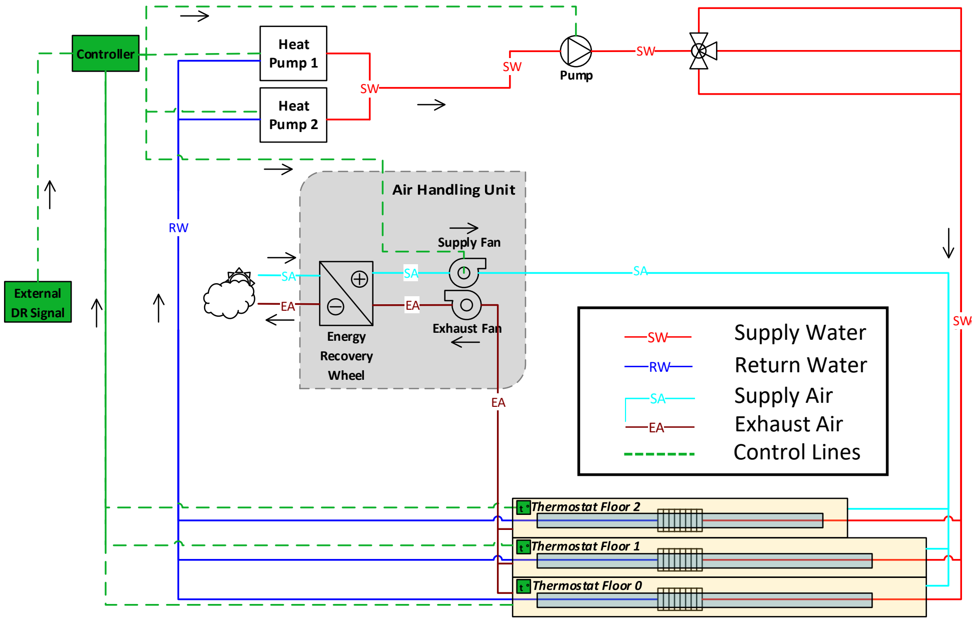


Figure 9: Heating and ventilation system model in TRNSYS

Table 3: List of input parameters in parametric study

Parameters	Possible Values
Set-point changes[°C]	-1...-4
DRE starting hour[24-Hour]	06:00...17:00
DRE duration [hours]	2...6

hour, and the other two parameters were set as constants. A set-point change of -3°C and a DRE duration of 4 hours were chosen.

Excluding historical effects Using the model of the building and HVAC system, a parametric analysis of various DREs will be performed for each day of the week starting on February 7 and ending on February 14. One input parameter was chosen as aforementioned. For each day, the result with the highest energy flexibility is chosen. The following day, the same process takes place assuming no previous DRE was performed. As a result, a benchmark as an upper limit of the available energy flexibility, is provided for each day of the whole week chosen.

Including historical effects and sub-optimal strategy In reality, DREs might take place on a daily basis, which means historical effects will impact the subsequent DRE depending on the 'state of charge' of the thermal mass, the DRE specifications (duration, start time, or set-point), the climate and occupant behaviour. In this case, the same DREs as in the case of excluding historical effects will be simulated for a chosen sequence of days, however, for each subsequent day, any previous DRE(s) is(are) included, therefore accounting for potential historical effects. It should be noted that the results chosen still satisfy the highest energy flexibility criteria. Therefore, the input parameter providing the result may differ compared to the case without historical effects.

4 Results

Regarding the *first and second part of the research question*, the aim is to determine the maximum energy flexibility that can be provided given various control strategies (Table 3). The input parameters result in a combination of 120 strategies for each representative day. The three representative days chosen provide the 'best-case scenario', resulting in a total of 360 simulations. The days were chosen based on a preliminary seasonal analysis to determine the month with the highest power (π^-) and energy flexibility ϵ^-.

Figure 10 provides four distributions of the energy (ϵ^- and E^-) and power (π^- and Π^-) capacity categorised by the duration of the DRE for both building D and the whole building compound, i.e. all 8 buildings. The distributions are a result of the parametric analysis including all representative days and set-point change magnitudes. Based on these results, it can be deduced that heat pumps solely are insufficient to participate in electricity markets due to the minimum 1 MW requirement previously mentioned. Furthermore, the down regulation does not continuously keep the heat pump off, due to the thermostat maintaining the minimum indoor air temperature as shown in Figure 11. This may be improved by implementing pre-heating strategies with a predictive controller as opposed to the real-time, rule-based control (RBC) controller used in this case. However, other equipment and systems in the building compound aggregate to an amount higher than 1 MW. Hence, allowing BAM to have a role in the electricity market such as a trader or balance service provider.

The power capacity is mostly negative as expected due to the downward set-point regulations during the DREs, while the top 25th percentile, which is positive, represents the heat pumps maintaining the minimum indoor air set-

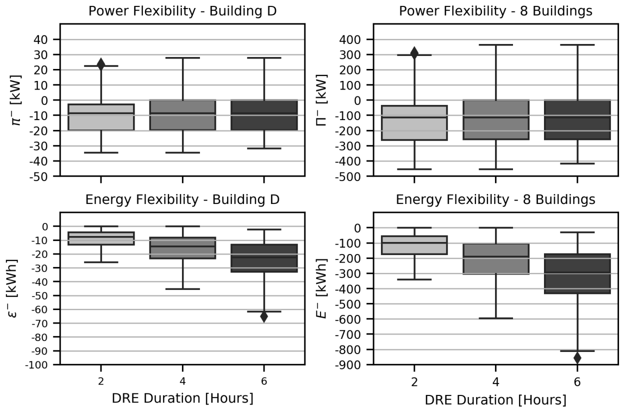


Figure 10: Load shift/conservation (ϵ^- and E^-) and peak clipping (π^- and Π^-) potential of all demand response events categorised into demand response duration

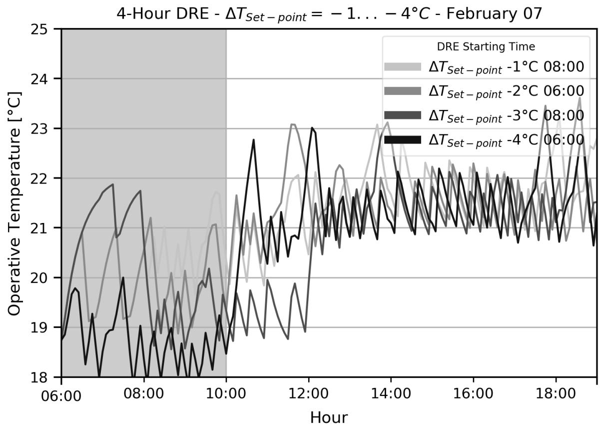


Figure 11: Maximum flexibility of 4-Hour demand response events (DREs) for 4 different climate control strategies ($\Delta T_{set-point} = -1... - 4°C$)

points. Both indicators are normally distributed for 4- and 6-hour DREs, while the 2-hour DRE is skewed more to the lower power, i.e. higher flexibility. Such behaviour is due to the 2-hour DREs having a lower impact on thermal comfort constraints compared to DREs with longer duration. The same behaviour is observed for energy capacity (ϵ^-). However, the power capacity (π^- and Π^-) have approximately the same median, regardless of duration. The minimum and maximum values differ due to the longer duration, which results in higher heating demand to maintain or restore indoor air temperature set-points. On the other hand, there is an increasing trend in energy capacity as the duration increases, which is expected. This trend is more apparent in Figures 12a and 13a, where the energy flexibility increases with respect to the magnitude of duration and set-point change.

Figure 12a and 13a show the energy capacity (ϵ^-) that is provided by the heating system categorised by DRE duration for both the case study building and the whole building compound. It must be noted that each bar is the maximum energy flexibility for each representative day (T_{out}) and associated set-point change magnitude ($\Delta T_{set-point}$). Moreover, each bar represents one parametric run, meaning no previous or subsequent DRE were performed. Based on a simple visual inspection, it can be deduced that the energy capacity is proportional to duration (time) and set-point change magnitude, however, the trend is not the same for net earnings. The reason for this is, net earnings include not only the revenue due to the provided flexibility, but also the increased or decreased energy import costs ($\Delta C_{imports}$) that is a consequence of the downward set-point regulations. Furthermore, the dynamic pricing of the electricity market varies between the different representative days (Table 2).

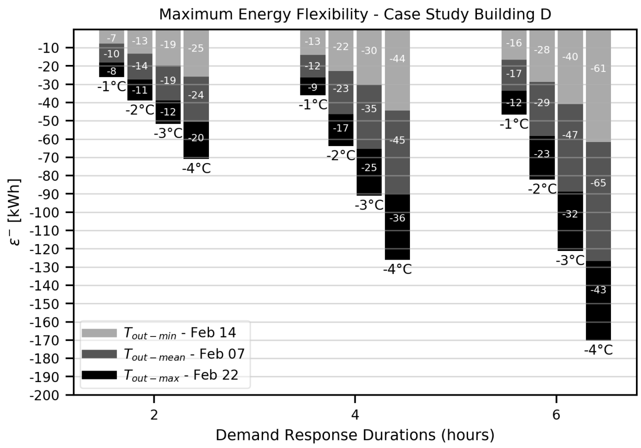
Based on the parametric analysis, Figure 12b and 13b show that one DRE per day will potentially result in a positive net earning to the building owner, considering only energy costs. Results may differ depending on other operational costs including labour, maintenance and other administrative costs.

It is expected, in the future, that the imbalance market will have a more prominent role due to the stochasticity of wind and solar energy sources. Therefore, Figure 14 shows the results of future imbalance market price scenarios, where the first bar represents the current and worst-case scenario and the two subsequent bars represent a 50% and 100% increase in the price amplitude per time step of the negative imbalance market. It is worth noting that increasing the price by a factor of two does not necessarily increase the net earnings by the same factor due to the fixed price of energy imports. In all three days, the increase between the 'Base' and '50%' case is 26% and 20% between '50%' and '100%'. This shows that the cost of energy imports are an important factor in the economic analysis.

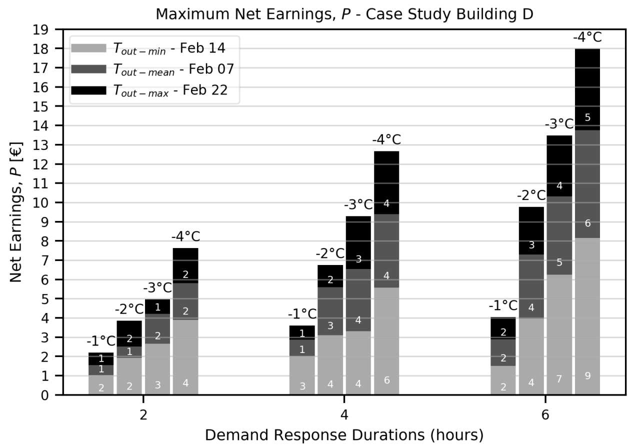
Albeit Figure 12a and 13a give a theoretical maximum on how much flexibility can be provided, a whole year analysis is necessary to understand the seasonality and cyclic nature of this 'heat battery'. There are many degrees of freedom when determining the 'state of charge' of a thermal mass including occupancy, weather and HVAC system performance. Determining the full potential of a building's thermal mass is out of the scope of this paper, however, determining the requirements for an approach is what the *third research question* addresses.

Figure 15a and 15b shows the difference in energy capacity and net earnings between cases of including- and excluding historical DREs, when attempting to quantify the energy flexibility that may be provided. In this case, only one DRE per day is simulated, where a drop of up to 37% in energy capacity may occur. This may increase if more than one DRE is conducted per day. As an indicator of the thermal mass's state, surface temperatures are presented, where it can be seen that there is a steady drop in the case when historical effects are included. Such results show the limitations of rule-based control (RBC) if the objective is to determine a seasonal or annual potential of energy flexibility. Despite the flexibility is reduced, the earnings are still positive meaning a profit for the owner.

In a preliminary analysis, the downward regulation in most cases was shown to reduce overall energy consumption as shown in Figures 17a and 17b, meaning there is no significant "rebound effect". This may be explained by the application of one DRE per day per simulation, which does not significantly influence the surface temperatures. Only indoor air temperature is significantly influenced as shown in Figure 11 due to air's low specific heat capacity. According to Figure 1, this may be classified as load conservation. It must be noted however, in some cases, control strategies including set-point magnitude, duration and starting time do increase the import of costs, such as when the end of a DRE coincides with a drop in internal gains during occupied hours. On the contrary, it was found that when a sequence of DREs are performed over multiple days, there is a slight increase in energy consumption as shown in Figure 17b when compared to the case excluding historical effects in Figure 17a.

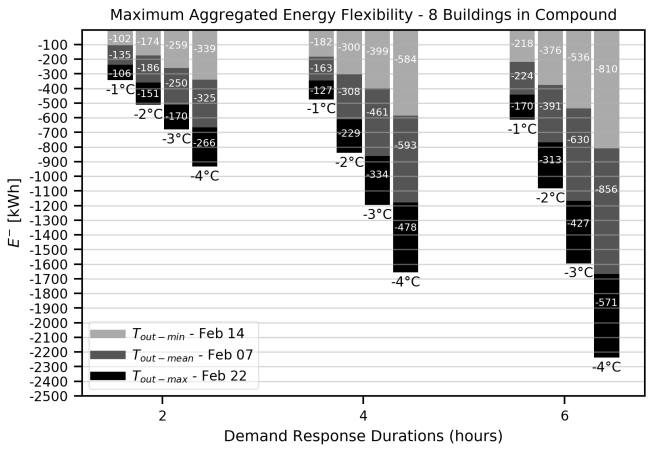


(a) Load shift or conservation per representative day

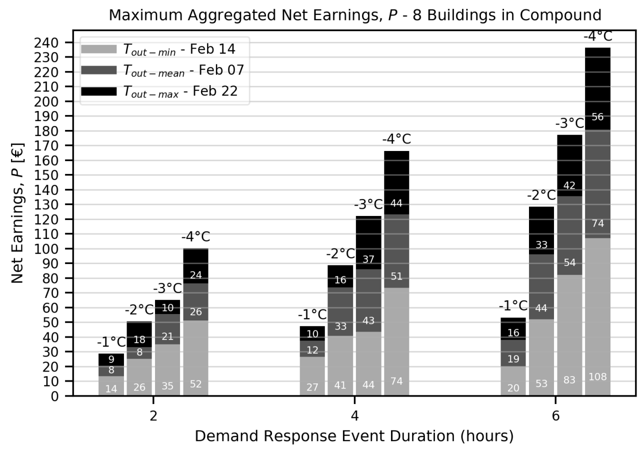


(b) Net earnings per representative day

Figure 12: Maximum load shifted or conserved (ϵ^{-}) and net earnings (P) of all three representative days categorised into demand response duration and indoor set-point magnitude change



(a) Load shift or conservation per representative day



(b) Net earnings per representative day

Figure 13: Maximum aggregated load shifted or conserved (E^{-}) and net earnings (P) of all three representative days categorised into demand response duration and indoor set-point magnitude change

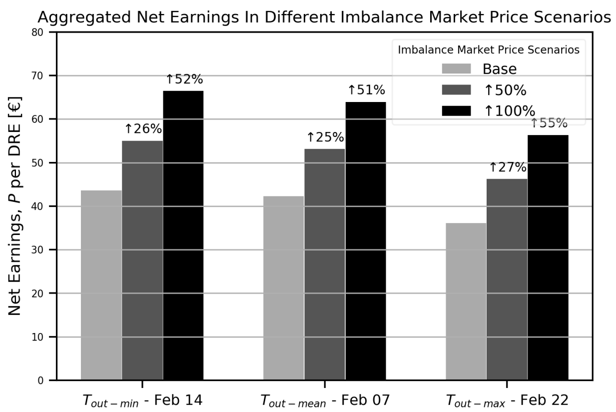


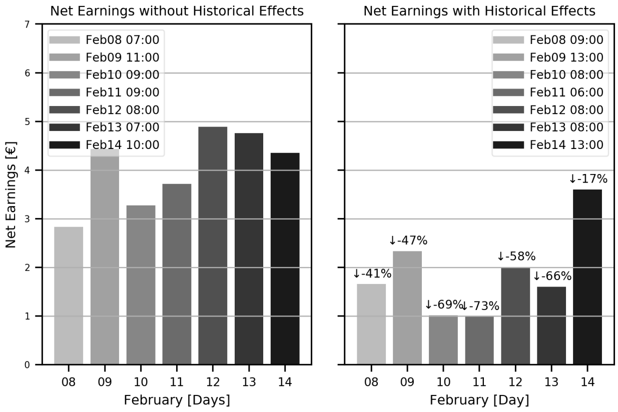
Figure 14: Net earnings of a 4-Hour demand response event (DRE) with a $\Delta T_{set-point} = -3°C$, for each representative day. The 'Base' scenario represents current prices, where '50%'and "100%' represent future scenarios.

5 Discussion

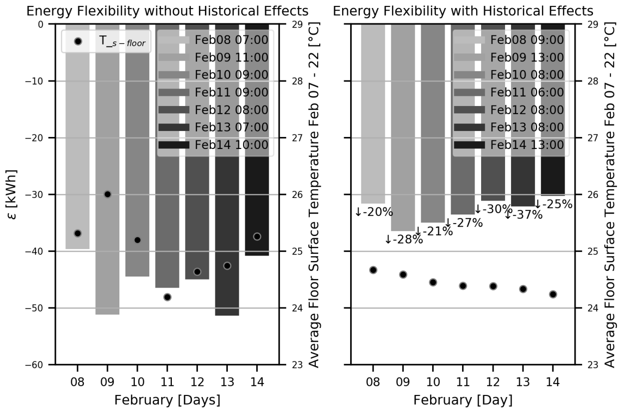
Hurtado et al. [2] found a down regulation power capacity (π^{-}) potential of around 35 kW for Dutch office buildings with an average area of approximately 4000 m^2, which equates to an intensity of around 8.6 W/m^2. In this case study, the results are in the same order of magnitude with an intensity of around 8.0 W/m^2 derived from the results shown in Figure 10. The similarity in the results can be attributed to the similarity in the heat source used, i.e. an air-source heat pump. However, the heat emission systems are different, where Hurtado et al. [2] use a direct-expansion (DX) coil with a constant volume (CV) fan, while a radiator system and a variable speed fan with a heat recovery wheel is used in this paper.

Longer duration DREs may have higher load shifting or load conservation potential, however, this may have a 'discharging' effect similar to what is seen in batteries, where the effect is evident in the trend of surface temperatures as shown in Figure 15b. This further strengthens the need for a model-based predictive controller, which translates the state of a building to the controller before implementing any control strategy.

Limitations in this study include the lack of whole-year analysis, where weather, occupancy and energy prices vary. Furthermore, some cases when implementing a control strategy of $\Delta T_{set-point} - 4°C$ exceeded adaptive thermal comfort limits, therefore caution needs to be taken in determining the feasibility. The use of current imbal-



(a) Net Earnings with- and without- historical effects



(b) Energy flexibility (ϵ^-) with- and without- historical effects

Figure 15: Sub-optimal control strategies found for days between February 8 and 14. Figure 15a shows net earnings (P) and Figure 15b shows the load shifted (ϵ^-). In the case without historical effects, each day was a separate simulation, as opposed to the cases with historical effects, where each subsequent day included demand response events starting on February 8

ance market prices does not reflect a renewable-energy powered grid scenario due to the existing low-cost gas power plants, which provide flexibility. The use of a real-time controller, where pre-heating strategies were excluded, may result in higher peaks for heating power, thereby increasing the power capacity π^- computed in some cases. However, the energy capacity (ϵ^-) may also be increased if preheating strategies are implemented due to prolonged heat pump off-time. Furthermore, the COP of 'Heat Pump 1' is lower when working in tandem with 'Heat Pump 2' as shown in the lower curve in Figure 18, thereby increasing the provided flexibility. The reason for the lower COP is caused by the lower flow rate, which leads to a lower heat output. Another factor includes the control system, where traditional on/off thermostats with step functions were used as opposed to a P- or PI-controller with a variable speed heat pump. The latter type of control system may result in an increase in efficiency by 6-18% [57], thereby reducing the available flexibility.

It is important to note the variance in the COP between the representative days, where the median COP for $T_{out-min}$, $T_{out-mean}$, $T_{out-max}$ are approximately 1.6, 2.3 and 3.1 respectively. Therefore, the power capacity clipped and energy capacity shifted/conserved are impacted due to the increased energy consumption. Albeit the total load during colder days being higher, the available flexibility is theoretically lower due to the higher conductive and convective losses to the outside. As may be seen in Figure 12a and 13a, the amount of flexibility provided in the days of $T_{out-min}$ and $T_{out-mean}$ have similar values despite a difference in 0.7 in the median of COP. Such behavior may be explained due to this difference in COP, where the magnitude of power is higher over a shorter period of time.

When it comes to air temperature, the controller performs well in maintaining the set-point to avoid sacrificing thermal comfort as shown in Figure 16. However, this comes at the expense of higher duty cycling of the heat pump. As aforementioned, pre-heating control strategies may solve this problem in pro-longing the off-time of the heat pump.

The reduced energy flexibility due to historical effects adds a degree of complexity for electricity market actors including system operators (SOs) and aggregators to forecast and therefore bid on behalf of the building. The risk is also higher due to the rules of the electricity market, where if a specific amount is promised, the market will penalise a seller's lack of commitment. Currently, quantification methods of energy flexibility using thermal mass is limited to control strategies that provide higher flexibility, where apart from model-based methods and as to the authors' knowledge, no holistic control strategy takes into account a thermal mass' state of charge in addition to other factors such as electricity prices, comfort constraints, weather and system efficiency. Further research is required in order to establish the possibility of an approach in quantifying energy flexibility given the state of the building when no model-based control system exists.

Reynders et al. [46] reviewed quantification methodologies in thermal storage applications. Most methodologies implement a predictive aspect for each time step to reevaluate the availability of flexibility based on the current state of the building and/or systems. However, one of the five reviewed assumes consecutive DREs to be independent thereby an uncertainty in the results will occur similar to what is shown in Figure 15b. Hurtado et al. [2] quantifies flexibility, by simulating different DREs throughout the year, however, there was no indication of uncertainty in the availability of flexibility due to historical effects. Therefore, care should be taken into reporting potentials without indicating the possible under- or over-estimating of energy or power capacity.

From an economic perspective, there is a distinct discrepancy between the historical and non-historical effect inclusion in calculating the net earnings for each DRE. The energy consumption without historical effects seemed mostly to be lower than the reference case, while the energy consumption with historical effects was in more cases were higher as shown in Figure 17b. The reason for such behavior may be attributed to the thermal mass discharge (Figure 15b), where the surface temperature is decreasing over time in comparison to the case without historical effects. The advantage of excluding the buffer tank is the ramping down of the average surface temperature over two weeks for each subsequent day. This can be used an indication of an overall discharge in the thermal mass over time regardless of weather and DRE starting times.

There exists a risk of an increase in total energy consumption that may outweigh the financial incentives brought by supporting the grid. Figure 14 shows that even if the imbalance prices were to increase by 50 or 100%, the total increase is approximately half of that at 20 and 26% respectively. Therefore, if buildings were to participate in electricity markets, predictions of DREs need to be inclusive of historical effects or the current state of buildings.

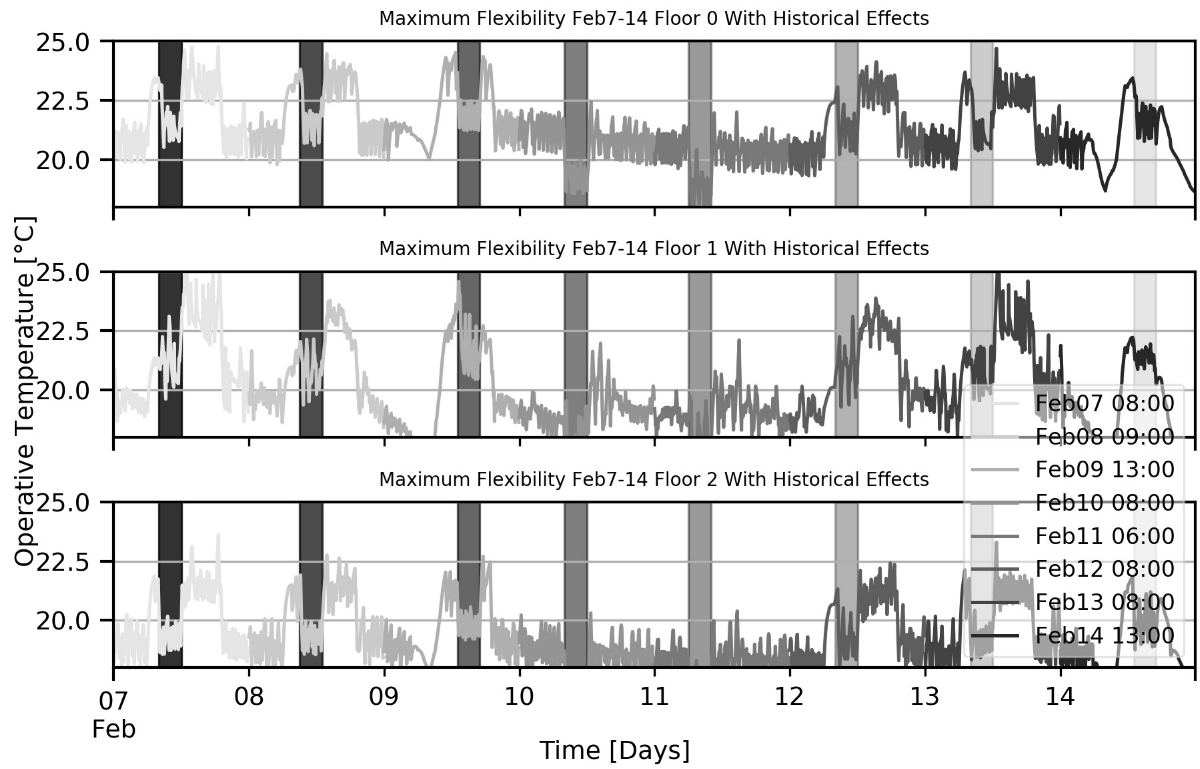
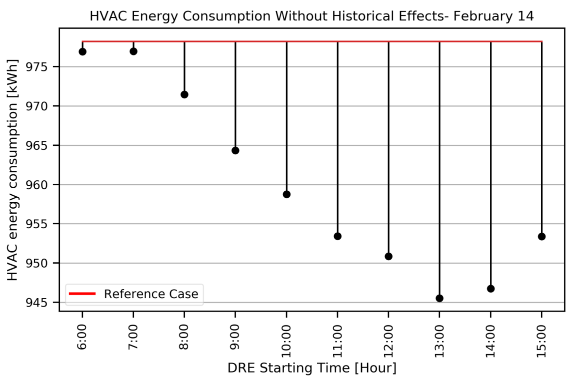
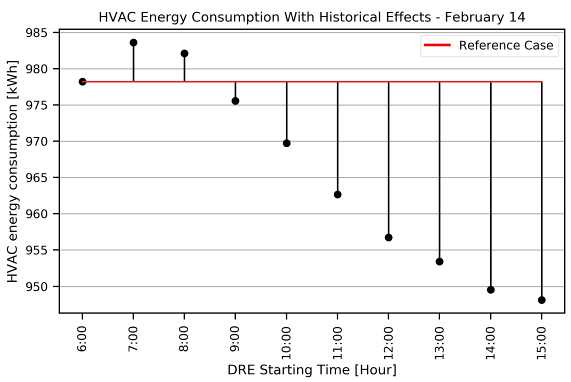


Figure 16: Multi-day comfort response to one DRE per day for 8 consecutive days (Feb 07-14). Limited to a 4-hour DRE with a set-point change magnitude of -3°C



(a) Without Historical Effects



(b) With Historical Effects

Figure 17: Comparison of total HVAC Energy consumption categorised into DRE starting time. Example from a 4-hour DRE with a set-point change magnitude of -3°C

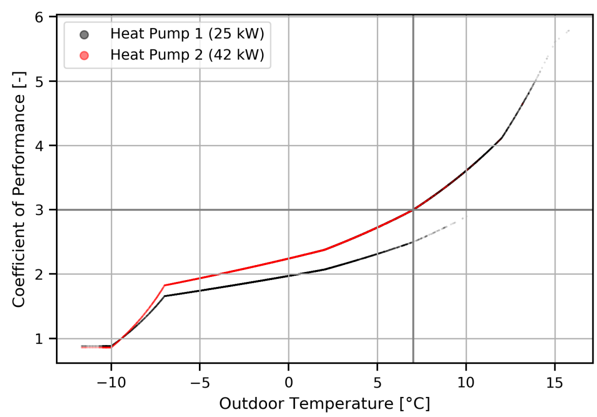


Figure 18: COP of both heat pumps in relation to outdoor ambient temperatures

6 Conclusions and Recommendations

In this paper, a theoretical upper limit of energy flexibility provided by an air-source heat pump through a case study's thermal mass was calculated. Furthermore, a preliminary analysis on the behavior of thermal mass' charging and discharging characteristics was performed by comparing two cases, one including and one excluding historical DRE effects. The latter provides an important aspect, which needs to be considered before extrapolating the quantification to multi-day or annual scale. The quantification aside from the temporal aspect also is far from simple in the climatic aspect as not only is the building heating demand varies, the COP of the heat pump also varies.

However, based on the results, it can be concluded that exploiting thermal mass may be rewarding both for the owner and system operators. Questions still remain as to who will manage the HVAC system operations and monitor the availability of flexibility. This may be an added cost if buildings are to participate in electricity markets. Regardless of whomever takes such responsibility, quantification methods should begin with the current state of a building for each time step in order to adequately obtain the possible load shifting/conservation or peak clipping potential when bidding to the electricity market.

7 Further Research

The potential of implementing control strategies in building systems for the purpose of providing flexibility as grid services or self-consumption provide benefits, such as reduced electricity bills and overall security of electricity system operation. However, building owners or facility managers have an obligation to maintain building systems including bearing investment, operation and maintenance costs in providing comfort to the occupants. The following are possible further research topics that can be investigated:

- Using model predictive control (MPC) to investigate the thermal mass characteristics on annual scale
- Impact of short cycling on maintenance costs and lifespan of equipment
- Influence of solar gains including shading control
- Influence of on-site energy generation
- Simultaneously or independently regulating ventilation fans as demand response
- Increasing temporal granularity of DREs including frequency and imbalance price

Thermal comfort was based on 65% acceptability limits in order to evaluate the 'best-case' scenario. Further investigation may be necessary to assess the impact on the occupants' comfort perception such as through surveys. As a result, some of the proposed control strategies may be eliminated, thereby affecting the available energy flexibility that may be provided.

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Table 4: Building characteristics of ground floor

Surface ID	Surface Type	Construction Type	Area (m^2)	Category	Orientation (cardinal_directions_azimuth_inclination)
1	Wall	StoneOnConcrete	97.2	External	N_180_90
2	Ceiling	BAMFloor	453.6	Adjacent	-
3	Floor	BAMFloor	453.6	Boundary	-
4	Wall	StoneOnConcrete	34.02	External	W_90_90
5	Wall	PanelWall	34.02	External	E_270_90
6	Wall	PanelWall	97.2	External	S_0_90

Table 5: Window characteristics of ground floor

Surface ID	Associated Surface	Surface Type	Construction Type	Area (m^2)	Category	U-value ($W/m^2{\cdot}K$)	g-value (%/100)
7	4	Window	BAMWindow	4.864	External	1.51	0.37
8	5	Window	BAMWindow	12.802	External	1.51	0.37
9	6	Window	BAMWindow	35.444	External	1.51	0.37

A Modelling Methodology

A.1 Modelling technique

In order to capture the dynamic performance of a building HVAC system in predicting the flexibility a building may provide, a white-box approach was chosen where each system was modelled and coupled using TRNSYS as the tool that provides such flexibility. Modelling a mechanical system in TRNSYS comes with high flexibility due to the ability to choose from a wide range of components made up of a system of equations that can be connected only through input and output to any compatible component. For example, connecting a heat pump to a radiator or a radiator back to a heat pump forming a closed-loop system. The connections may be physical such as mass or energy flows or electrical signals for controls. However, there are disadvantages, including the time and level of uncertainty that come as a model becomes more complex. Therefore, care was taken in minimising details that are not fit-for-purpose such as the control system complexity, where a rule-based control (RBC) strategy was chosen. The objective of the model was not to have an annual or seasonal overview of actual flexibility but only to provide a theoretical upper limit and understand the behavior of thermal mass's heat storage characteristics on a multi-day scale.

A.2 Level of complexity

Identifying important factors affecting the HVAC performance and thermal mass storage characteristics are the essential requirements. Both systems encompass the building's performance when assessing energy flexibility on a day to multi-day scale. These factors include the electrical consumption of a heat pump system, which is a complex component of the HVAC system with dynamic behaviour due its dependence on multiple variables including indoor and outdoor climates. The thermal mass storage potential depends on the climate, occupancy and HVAC system used. Furthermore, the accumulation or dissipation of heat on a multi-day scale requires a dynamic model to allow for the dependency on a temporal scale. Furthermore, the terminal system has an important effect since the heat pump performance is influenced by the inlet and outlet conditions that forms a closed-loop system with a heat pump as shown in the schamtic in Figure 9.

A.3 Model objectives

The model setup must have the ability to respond to grid signals. Such signals can be assumed to simulate demand response events (DREs). The signal results in a modification of the set-point of all three thermostats of all zones. There can be other regulating methods such as fan power, however, it was deemed too extensive for this paper and therefore is not part of the scope of the simulations. The model however, should have the flexibility to have the ability to integrate such control strategies for future studies. As previously mentioned, the performance of both the building thermal mass and HVAC system must provide an indication of the available flexibility on a day to multi-day scale. Therefore annual, mean COPs would be deemed inaccurate when comparing performance between different days.

B Building Energy Model Details

B.1 Architectural characteristics

Architectural elements were modelled as per the case study building specifications and are summarised in Tables 4, 6, 8, 5, 7, 9, 10, and 11.

B.2 Internal heat gains and weather

B.2.1 Lighting

The lighting system comprises of fluorescent and LED lighting in the case study building. The ground and first floor however are dominated by fluorescent tube lighting, where ASHRAE Fundamentals 2013 Chapter 18, which documents different luminaire heat gains including fluorescent lighting. On the other hand, the second (top) floor is dominated by LED luminaires, which is not very well documented therefore, an ongoing project of ASHRAE RP-1681 was used in which [58,59] have conducted experiments in an office space mock-up investigating LED lighting heat gain split between

Table 6: Building characteristics of first floor

Surface ID	Surface Type	Construction Type	Area (m^2)	Category	Orientation (cardinal_directions_azimuth_inclination)
10	Floor	BAMFloor	453.6	Adjacent	-
11	Wall	PanelWall	97.2	External	S_0_90
12	Wall	StoneOnConcrete	97.2	External	N_180_90
13	Roof	Ceiling	1.676	External	H_0_0
14	Wall	StoneOnConcrete	34.02	External	W_90_90
15	Ceiling	BAMFloor	386.048	Adjacent	-
16	Roof	Ceiling	67.552	External	H_0_0
17	Wall	PanelWall	34.02	External	E_270_90

Table 7: Window characteristics of first floor

Surface ID	Associated Surface	Surface Type	Construction Type	Area (m^2)	Category	U-value ($W/m^2{\cdot}K$)	g-value (%/100)
18	11	Window	BAMWindow	35.431	External	1.51	0.37
19	12	Window	BAMWindow	28.791	External	1.51	0.37
20	14	Window	BAMWindow	4.864	External	1.51	0.37
21	17	Window	BAMWindow	12.802	External	1.51	0.37

Table 8: Building characteristics of second floor

Surface ID	Surface Type	Construction Type	Area (m^2)	Category	Orientation (cardinal_directions_azimuth_inclination)
22	Wall	StoneOnConcrete	82.724	External	S_0_90
23	Floor	BAMFloor	386.048	Adjacent	-
24	Wall	StoneOnConcrete	34.02	External	W_90_90
25	Wall	StoneOnConcrete	34.02	External	E_270_90
26	Roof	Ceiling	386.048	External	H_0_0
27	Wall	StoneOnConcrete	82.725	External	N_180_90

Table 9: Window characteristics of second floor

Surface ID	Associated Surface	Surface Type	Construction Type	Area (m^2)	Category	U-value ($W/m^2{\cdot}K$)	g-value (%/100)
28	22	Window	BAMWindow	34.108	External	1.51	0.37
29	24	Window	BAMWindow	4.864	External	1.51	0.37
30	25	Window	BAMWindow	16.8	External	1.51	0.37

Table 10: Thermal characteristics of architectural elements

Construction Type	No.	Layer	Thickness (m)	Type
BAMFloor			0.197	0.385 $W/m^2{\cdot}K$
	1	Wool	0.005	Massive
	2	Plaster	0.002	Massive
	3	Concrete	0.1	Massive
	4	Insul	0.09	Massive
Ceiling			0.15	0.371 $W/m^2{\cdot}K$
	1	Concrete	0.05	Massive
	2	Insul	0.1	Massive
PanelWall			0.247	0.382 $W/m^2{\cdot}K$
	1	Plaster	0.001	Massive
	2	Concrete	0.15	Massive
	3	Insul	0.095	Massive
	4	Tile	0.001	Massive
StoneOnConcrete			0.255	0.388 $W/m^2{\cdot}K$
	1	Plaster	0.001	Massive
	2	Concrete	0.07	Massive
	3	Insul	0.093	Massive
	4	Concrete	0.07	Massive
	5	Cement_Mor	0.001	Massive
	6	Stone	0.02	Massive

Table 11: Thermal characteristics of windows

Window Type	ID No.	U-value ($W/m^2{\cdot}K$)	g-value (%/100)	Maximum irradiance close blinds($kJ/hr{\cdot}m^2$)	Minimum irradiance open blinds ($kJ/hr{\cdot}m^2$)	Solar absorptance	Emissivity
DOUBLE	201	1.1	0.62	648	576	0.6	0.9
BAMWindow	11405	1.51	0.37	648	576	0.6	0.9

Table 12: Internal gains - lighting

Building Floor	Total Gain Intensity (W/m^2)	Radiative Fractions (-)	Convective Fractions (-)
Ground and First Floor	6.97	0.73	0.27
Second Floor	3.98	0.41	0.59

Table 13: Internal gains - occupants

Occupant (W/occupant)	Floor (W/floor)	Intensity (W/m^2)
71.8	1795	3.96
Radiative	Convective	
60%	40%	

conductive and radiative as well as between conditioned and plenum space. Table 12 summarises the internal gains due to the lighting system per floor.

B.2.2 Occupancy

Based on ASHRAE Handbook of Fundamentals Chapter 18, Table 13 below summarises the heat gains categorised according to radiative and convective fractions. The total occupancy count of the case study building is 74 therefore, it was assumed 25 are present per floor.

B.2.3 Process and Plug Loads

Similarly to occupancy gains, process and plug loads (PPL) heat gains were derived from ASHRAE Handbook of Fundamentals, Chapter 18. The classification of office building in terms of PPL are according to type of end-uses utilised. In the case study building, all occupants correspond to one laptop and two screens. Based on this information a PPL internal gain intensity of 3.55 W/m^2 was used with a a 30% radiative and 70% convective fraction as summarised in Table 14.

B.3 Heating source

Type 941 from the TESS library was used to model the air-source heat pump. A performance map obtained from a manufacturer is required, which is based on the outdoor ambient temperature, inlet and outlet water conditions, and inlet and outlet water conditions. Each heat pump used the same performance map due to the normalisation of the performance map. The rated heating power (kW$_{electrical}$) and capacity (kW$_{thermal}$) of each heat pump, in design conditions, were derived from the manufacturer's specifications. Moreover, the heat pump models were validated using the manufacturer's COP at the design conditions.

B.4 Heating distribution and terminal

Since each floor was modelled as one zone, one radiator per floor was modelled and sized based on the heating demand. The radiator was sized per zone, where Type 1231 was used obtained from the TESS library. a radiative fraction of 60% and convective fraction of 40% were used to define the sensible heat output of the radiators to each zone.

B.5 Ventilation Fans and Circulation Pumps

An air handling unit was modelled using two components, including one variable speed fan which has the capacity of both supply and exhaust fans combined to simplify the mass and energy balance. Type 147 was chosen, which calculates the partial load efficiency based on manufacturer-provided coefficients. The only assumption in this case, is the synchronised upward and downward regulation of the fan speeds of the supply and exhaust fans. The other component is the sensible energy recovery wheel (ERW), which has a 75% effectiveness. Type 760 was chosen to model the ERW.

The partial load efficiency of the fan was modelled using the manufacturer's supplied performance curves. The only assumption in this case is the pressure loss being static. The disadvantage is the fan efficiencies may be over- or under-estimated.

B.6 Controls

A rule-based control (RBC) strategy was utilised where, the rules are based on comfort constraints, i.e. signals from the thermostat in case any of the three zones require heating. Forcing functions were used to send binary signals to modify schedules of the thermostats that allows the change of set-points for specific duration of time. This served as a supervisory control, where lower level controls were maintained including, staged operation of the heat pumps, variable speed of the circulation pump, diversions to zones that only require heating, and bypass loops to maintain lower return temperatures to the heat pump. Furthermore, a basic shading control strategy was used, where a differential controller

Table 14: Internal gains - process and plug loads

Total Gain Intensity (W/m^2)	Radiative Fractions (-)	Convective Fractions (-)
3.55	0.3	0.7

Table 15: Modelled heat pump specifications

System	Rated Capacity (kW)	Rated power (kW)	Auxiliary power (kW)	Air flow rate (L/s)
Heat Pump 1	25	8.3	2.8	3700
Heat Pump 2	42	41.7	13.9	3700

Table 16: Modelled radiator specifications

Floor	Rated capacity (kW)	Design surface temperature (°C)	Design air temperature (°C)	Design ΔT exponent
Ground	52.1	50	21	1.4
First	33.3	50	21	1.4
Second	62.5	50	21	1.4

with an upper dead-band total surface irradiance differential of 250 W/m^2 and lower dead-band total surface irradiance differential of 120 W/m^2.

B.7 Thermal comfort

Based on the Dutch regulations for indoor climate comfort, the heating system was sized, based on the 100-hour limit 25°C. However, based on hourly simulations, the total number of unmet hours were 144 hours, of which 31 hours were due to overheating and 113 hours due insufficient heating. Furthermore, the indoor operative temperature was used to calculate the unmet hours.

C Energy flexibility in other months of heating season

Similar to the method used for determining an upper limit of the energy flexibility for February, the analysis was extended to the starting and ending months of the heating season, i.e. October and April respectively. Tables 18 and 19 depict the average daily ambient temperature and the maximum imbalance market price (excluding any outliers) for each day.

Figures 19a, 19b, 20a, and 20b depict the results for the month of October. Due to the warmer ambient temperatures of, the heating demand in October is lower than that of February. Albeit the longer duration in which indoor air temperature can be maintained in October, the energy capacity (ϵ^- and E^-) is lower. Therefore, the heating demand, in most cases, is a major factor in the amount of energy capacity (ϵ^-). While, energy capacity may be higher, the net earnings is not as straightforward. The lower heating demand in October also implies lower costs of energy imports. Furthermore, it was previously mentioned that the energy import costs have a significant influence on the net earnings (P). For example, a 2-hour DRE on October 22 ($T_{out-mean}$) has an imbalance price 38% than that of February 07 ($T_{out-mean}$), however, the resulting net earning (P) is %212 higher in the case of $\Delta T_{set-point} = -1°C$. This may be explained by the energy import costs ($\Delta C_{imports}$), where in both cases the DRE resulted in a load conservation as opposed to a load shift. However, in October, the load conservation was higher due to the warmer ambient temperature.

Figures 22a, 22b, 23a, and 23b depict results for the month of April. Similar to October, warmer ambient temperatures result mostly in lower energy flexibility compared to February. On the other hand, the net earnings (P) are significantly lower than in both October and April. This may be attributed to the low imbalance market prices shown in Table 19. Using the same example of a 2-hour DRE with a $\Delta T_{set-point} = -1°C$ on the mean outdoor temperature day (April 23), the net earnings (P) are negative, or in other words, a financial loss for the building owner. Albeit the imbalance market price being 16% higher and 16% lower in comparison to the days of February 07 and October 22 respectively, the lower energy capacity (ϵ^-) nevertheless results in having the lowest revenue (R). Furthermore, the energy import cost difference ($\Delta C_{imports}$) is higher in April compared to February and October, which is caused by a rebound effect exceeding the energy capacity (ϵ^-) provided during the DRE. The rebound effect may be explained by the starting time of the DRE, i.e. 06:00 in the morning, where the surface temperatures are lowest as can be seen in Figure 38 and the ambient temperature still decreasing (Figure 40), resulting in a lower surface temperature subsequent to the DRE, i.e. 08:00 a.m. Therefore, the heat pumps will have to operate for a longer duration in order to restore the set-point.

Finally, Figure 25 shows the results taking into account all three months, providing an annual range, which represents the upper limit of energy flexibility provided by building D and the building compound.

D Reference case for chosen days of each month

Figures 26 to 52 are results of building performance simulation of building D without any DRE, which represents the reference case used to calculate the energy flexibility and economic indicators. In total, nine days of the year were used to assess the energy flexibility distributed equally into the months of February, April and October as summarised in Tables 2, 19 and 18 respectively.

Table 17: Modelled ventilation pumps and circulation pump specifications

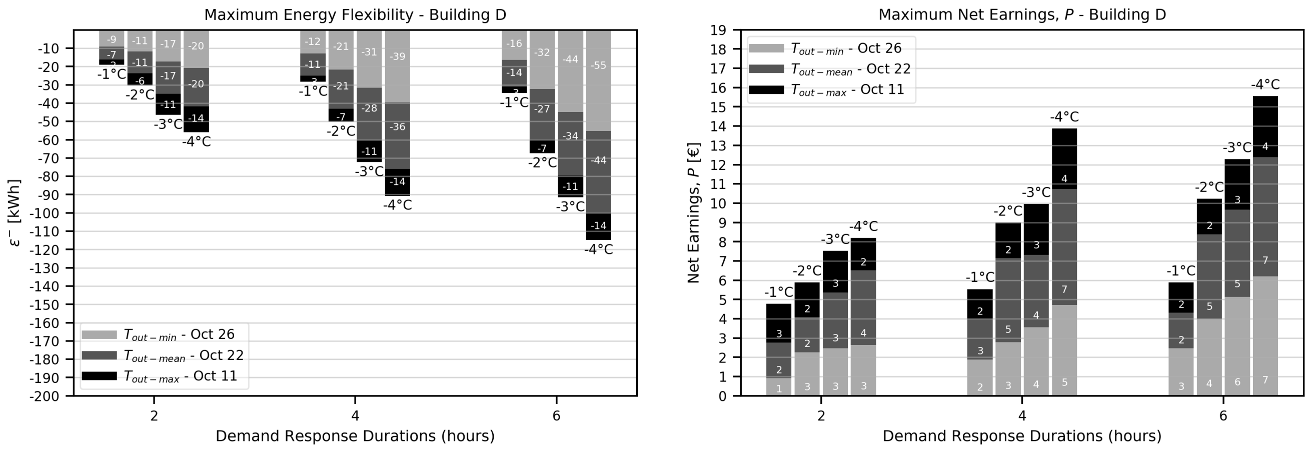
Product	Brand	Mark	Rated flow rate (kg/hr)	Rated power (W)
Centrifugal fan	Comefri	THLZ450	19394	9000*
Circulation Pump	Grundfos	MAGNA 32-120 F	4000	400

Table 18: Days chosen in month of October

Description	Statistic	Day	$T_{ambient-average}$ [°C]	Electricity Price$_{max}$ [€/MWh]
$T_{out-min}$	Minimum	Oct 26	5.4	55.0
$T_{out-mean}$	Mean	Oct 22	10.6	65.1
$T_{out-max}$	Maximum	Oct 11	16.1	60.6

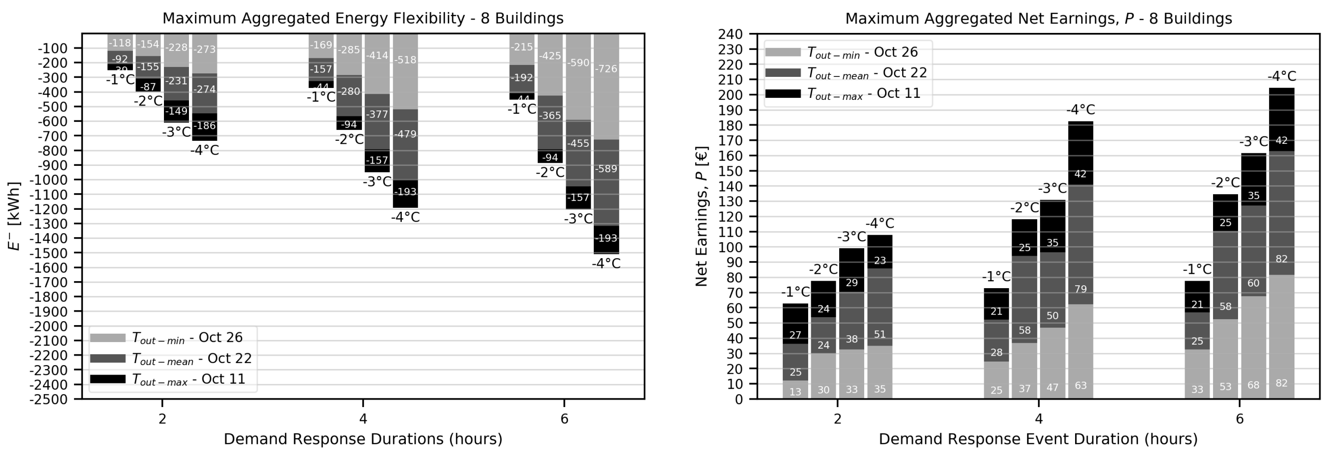
Table 19: Days chosen in month of April

Description	Statistic	Day	$T_{ambient-average}$ [°C]	Electricity Price$_{max}$ [€/MWh]
$T_{out-min}$	Minimum	Apr 03	2.2	44.0
$T_{out-mean}$	Mean	Apr 23	7.9	54.5
$T_{out-max}$	Maximum	Apr 11	14.7	42.2



(a) epsilon$_{October}$ (b) earnings$_{October}$

Figure 19: Maximum ϵ^- in parametric analysis categorised into minimum, mean and maximum outdoor temperature days and indoor set-point magnitude change for October



(a) epsilon$_{October}$ (b) earnings$_{October}$

Figure 20: Maximum aggregated ϵ^- in parametric analysis categorised into minimum, mean and maximum outdoor temperature days and indoor set-point magnitude change for October

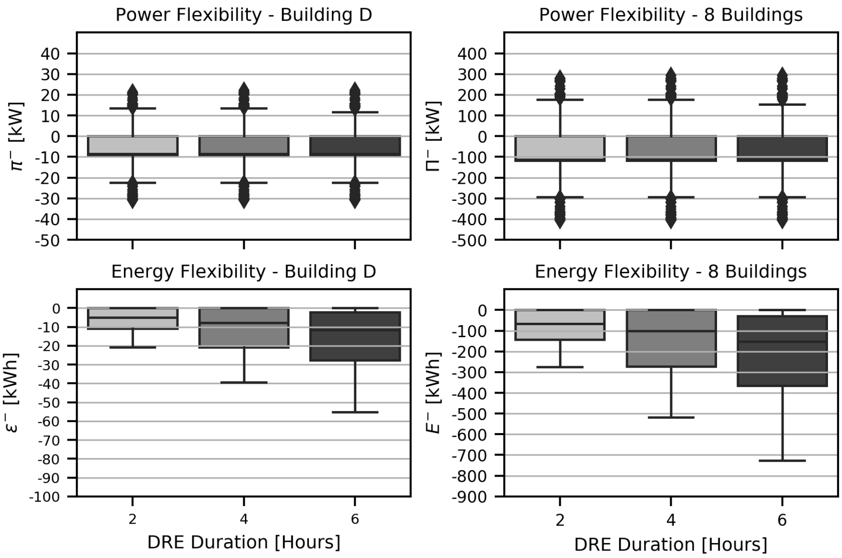
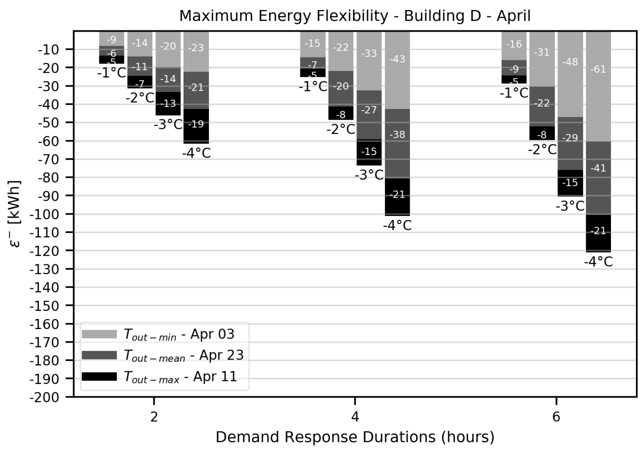
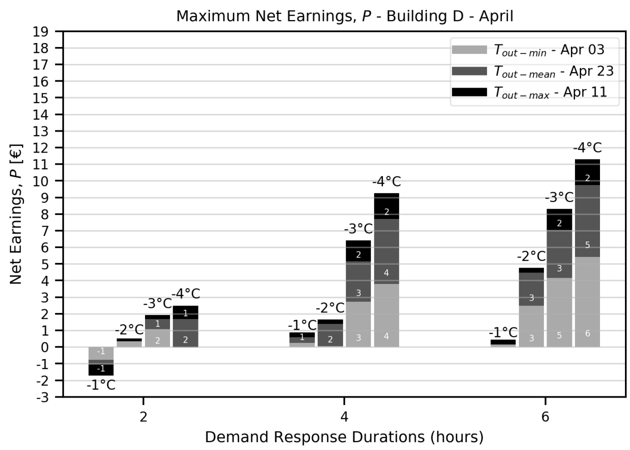


Figure 21: ϵ^-, E^-, π^-, and Π^- of All demand response events categorised into demand response duration for October

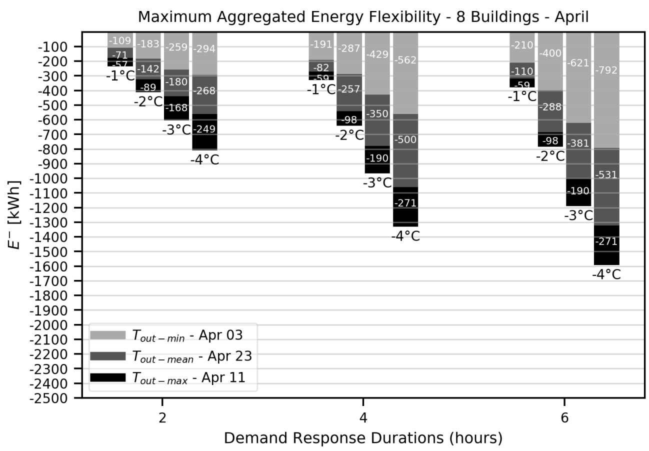


(a) epsilon_{April}

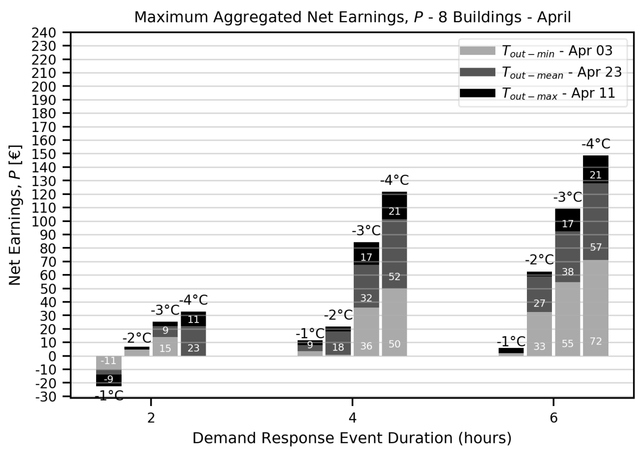


(b) earnings_{April}

Figure 22: Maximum ϵ^- and associated earnings, P in parametric analysis categorised into minimum, mean and maximum outdoor temperature days and indoor set-point magnitude change for April



(a) epsilon_{April}



(b) earnings_{April}

Figure 23: Maximum aggregated ϵ^- and associated earnings, P in parametric analysis categorised into minimum, mean and maximum outdoor temperature days and indoor set-point magnitude change for April

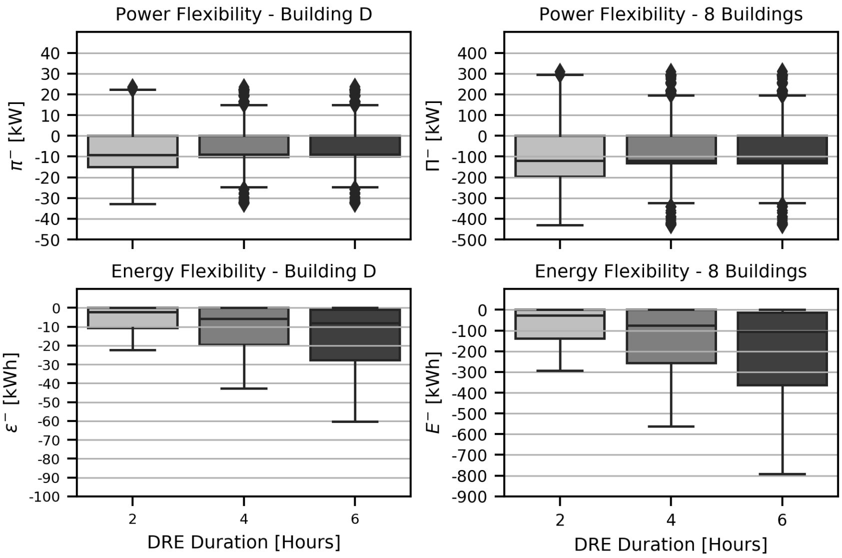


Figure 24: ϵ^-, E^-, π^-, and Π^- of All demand response events categorised into demand response duration for April

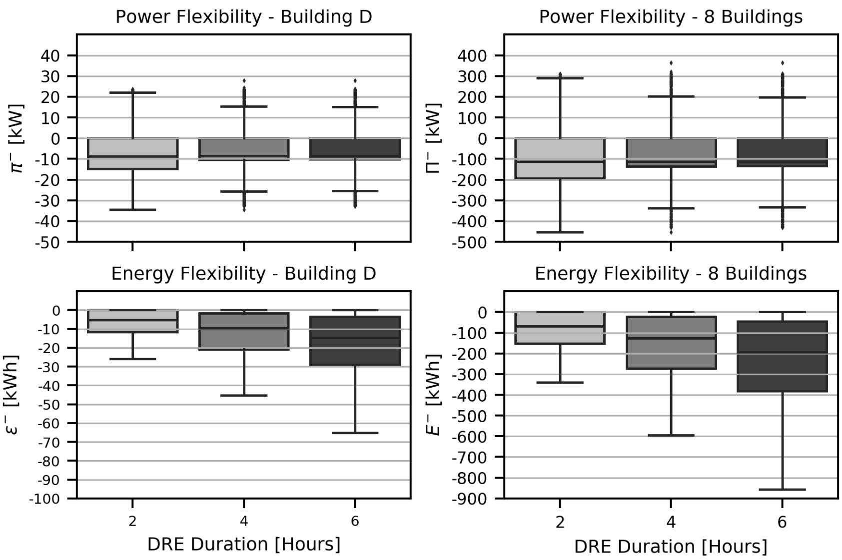


Figure 25: ϵ^-, E^-, π^-, and Π^- of All demand response events categorised into demand response duration for February, April and October

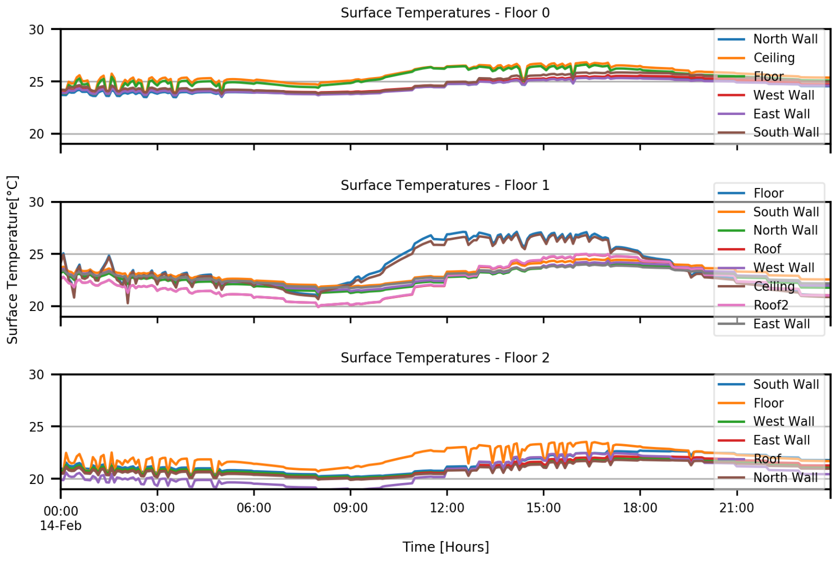


Figure 26: Surface temperature per floor for February 14

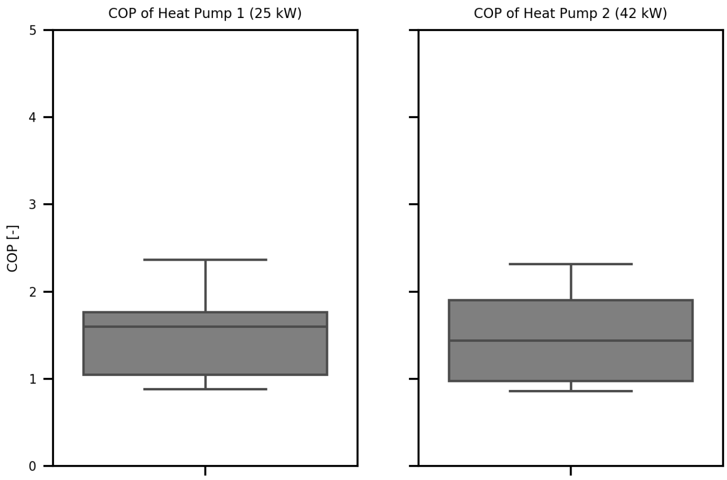


Figure 27: COP on February 14

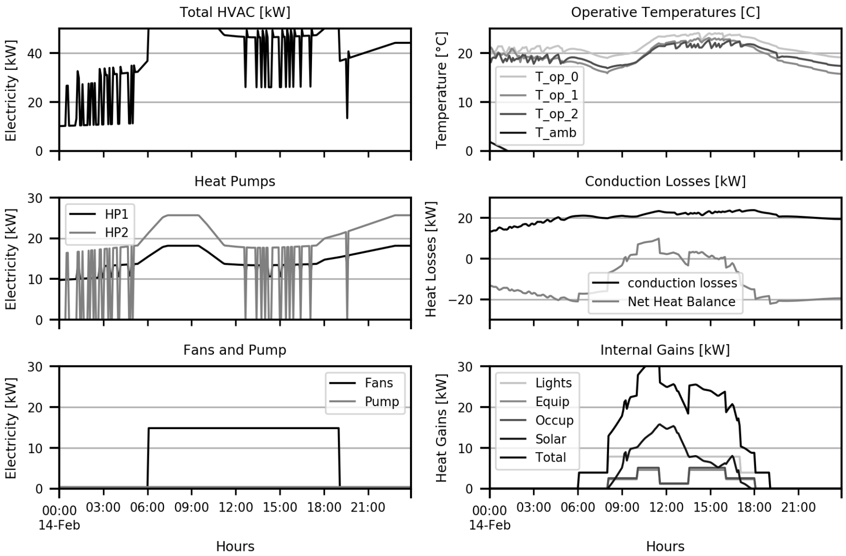


Figure 28: Overview of building performance simulation model for February 14

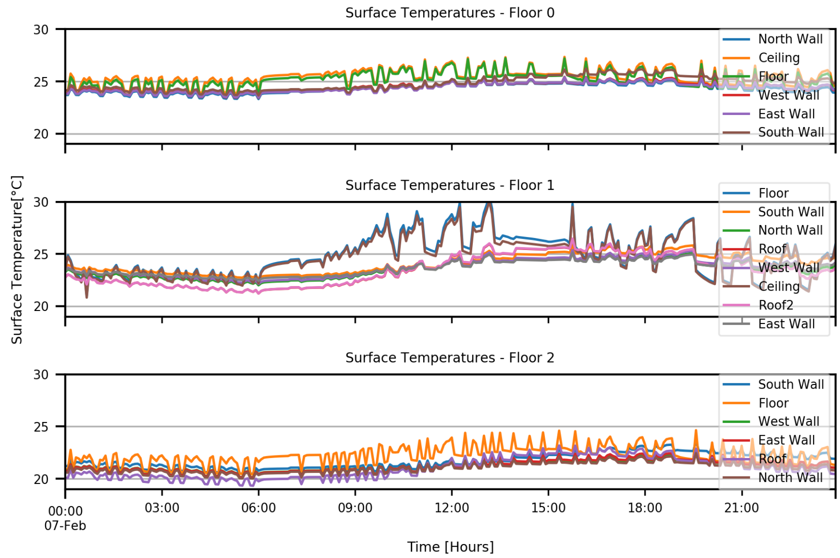


Figure 29: Surface temperature per floor for February 07

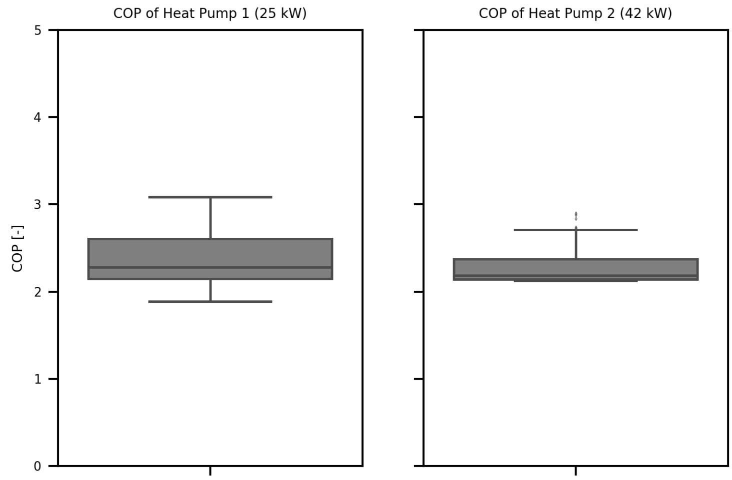


Figure 30: COP on February 7

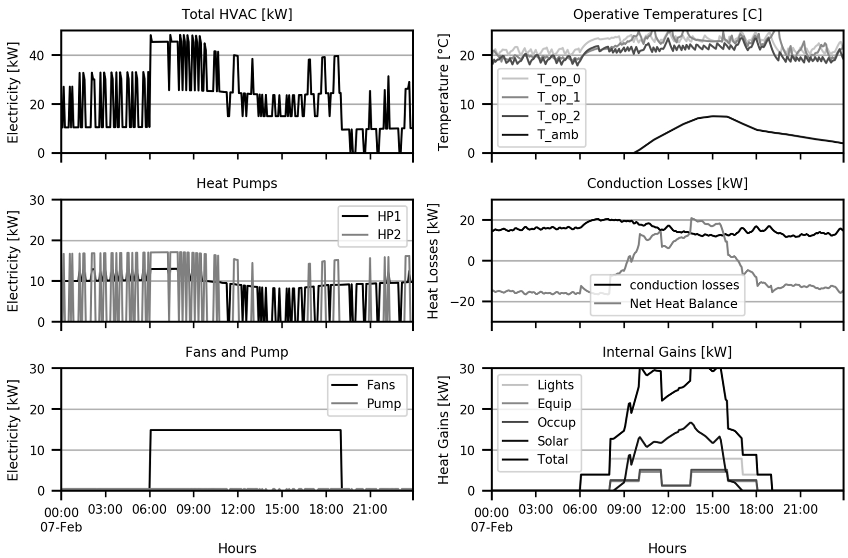


Figure 31: Overview of building performance simulation model for February 7

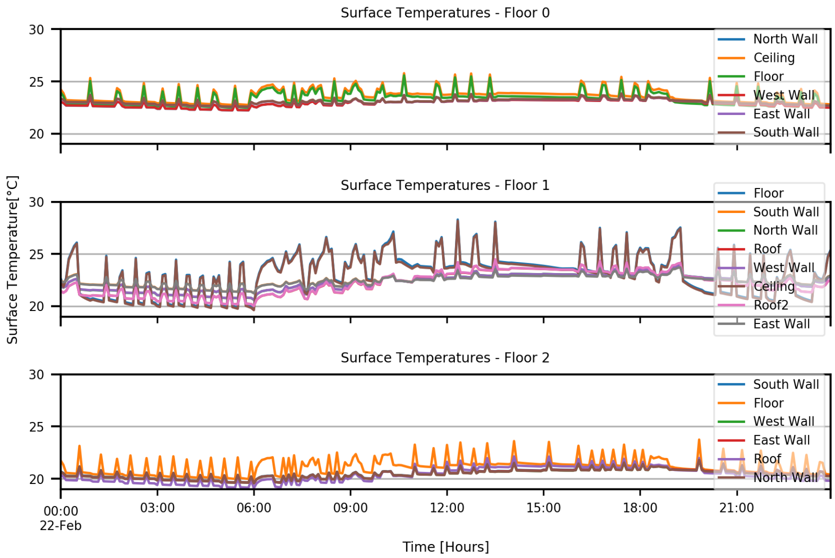


Figure 32: Surface temperature per floor for February 22

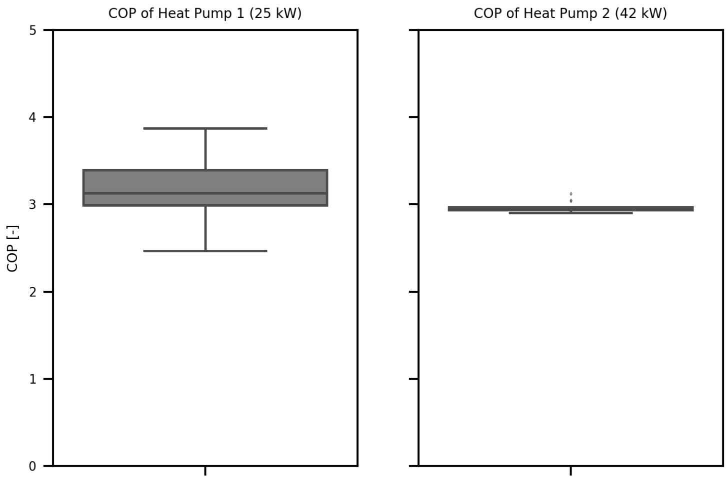


Figure 33: COP on February 22

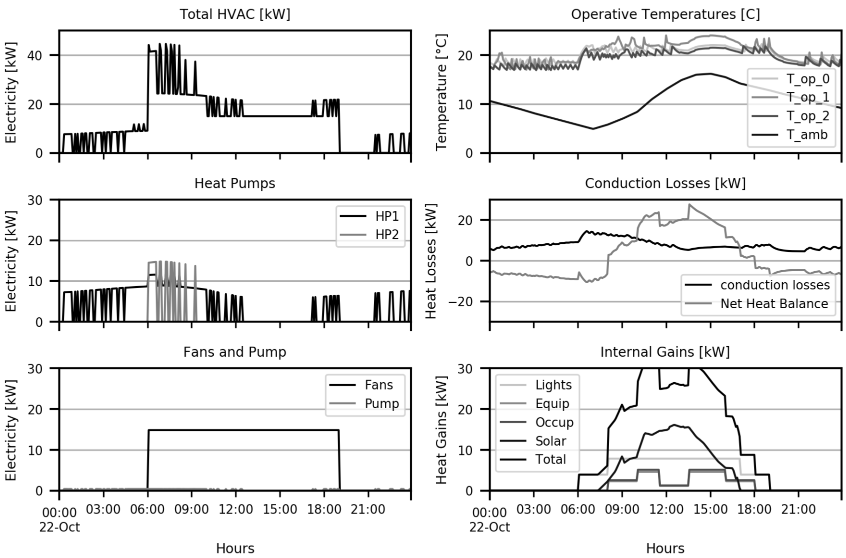


Figure 34: Overview of building performance simulation model for February 22

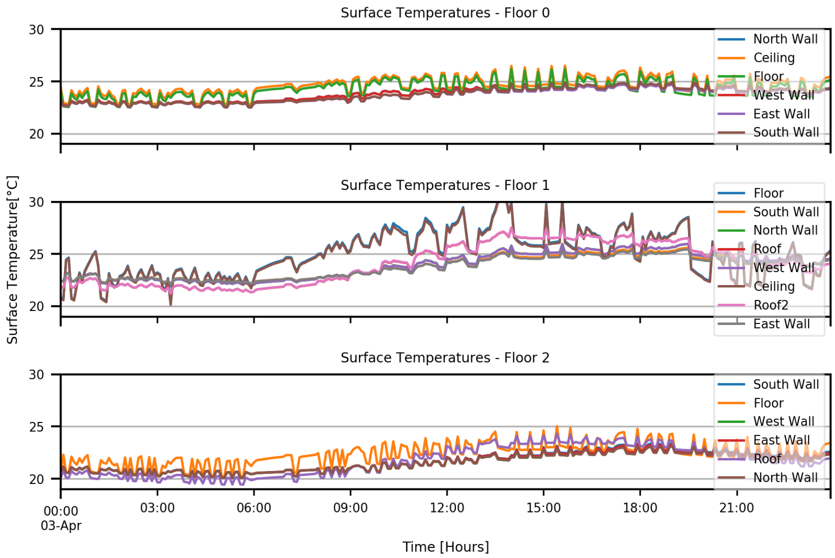


Figure 35: Surface temperature per floor for April 3

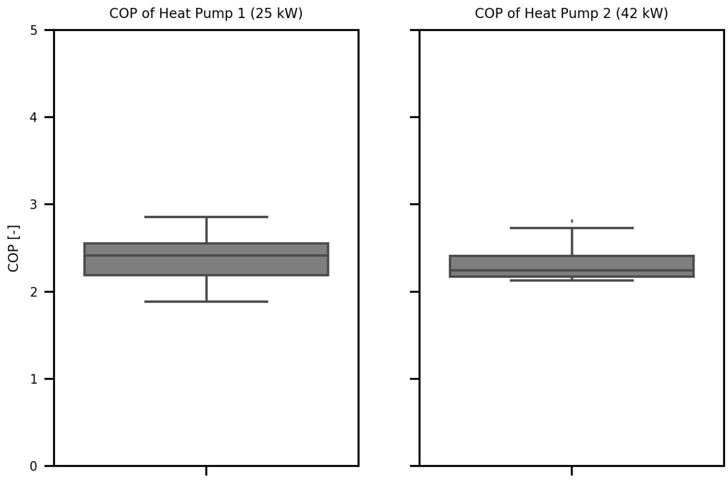


Figure 36: COP on April 3

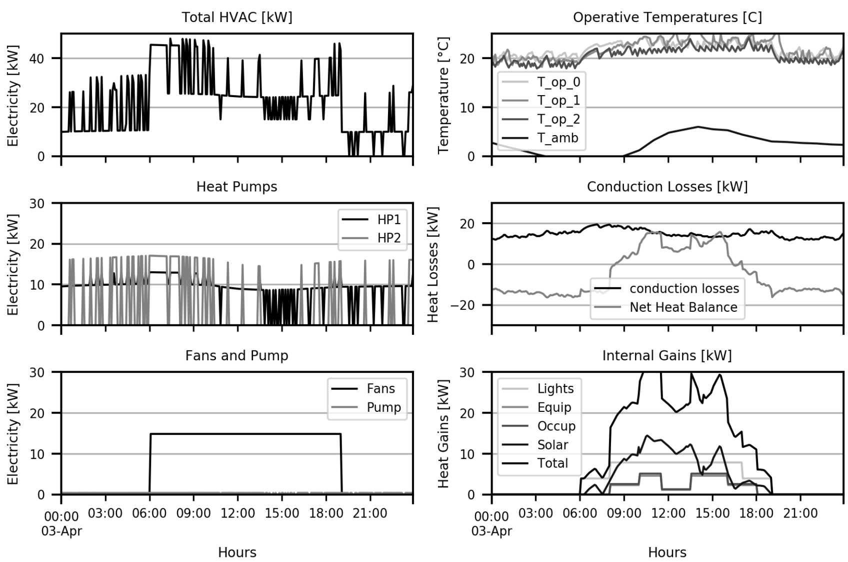


Figure 37: Overview of building performance simulation model for April 03

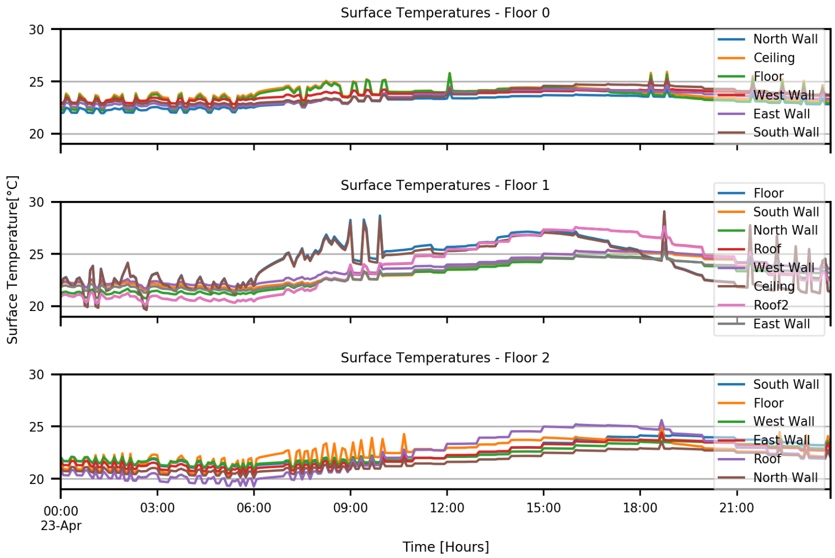


Figure 38: Surface temperature per floor for April 23

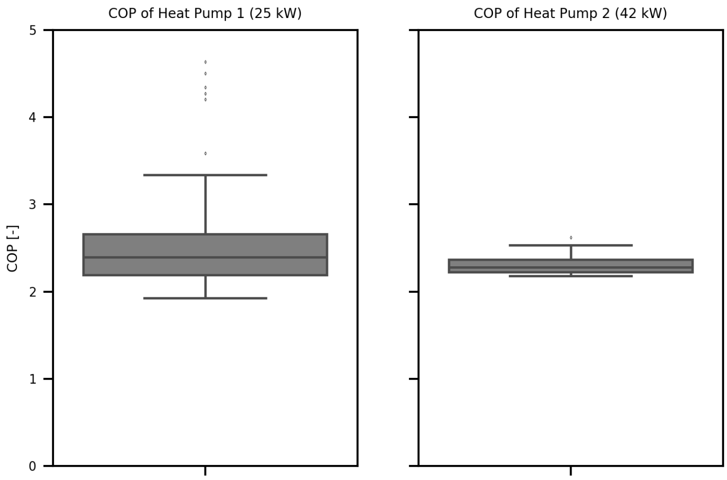


Figure 39: COP on April 23

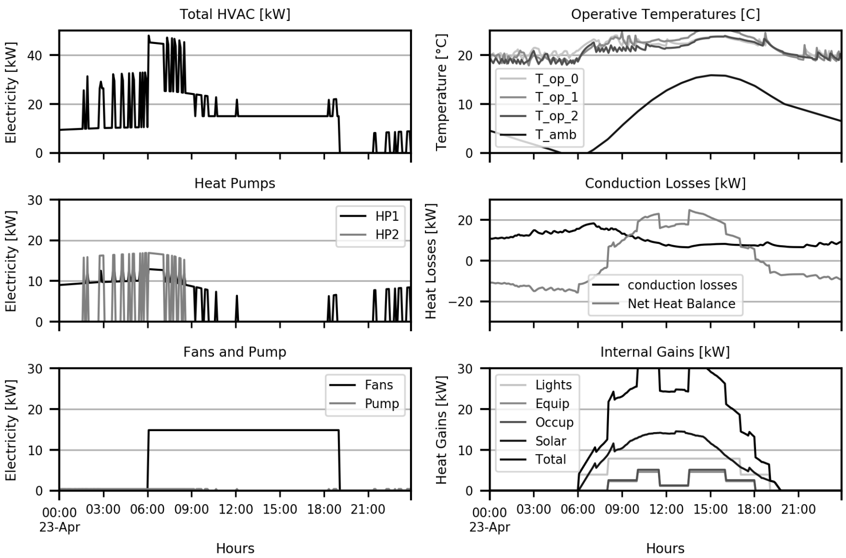


Figure 40: Overview of building performance simulation model for April 23

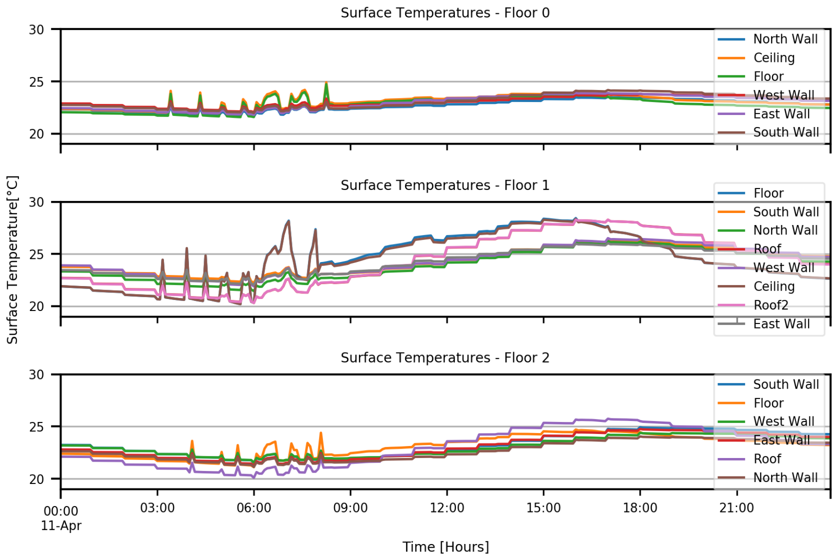


Figure 41: Surface temperature per floor for April 11

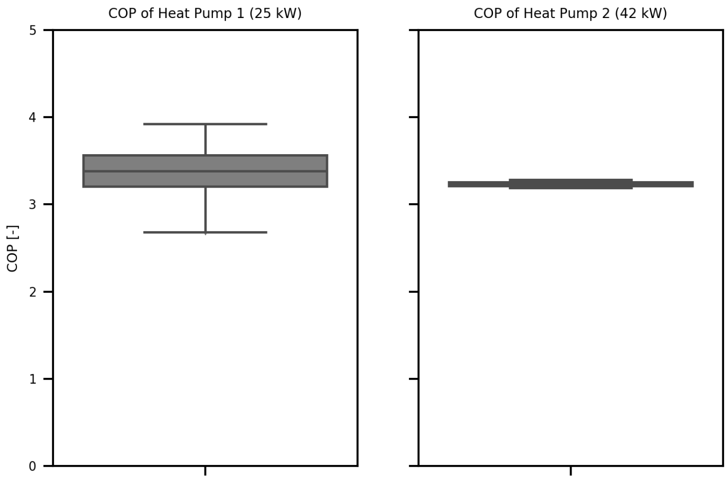


Figure 42: COP on April 11

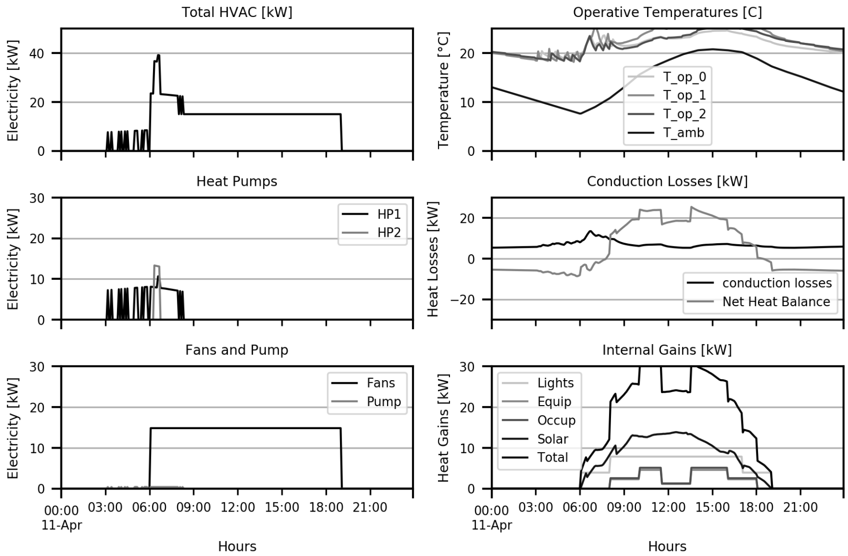


Figure 43: Overview of building performance simulation model for April 11

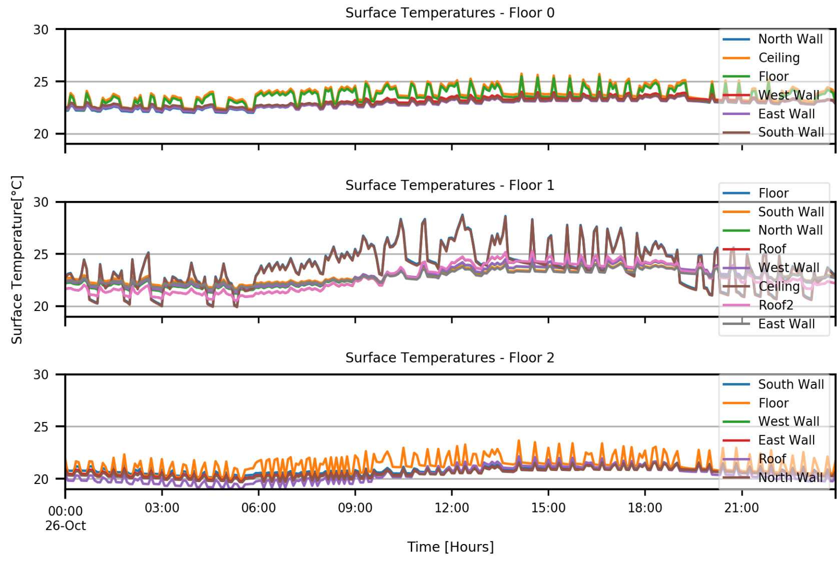


Figure 44: Surface temperature per floor for October 26

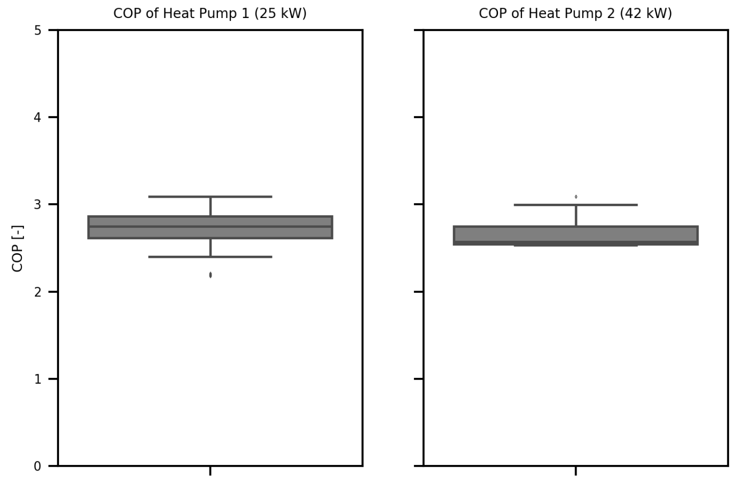


Figure 45: COP on October 26

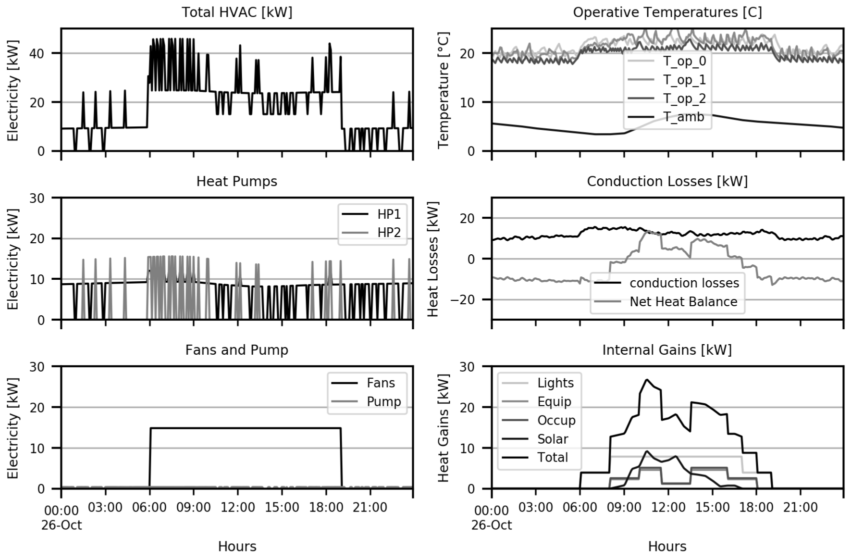


Figure 46: Overview of building performance simulation model for October 26

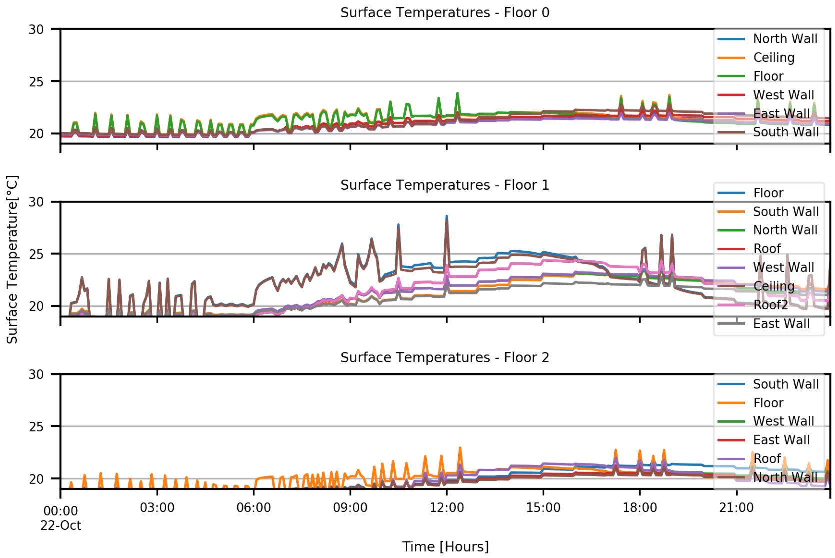


Figure 47: Surface temperature per floor for October 22

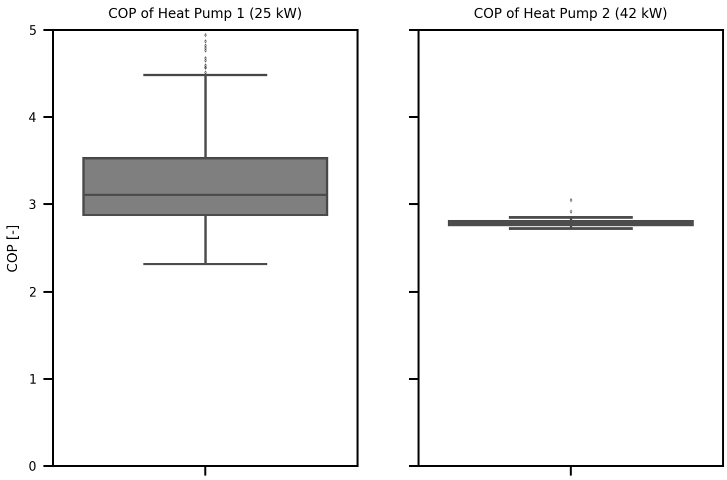


Figure 48: COP on October 22

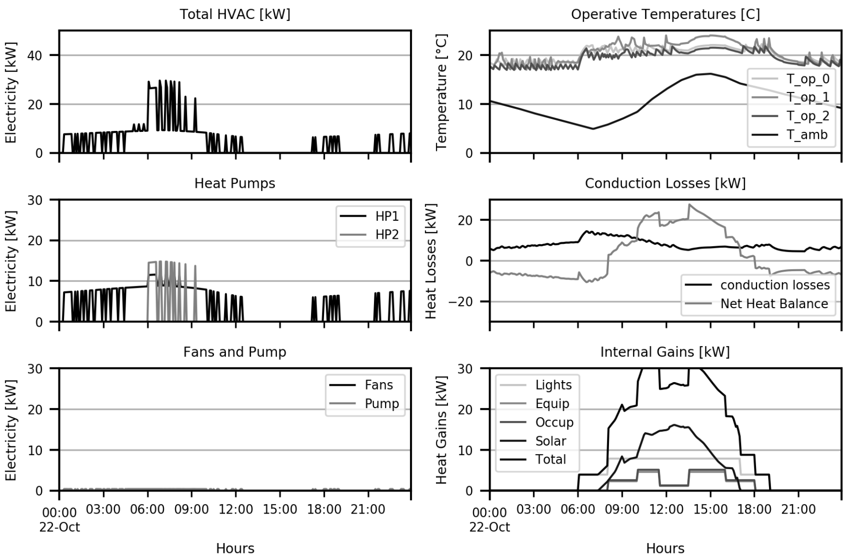


Figure 49: Overview of building performance simulation model for October 22

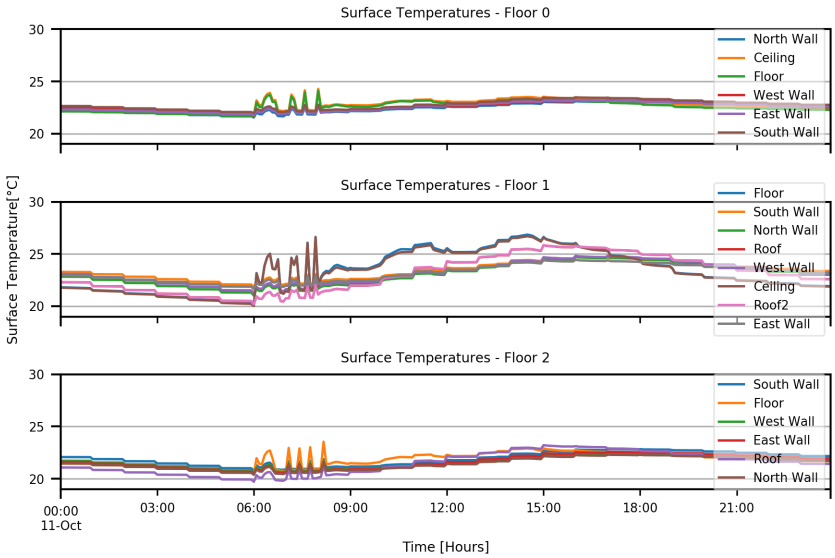


Figure 50: Surface temperature per floor for October 11

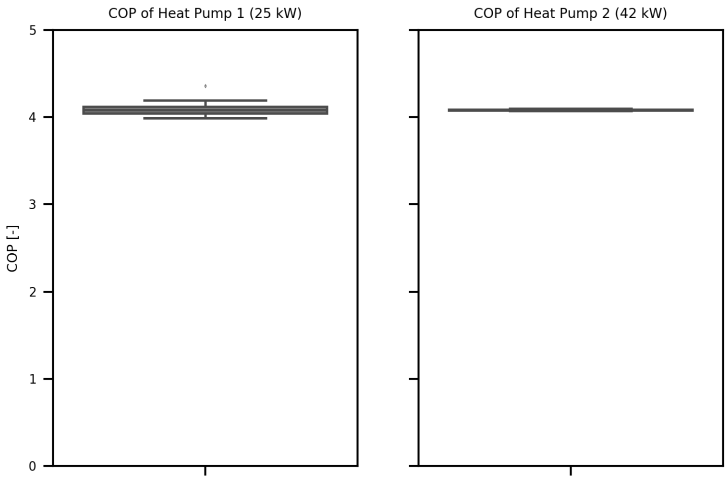


Figure 51: COP on October 11

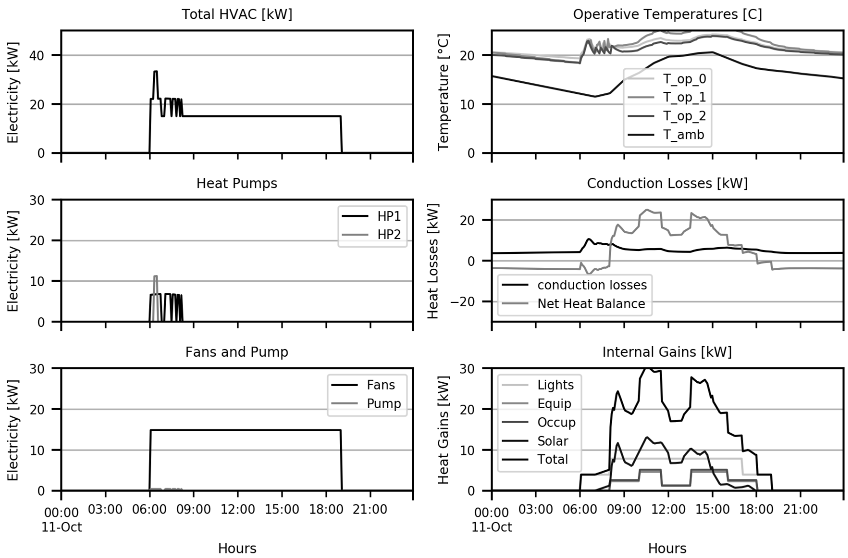


Figure 52: Overview of building performance simulation model for October 11

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