The technical flexibility potential of heat pumps and electric vehicles

Part 1: Analysis at the individual user level

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1. GENERAL INTRODUCTION

Both heat pumps and electric vehicles are increasingly proliferating in Belgium and across the world, as part of the societal response to climate change. In the FlexSys project, we investigate the potential of these assets to contribute to the security of our electricity supply by exploiting the flexibility of their electricity consumption profile. In this document – which is Deliverable 1.1 of the project – we report our assessment of what these assets are capable of from a technical perspective, which is what we refer to as the "technical flexibility potential". As will become clear throughout this report, figuring out what electric vehicles and heat pumps can bring to the table in terms of flexibility is already a complicated endeavour when the assets are deeply investigated but the users themselves are represented in a simplified way. In another part of the FlexSys project (D1.5), the impact of human behaviour on this technical potential is examined in more detail. This will lead to a better understanding of how a technical flexibility potential translates into a 'realistic' potential. The realistic potential will take both the technical capabilities of the assets themselves into account – as thoroughly examined in this report – as well as the complicated behaviours and preferences of the residential users interacting with them.

2. EV TECHNICAL FLEXIBILITY POTENTIAL

2.1. Introduction

EVs (EVs) are currently seen as an opportunity to reduce greenhouse gases and other local polluting emissions by the transport sector, which is currently still essentially reliant on carbon-intensive fuels. Recent events have also spotlighted the uncertainty surrounding the future of fossil fuel prices and strengthened resolve to press ahead with reducing oil dependency. In Belgium, Flanders has banned the sale of new cars with Internal Combustion Engines (ICE) from 2029. The Belgian Federal Government has decided that, starting from 2023, the average CO_2 emissions of company cars must gradually lower, reaching zero in 2026. Meanwhile, the debate about a European ban on the sales of new ICE vehicles starting in 2032-2035 is still ongoing.

There are various EV propulsion and energy storage technologies under development. These include battery EVs (EVs) that rely solely on an electrochemical battery to power an electric motor; plug-in hybrid EVs (PHEVs) equipped with both an electric motor and a combustion engine; and fuel-cell EVs (FCEVs) that use an on-board hydrogen tank and fuel cell to power the motor. Other hybrids that can't be plugged in for charging and rely solely on fuels like petrol or biogas aren't covered in this discussion since they don't interface with the electric grid. It must be noted that PHEV only have a limited battery and still have an ICE onboard, meaning the sale of new PHEVs can expected to decrease or be outright banned (e.g. in Flanders). Furthermore, due to the technical challenges and cost of hydrogen, FCEV are not expected to still make a breakthrough, in stead being limited to certain transport niches. In this text, we therefore assume EV to always be EV, unless stated otherwise.

Integrating a vast number of EVs into the power grid presents both challenges and opportunities, necessitating more research. Uncontrolled charging of numerous EVs during peak times could strain the grid. However, EVs also offer demand-side flexibility, potentially aiding in further reducing carbon emissions from both electricity and transportation sectors. Various studies have explored different aspects of this integration, from hourly supply-demand matching to grid flows and frequency regulation. Most research focuses on local scales or current systems, with few looking at future scenarios beyond 2030.

EVs can thus be considered game-changers or game-breakers in future decentralized and renewable energy systems. EVs have a high electricity demand and, potentially, a high level of flexibility in their charging sessions. With smart charging, EVs can balance the energy system, avoiding grid investments and optimizing the use of renewable energy. Without smart charging, full adoption of EVs will lead to daily low-voltage grid congestion and frequent imbalances in (renewable) electricity supply and demand.

2.2. Methodology

The charging flexibility of EVs is a loosely defined concept that relates to the amount of freedom of a charging session to shift and extend the charging. This includes a dimension of time and a dimension of energy. Quantification of the charging flexibility has gained significant research interest over the past years. This is partially due to the ongoing transition towards sustainable energy and electrified mobility. However, existing research fails to capture the complete picture of the charging flexibility. Mainly as a result of the limited availability of realistic and detailed data on travel behaviour.

2.1.1. Modelling travel behaviour

Over recent years, numerous mobility models have emerged to examine the growth of EVs and their interplay with transportation infrastructure and the electricity sector, both locally and nationally. They can be broadly categorized into four primary groups.

The first category is 'Summary Travel Statistics Models'. These models utilize average data from travel surveys to derive EV charging patterns based on average travel distances and connection durations, or the standard distributions of these metrics. [1] [2]

The second category is 'Direct Use of Activity Travel Schedules'. Instead of using average trip parameters, these models simulate individual trips from travel surveys. This approach captures the varied mobility patterns more accurately. [3][4]

A third category, 'Activity-Based Models', can also employed to study EVs. These models require more comprehensive input data, such as details about transportation infrastructure or the locations of homes, workplaces, and recreational areas. They are frequently used in urban planning research or studies focusing on other transportation aspects unrelated to EVs. [5][6]

Lastly, there are the rarer 'Markov Chain Models', which adopt a probabilistic method to calculate a time vector representing each vehicle's state. [7]

To examine the effects of a vast number of EVs on the national electricity supply-demand balance, the input data should span an entire year and match the time-resolution of the electricity markets being analysed, typically on an hourly basis. The data should also allow for the exploration of different EV growth and daily usage patterns. Moreover, the outcomes should be grouped by categories such as vehicle type, charging location, connection habits, etc.

It should also be noted that in the travel data, local mobility data should be separated from long-distance trips, meaning trips which exceed the drive range of some EVs. Typically, these trips will be undertaken by using fast-charging stations, and as such have little opportunity to provide flexibility to the electrical system.

2.1.2. EV parameters

Another important required input are the EV's attributes, such as type, battery capacity, charging speed and available charging points (home-only, work-only, public stations-only, or a mix. Currently, there is a large variety in both battery capacity as well as in charging speed. Furthermore, these parameters are continuously evolving.

2.1.3. Grid connection behaviour

The behaviour of EV owners can be expected to vary signifcantly. Some will plug in their vehicles daily, whereas others will only do so when the battery level is low. The availability of a charging point plays a significant role in this behaviour. Some EV owners have charging points at their residences, while others depend on public charging facilities. Consequently, three distinct grid connection behaviours can been identified. Lauvergne et al. summarises these as follows. [8]

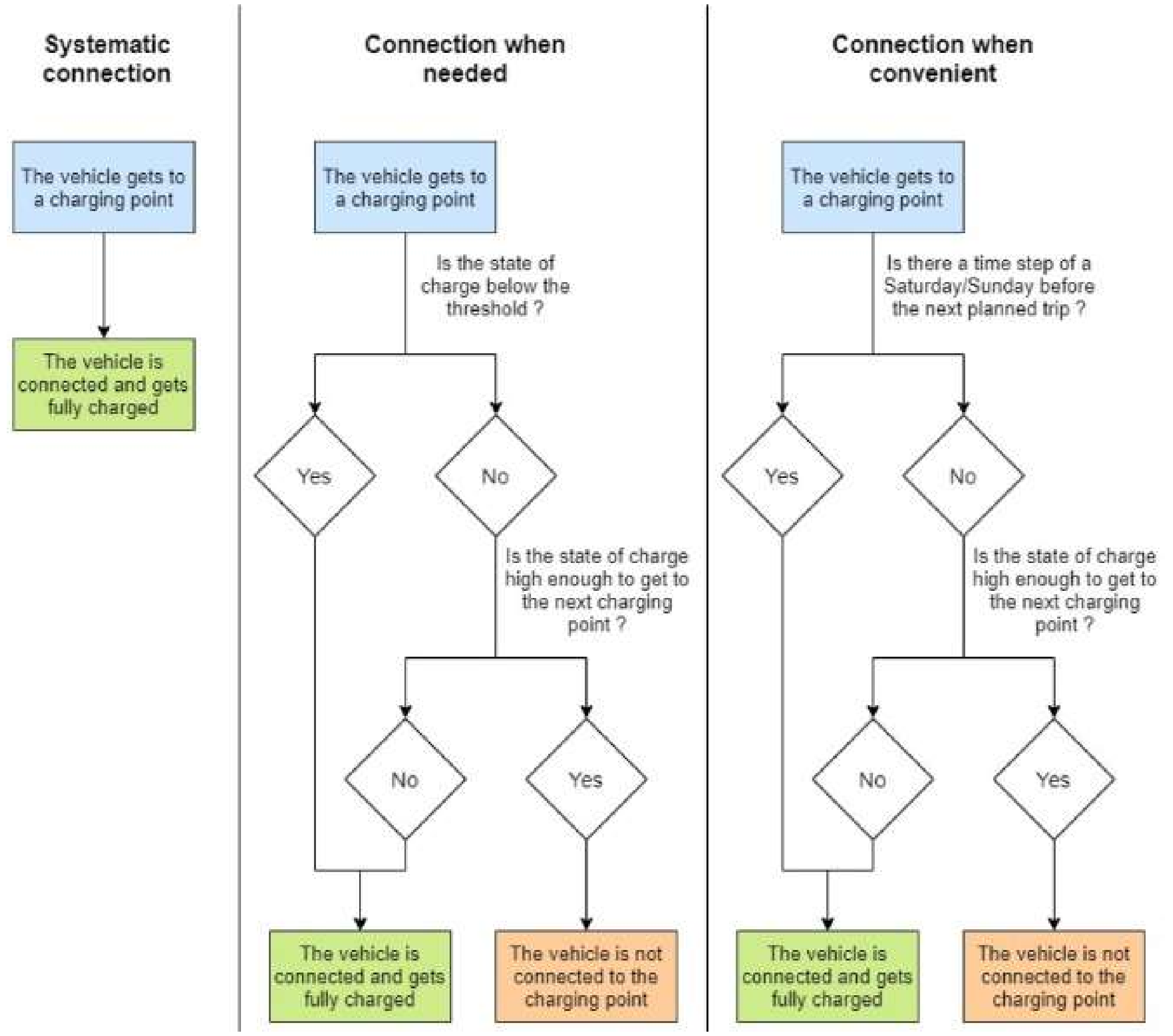


Figure 1: Flowchart of the three connection-to-grid behaviours as described in [8]

Firstly, there's the "systematic connection" behaviour where the vehicle is plugged in every time it's parked and a charging point is accessible.

Secondly, the "connection when required" behaviour is characterised by the EV owner plugging in their vehicle only when a charging point is available, and the battery's charge is below a certain level. This level can be defined by either the distance the vehicle can travel before the battery runs out (usually around 50 km) or a specific percentage of the remaining battery charge (often around 30%). Additionally, the vehicle is connected whenever the remaining charge isn't sufficient to reach the next scheduled charging point in electric mode. This ensures that EVs can complete their planned trips and PHEVs can maximize the distance they travel using electricity.

Lastly, the "connection when it's convenient" behaviour involves EVs being plugged into the grid at the convenience of their owners. It can be assumed that this primarily happens on weekends. Similar to the "connection when required" behaviour, vehicles are also connected if they can't make it to the next charging station.

2.3. Discussion on the findings

Based on previously discussed parameters, several attempts have been made at constructing EV demand curves and extrapolating an amount of flexibility. Lauvergne performed a case study at hourly resolution of high penetration of EVs and renewable energy sources in Europe at the 2040 time-horizon, in line with the 'National Trends Scenario' grid mix under the pan-EU ENTSO-E Ten-Year Network Development Plan and with data from the French 2008 National travel survey. [8]

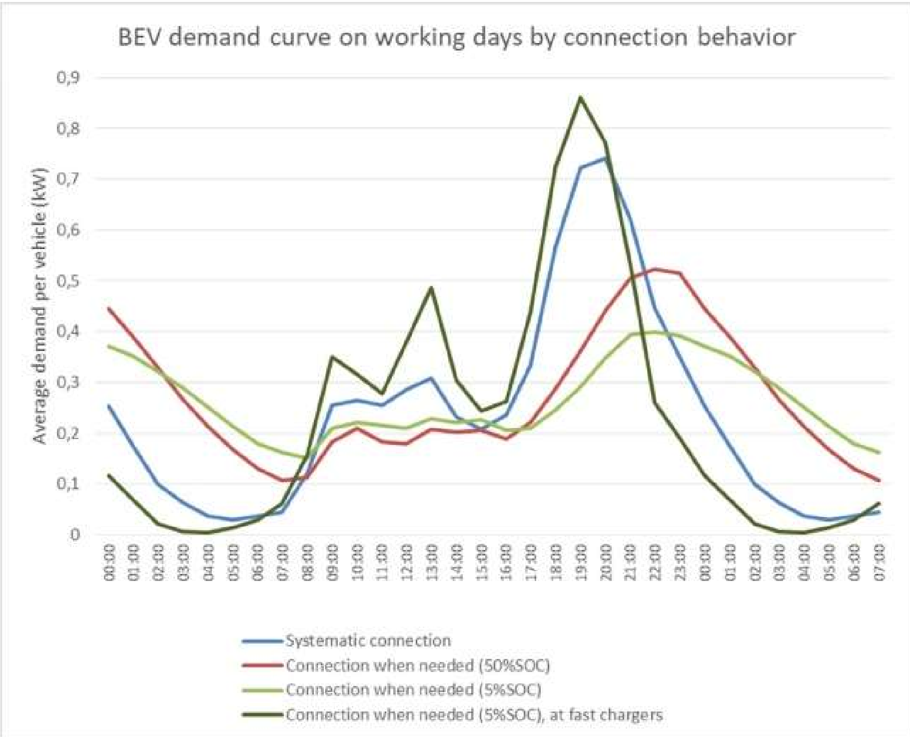


Figure 2: EV demand curve on the average weekday, for various connection behaviours as described in [8]

The authors found that, with unregulated charging, a significant portion of EV charging aligns with peak demand, often post-solar generation hours. This necessitates reliance on thermal power plants and imports during peak periods. Conversely, in the daily EV flexibility scenario, smart charging ensures EVs charge primarily during peak solar generation, reducing the need for electricity imports or gas-fueled power generation. Optimally, EVs strategically charge during high renewable energy production periods, cutting down on imports, gas generation, and curtailment of renewable energy compared to other models. However, the benefits of EV charging flexibility vary throughout the year. Extended durations of low renewable production make it challenging for flexibility to consistently reduce emissions and costs.

In order to promote the strategic charging behaviour, several time-of-use tariff were introduced, ranging from a basic control signal, where the charging of each vehicle connecting at peak demand (18:00-21:00) is postponed by three hours, to an optimized tariff profile at the weekly level.

The authors found that basic controls via time-of-use tariffs can decrease the system's operational cost compared to a scenario without controls. The flexibility is notably enhanced when a more refined tariff profile is applied. However, tariffs structured on a weekly basis don't offer much improvement in profile development, as weekly flexibility is primarily beneficial for adjusting to days with low renewable energy output.

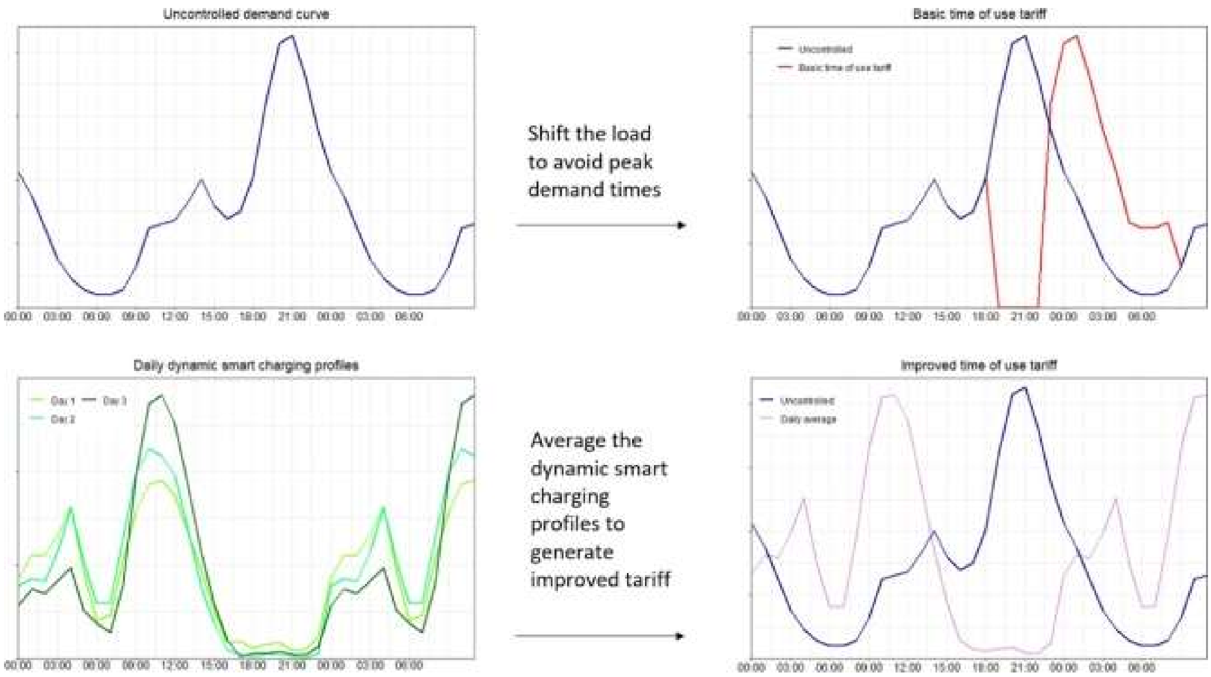


Figure 3: Time-of-use tariffs load curves generation methodology from [9]

Guthoff et al. proposes a method to accurately assess the flexibility potential of EVs and to incorporate it into an electricity market model, taking into account feedback effects with other parts of the energy system. EV-specific data is derived from empirical mobility statistics for Germany using a mobility tool wherein individual car mobility profiles are generated through a Markov-Chain Monte Carlo simulation. Using these profiles, the EV's load curve, and consequently its flexibility potential, is established as input for an electricity market model. The analysis is performed on aggregated mobility profiles. [9]

Figure 4: Mobility profile for a Monday in spring, normalized by aggregated EVs from [9]

When charging patterns are based on the identified mobility behaviour, the aggregated charging curve for the projected EVs is shown for both Monday and Saturday during winter. The graph indicates that peak charging power is observed during the evening, gradually diminishing until the early morning. There's minimal charging demand in the morning, a trend also evident on Saturdays. On Saturdays, though the peak is lower, there's a consistent high charging demand from midday to evening.

The authors consider all vehicles to be plugged into the grid until they embark on their initial trips. Post-trip, they're reconnected for recharging. The grid interaction curve is deduced from driving patterns and charging power needs. The potential for load increase is calculated by comparing the grid interaction curve with the user-directed charging curve. The authors reveal a significant potential for load augmentation, particularly during the early morning until around 7:00 a.m. During midday, the combination of reduced peak charging power and grid interaction results in minimal upwards power consumption potential. As the day progresses, the potential for load reduction grows. User-directed evening charging diminishes the potential for positive load shifts during those hours, while the potential for load reduction becomes more pronounced.

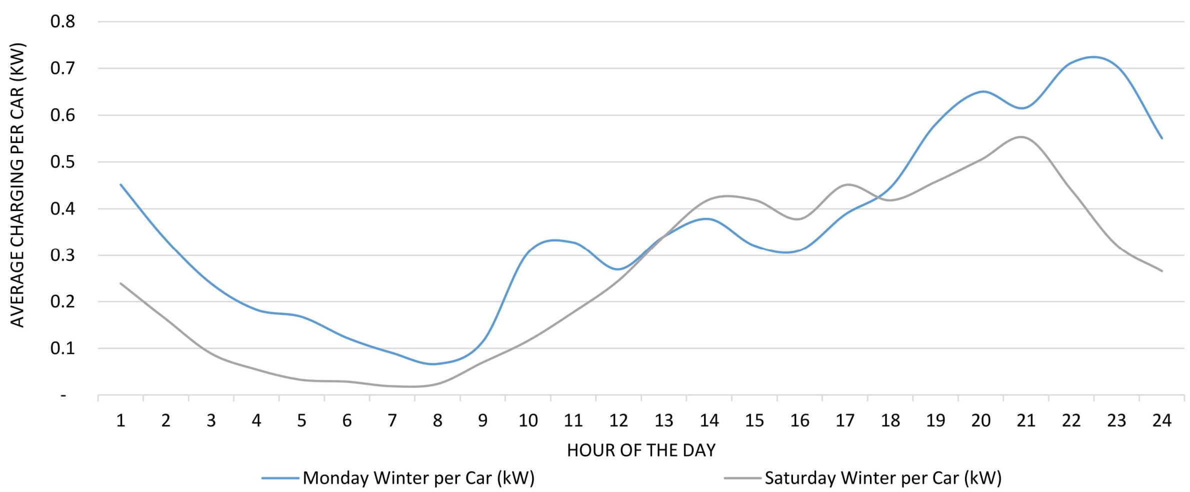


Figure 5: Load per EV for a Monday (blue line) and a Saturday (grey line) in winter season from [9]

The authors then apply a flexibility model to simulate the maximum total potential of load-shifting possible. The model can therefore be simplified, assuming that all EV owners would be open to external control of their vehicles as long as it doesn't impede their daily routines. Furthermore, a “time limit’ is taken into account, designating a specific time (6 a.m.) by which all vehicles must be completely charged.

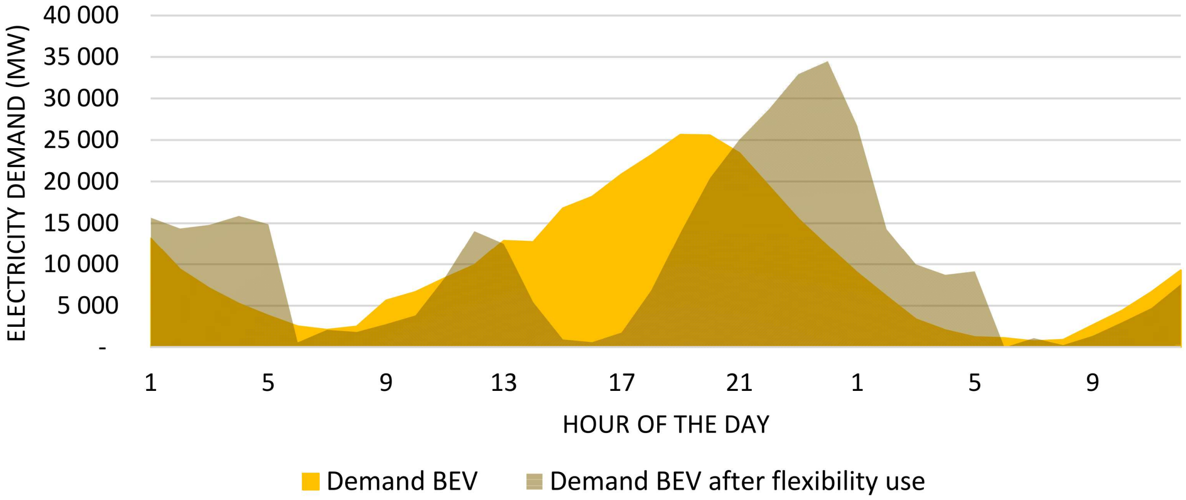


Figure 6: Electricity demand due to the EV-charging process before (yellow) and after the flexibility use (brown, transparent) for an exemplary day from [9]

The data illustrates that during periods of positive residual load, EV charging reduces the demand, while during times of negative residual load, the demand is amplified. It's also evident that flexibility is employed to decrease demand during negative residual load periods, enabling further demand reduction during times with even higher negative residual loads. This shift is also mirrored in the subsequent demand post-EV charging.

The peak demand originally caused by EV charging (highlighted in yellow) has shifted from the evening to nighttime. Due to the constraint that vehicles must be fully charged by 6 a.m., there's no potential to augment the load at this hour, only to diminish it. As a result, the ensuing charge power (depicted in translucent brown) is always either equivalent to or less than the initial charge power. This restricts the shift at this point, causing the curve to decline abruptly.

The authors conclude that the derived mobility patterns lead to an hourly electricity demand due to the charging activities of EVs. Notably, there are significant simultaneities, causing pronounced load peaks in the late evening. With a substantial influx of EVs, this dramatically alters the electricity generation profile needed to satisfy demand, subsequently increasing the need for flexibility solutions. However, EVs can offer systemic benefits and serve as a potential source of flexibility, taking into account that such flexibility is significantly limited by user behaviour, and its availability varies considerably over time.

Finally, Hogeveen et al. also consider an agent-based approach to modelling the load-curve of EVs and their flexibility potential. Realistically modelling mobility behaviour poses a variety of problems where agent-based approaches might be beneficial. Firstly, mobility behaviour is highly complex and irregular which quickly leads to unrealistic simplifications. Secondly, sufficiently detailed mobility data is often unavailable. Mainly because of complex dependencies of mobility on weather, holidays, family composition, multi-day dynamics, geography, culture, and external circumstances such as COVID-19. Finally, vehicles are used in a household context, rendering individual mobility data inadequate to study charging flexibility. [10]

Agent-based modelling is a bottom-up modelling approach where emergent system behaviour results from actions and interactions of individual agents. In this, an agent-based model consisting of four agent types: adults, vehicles, households and activities is developed. The agent diversity and input factors (such as household makeup, vehicle count, driver's licenses, employment specifics, income brackets, and battery capacity) are determined by a 'population database'. Another input database offers multi-day activity plans for every adult member in the designated population. Within this 'activity database', each entry represents a particular activity of an individual adult. This includes details about the location of the activity, its commencement time, duration of travel, mode of transportation, among other aspects. During a simulation run, each adult- and vehicle-agent represent actually performing the mobility and charging behaviour. Adult-agents follow their activity schedule and occasionally go on trips with their EVs. Upon arrival home, the state-of-charge of the vehicle is calculated based on the trip distance, the battery capacity, and energy economy of the vehicle. A decision to charge the EV is taken based on a linear probability correlated with the amount of charge left in the battery. This way, a bottom-up, representative and heterogeneous database of travel behaviour can be constructed.

In the study, the databases are provided by ALBATROSS, an activity-based travel demand model developed at the Eindhoven University of Technology. It generates realistic activity and travel patterns for individuals of each household in a specified (Dutch) region. ALBATROSS is algorithmically trained on large datasets of detailed Dutch mobility behaviour from a household perspective. To generate mobility profiles ALBATROSS uses socio-demographics from Statistics Netherlands (CBS), local accessibility of public transport modes and geographical mapping of visiting and employment areas.

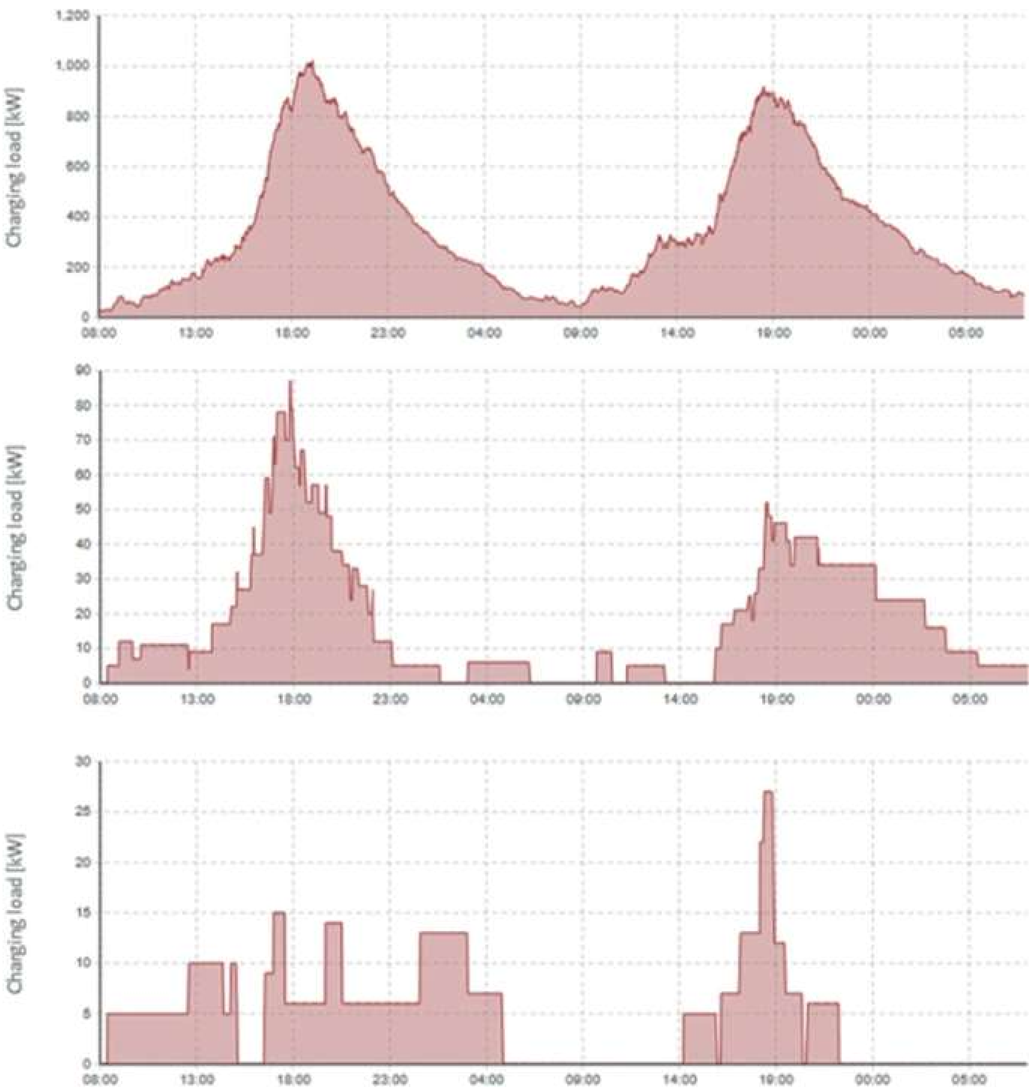


Figure 7: Synthetic charging profiles generated by the simulation model for a rural area with 1000 households (top), 50 households (middle), and 15 households (bottom) with EVs as generated in [10]

Like the previous studies, the agent-based approach also yields a similar result, with the standard charging hours of EV coinciding with the evening hours. However, the authors claim a promising perspective that 80–90% of the peak-load charging demand has a flexibility of 10 h or more.

2.4. Conclusions

EVs (EVs) are increasingly recognized as a viable solution to reduce greenhouse gas emissions and other pollutants from the transport sector, which predominantly relies on carbon-rich fuels. Recent global events have underscored the volatility of fossil fuel prices, further bolstering the push towards reducing oil dependence. Belgium, particularly Flanders, has taken proactive measures by announcing a ban on the sale of new Internal Combustion Engine (ICE) vehicles from 2029. Concurrently, the Belgian Federal Government has mandated a progressive reduction in average CO2 emissions from company cars, aiming for zero emissions by 2026. Discussions are also underway at the European level to potentially prohibit the sale of new ICE vehicles between 2032 and 2035.

The landscape of EV technology is diverse, with multiple propulsion and energy storage systems under exploration. Incorporating a large fleet of EVs into the power grid is a complex endeavour, presenting both challenges and opportunities that warrant further investigation.

We considered three studies using data from each of the neighbouring countries (France, Germany, the Netherlands). These found that unregulated charging during peak hours could overburden the grid. On the flip side, EVs can offer demand-side flexibility, potentially amplifying the reduction of carbon emissions across the electricity and transport sectors.

These findings abroad coincide with findings of Belgian TSO Elia in their most recent Adequacy & Flexibility study, which found similar patterns for both “natural” or uncoordinated charging and delayed charging operation modes. [11]

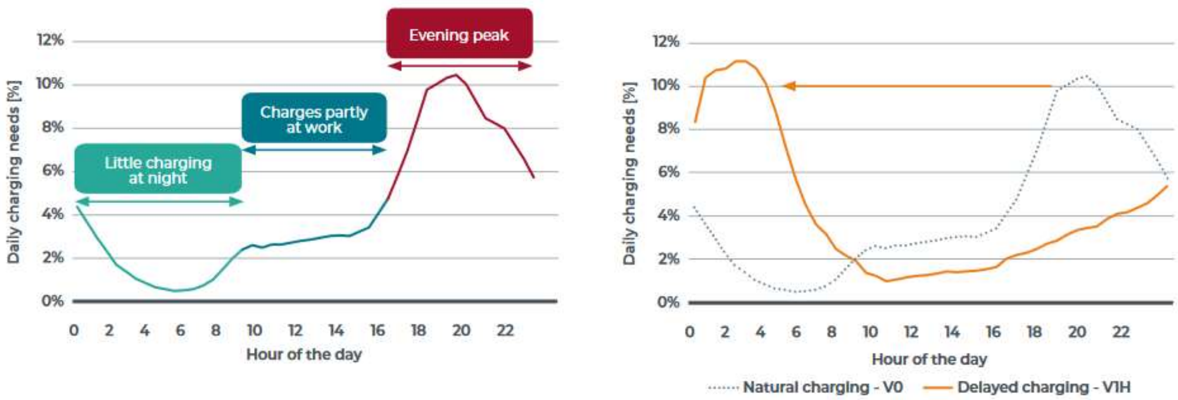


Figure 8: uncoordinated, natural charging vs delayed charging [11]

The penetration of various operating modes in the market is expected to differ, as there is a need for several enablers to achieve flexibility for each individual mode, including the creation of suitable market mechanisms. The key factors promoting increased flexibility in EVs include the rise of smart meters for accurate metering and smart chargers that operate based on control signals. Consequently, the flexible operation of EVs is anticipated to expand over time.

The current predominant EV operation mode, natural charging, is projected to decline to below 10% (approximately 200,000 EVs) by 2034. The majority of EVs, about 1.4 million, will adopt the delayed charging profile by 2034, adjusting their consumption using local cues like time-of-use tariffs. This growth is attributed to existing incentives and the anticipated rise in smart charger installations. The smart charging profile, expected to represent just under 1 million EVs by 2034, will adjust energy consumption based on market demands. This growth correlates with the proliferation of smart meters in Belgium and the anticipated market strategies targeting consumers with appealing flexibility service offers.

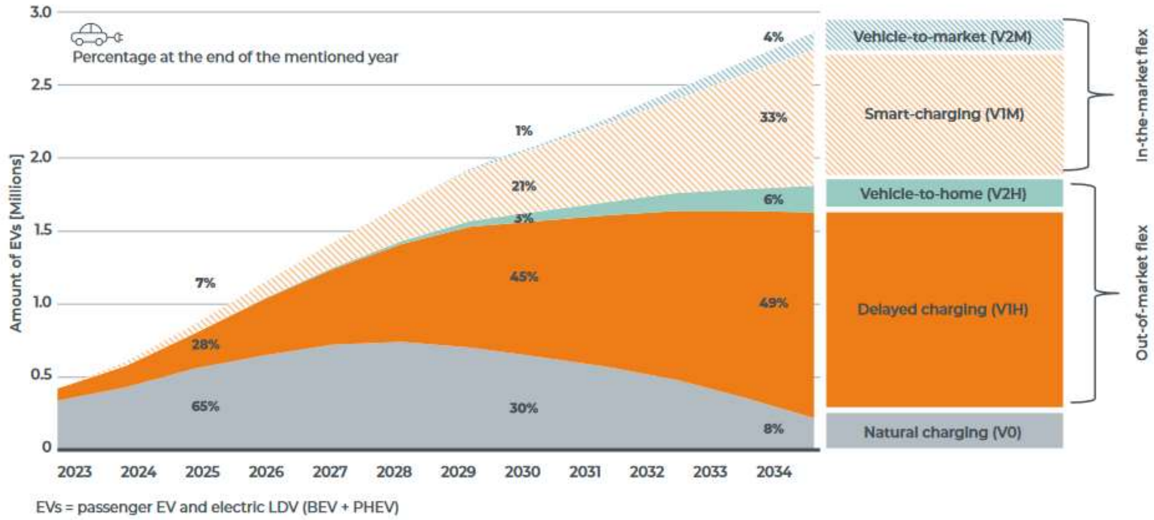


Figure 9: Evolution of EV operating modes in the central scenario including the relative share [11]

Together with the rising adoption of EVs in Belgium, which is expected to reach 1.9 million units by 2030, so will the impact, positive or negative, on the electricity system increase. By 2030, this could lead to decrease of firm, flexible capacity on the Belgian grid of 600MW. Conversely, if the EVs show little to no flexibility, all adhering to natural charging, there could be a need for close to 400MW of additional capacity.

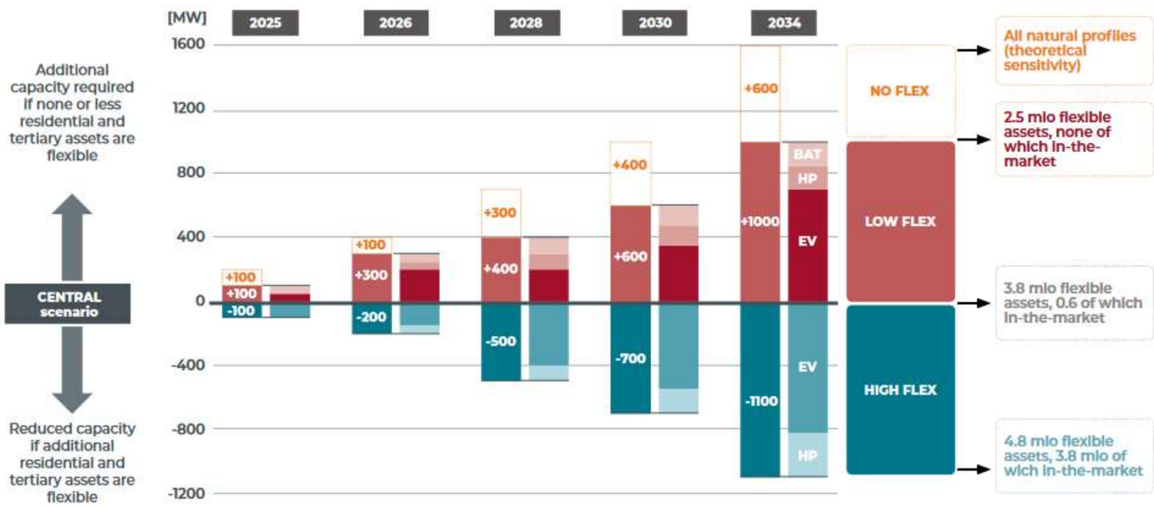


Figure 10: Impact of end user flexibility in Belgium on the gap volume in the EU-base scenario [11]

The two-way energy exchange between EVs and the grid, both in vehicle-to-home and vehicle-to-market operation, is currently not considered. While it is poised to revolutionize the electricity system, EVs with these abilities will most probably only start to emerge by 2026. It's estimated that market players will take several years to establish an offer that promotes the adoption of modes. In the long run, V2 technology is predicted to expand as it becomes standard in new EVs and chargers, reaching a total of 300,000 EVs by 2034.

3. HEAT PUMP TECHNICAL FLEXIBILITY POTENTIAL

2.1. Introduction

The decarbonization of heating systems is accelerating the uptake of heat pumps in Belgium and across the world. When this trend continues, the electricity use of all heat pumps combined will represent a significant part of the total electricity demand during the heating season.

In the FlexSys project, the potential to use heat pumps as flexible assets in the electricity grid is evaluated. In this part of the project (report D1.1), the potential is assessed on the individual building level, for the Belgian context. In a next step (report D1.3), the individual building level results are aggregated and extrapolated to assess the potential on the national building stock level.

In this report, the focus lies on the 'technical' potential, considering the heat pumps themselves and the buildings they operate in. Although it is inevitable to include rudimentary assumptions about the user in this analysis – for example to which temperature the building should be heated and during which hours of the day –, a more detailed consideration of user preferences and behaviours are out of scope. These behavioural aspects are subject of another part of the FlexSys project (D1.5).

3.1. Literature review

During normal operation, the electricity consumption profile of a heat pump is spread across the hours of the day in a particular way. Depending on the building and the indoor temperature requested by the user in each hour, this profile may be relatively 'flat' – with a more or less equal amount of electricity being consumed in every hour – or contain significant peaks and valleys. The observation that – whatever the profile is –, it can probably be changed to a certain degree to meet certain private or societal goals, or in other words that "heat pumps are flexible", is not new. For example, one may attempt to exploit heat pump flexibility to concentrate the consumption profile into the hours with the lowest electricity price. Assuming that the user has an electricity contract using dynamic hourly prices, this would cause a reduction in the electricity bill paid for operating the heat pump. Similarly, a user may want to self-consume as much of the electricity produced by his own solar panels. In such a case the goal would be to concentrate the heat pump's consumption profile as much as possible into the hours when the production of solar power takes place. In this project the focus lies on the degree to which changes in a heat pump's consumption profile can contribute to a national electricity system's security of supply. This means that we are primarily interested in the ability to temporarily reduce a heat pump's electricity consumption, questioning for example how long it can be turned off before a certain comfort threshold is reached. Before delving into the details of the research methodology we designed to study this, it is useful to briefly consider a few examples of how heat pump flexibility has been studied by others in the past.

Junker et al. studied shifting energy demand peaks from hours with high prices to hours with low prices [1]. They used a penalty function to enforce a heat pump's control system to shift around its electricity consumption. Considering this penalty function, the control system then shifted consumption away from the hours with a 'high penalty' and towards the hours with a 'low penalty'.

In similar work focussed on the Italian context, Vigna et al. [13] attempted to change a heat pump's electricity consumption profile in order for it to match the production of solar panels as well as possible. They did this by using a “smart” set-point for the desired indoor temperature, as indicated in Figure 3. Using this method, they demonstrated an 18% reduction in the CO_2 emissions related to the heating of the studied buildings. However, their method remains case specific and the results cannot be easily extrapolated.

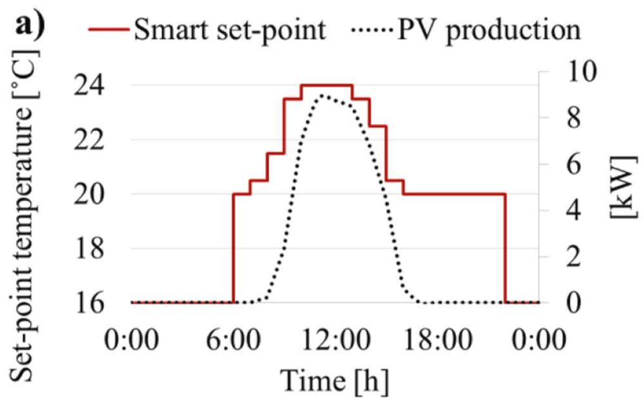


Figure 11: Using different set points for enforcing the control system to shift the working hours of the heat pump in the study of Vigna et al. [13]

Reynders et al. [14] assessed the flexibility associated with heating a building (with a heat pump) by first overheating it above the desired set-point temperature, to enable a longer period of reducing energy demand afterwards. Through this kind of ‘active demand response’, the building's thermal inertia is used as a kind of battery, whereby the amount of energy that can be stored and shifted in time is dependent on the building's physical characteristics and the choices made in terms of the boundary conditions. For example, by how much degrees above set-point the building is allowed to be pre-heated before the heat pump is turned off.

Crawley et al. [13] studied various ways in which heat pump flexibility can be quantified. After considering various alternatives and discussing their pro's and con's, they focussed simply on estimating the amount of time over which a building can shift its entire heating demand without causing discomfort. Temperature measurements were carried out for 193 buildings where the heating system was turned off, and the relationship between time and the drop in indoor temperature was studied. For the sake of illustration, the squired results for two of studied buildings are shown in Figure 5.

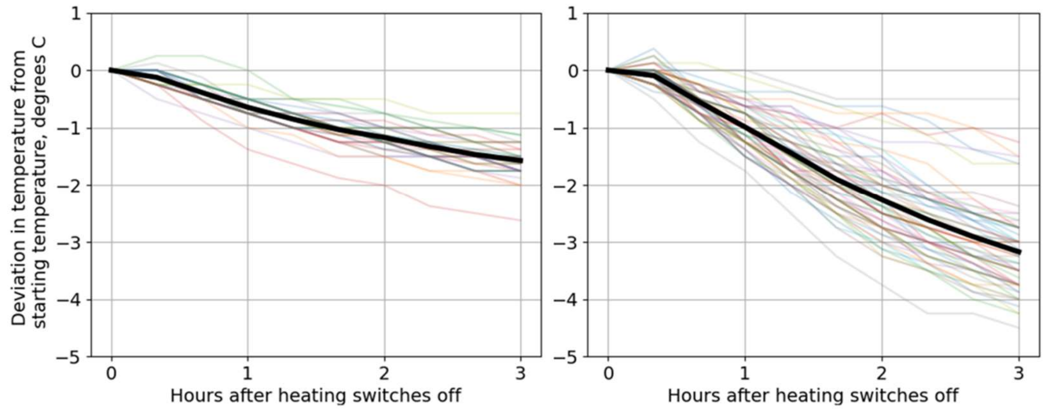


Figure 12: Internal temperature drops over 3 h for two homes in the study of Crawley et al. [13]. Coloured lines each represent one day; thick black lines represent the average value over all days.

3.2. Research methodology

To explain how we studied heat pump flexibility, we fist need to explain how we define this concept it in the first place, and which parameters we chose to quantify it. Only then do we dive into the details of the building simulation model which was developed and used for this analysis, followed by an explicit look at which variations in input parameters were used to develop a wide variety of simulation outputs. These input parameters deserve careful attention as they are fundamentally expected to drive the results, namely the "quantities of heat pump flexibility" that we end up with.

3.2.1. Flexibility definition

Broadly defined, heat pump flexibility refers to the ability of a heat pump to deviate from its typical electricity consumption profile during normal operation. Compared to normal operation, these deviations can influence the degree to which the heat pump is capable of maintaining the same level of comfort in terms of the indoor temperature. Therefore, it is important to note that assumptions about which levels of discomfort are deemed acceptable are inextricably linked with a more precise definition of heat pump flexibility. After all, if flexibility is only the degree to which a heat pump can deviate from its normal electricity consumption profile, but no limits on discomfort are explicitly considered, then one could say that a heat pump is infinitely flexible, in the sense that it can simply be turned off for an indefinite period – fully ignoring its role a heating device. Therefore, heat pump flexibility can be more precisely defined as the ability to deviate from its typical electricity consumption while will remaining within whichever comfort boundaries are deemed acceptable.

Quite obviously, a heat pump's flexibility is determined in large part by the building it resides in, which is why the definition given above may just as well focus on the "ability of the building" to allow for deviations in the electricity consumption profile of "its heat pump". Similarly, one could speak of the flexibility "of a heat pump in combination with its thermal buffer tank", if cases where such a buffer tank is available. In our analysis, thermal buffer tanks are left out of consideration, as we are fundamentally interested in the ability of a heat pump to exploit a building's thermal inertia for the purpose of flexibility. Moreover, space constraints in many homes severely limit the probability of large buffer tanks to proliferate across the building stock to a large enough degree for them to become relevant for inclusion in the broader analysis taking place in the FlexSys project.

Notably absent from our definition is the production of sanitary hot water (SHW), which is of course also an important function that most heat pumps serve. Without a doubt, strategically timing the production of SHW – for example, to concentrate it into the hours of the day when solar power is being generated – is a worthwhile endeavour, and can be called "flexibility" as well. However, we consider this a quick-win and – in a sense – a "no-brainer". When considering the 2030-2040 timeframe, as we do in this report, it speaks for itself that some form of strategically steering the production of SHW production will be broadly available to the owners of modern heat pumps. It does not present a significant research challenge and – compared to figuring out the flexibility potential of heating – it is not an area of vast and largely unexplored terrain.

3.2.2. Flexibility indicators

The devil is in the details

Regardless of how heat pump flexibility is defined, the devil is in the details. How it is quantified concretely, depends entirely on the exact parameters that are developed and chosen for this purpose, each giving a different "indication" of how much flexibility there is. The most basic example of such a 'flexibility indicator', or flexibility parameter, is to quantify "a number of kilowatts" of heat pump flexibility. This number would give a rough indication of the degree to which the reference electricity consumption profile (under normal operation) could be deviated from.

Problems arise quickly however, when you delve deeper into what such a parameter would entail precisely. How does the this claimed "amount of flexibility" – expressed as a single kW value – differ from moment to moment? Given the fact that a heat pump does not necessarily operate at a fixed level of electricity consumption across the hours of the day, let alone across the different months of the year, *when* flexibility is requested can obviously affect the amount of kW available.

Moreover, one should immediately ask "for how long" this kW value can be maintained, and – assuming the value represents the ability to *reduce* demand – how much *higher* the electricity consumption will be *after* the initial flexibility intervention took place. Given the fact that reducing a heat pump's electricity demand will allow a building to cool down below the user's set-point temperature, one should obviously expect an increase in demand afterwards, to 'restore' the temperature to its desired state.

The different dynamics of heat pump flexibility

Delving deeper into the question of which parameters should be chosen to quantify "an amount of heat pump flexibility", one quickly realises that there are many possibilities. Fundamentally, there are a number of 'dynamics' related to the flexible use of a heat pump, which are all – at least in principle – worth capturing in one way or another. Summarized briefly, we believe the most important of these dynamics are:

1) There is only a certain amount of power (expressed in kW) available.
2) When this amount of power is 'used' (e.g. the heat pump load is reduced by x kW), then this can only be maintained for a specific amount of time, not indefinitely.
3) When a heat pump's electricity consumption is reduced at one point in time (compared to its reference consumption), then this typically leads to an increase in electricity consumption at another time – and vice versa.

4) If the building is pre-heated in anticipation of a desired heat pump load reduction, to a temperature *above* the regular set-point, then the amount of time during which the load can subsequently be reduced, is longer.
5) The speed at which one flexibility intervention can follow another, and the overall frequency of flexibility interventions over a given period of time (e.g. one day), is limited somehow – i.e. one cannot expect to be 'completely unconstrained' in terms of this speed and frequency.

A reflection on potential heat pump flexibility indicators

Before concluding this section with an explanation of which parameters we ultimately chose to quantify in the analysis for this report and why, it is worth reflecting on each of the five dynamics mentioned above, and the ways in which they could in theory be captured using different hypothetical parameters – each focussing on a different aspect of heat pump flexibility and each potentially playing a role in describing and concretely quantifying "an amount" of such flexibility.

Starting with the amount of kW available in the form of a potential reduction in heat pump load, one could refer to the *maximum* load of a heat pump, or the *average* load, over a certain period of time. When taking a day as the considered time period, the question arises: does a heat pump's peak-load during a given day better reflect its "amount of flexibility" than its average load across the day? Reasonable people may disagree.

Other may avoid to answer this question entirely, arguing that the electricity consumption profile of a heat pump should 'simply' be considered at an hourly or even sub-hourly time resolution to quantify its flexibility in an sufficiently accurate manner. On the other side of the spectrum, some may already be satisfied with four kW-value's, one for each of seasons, or even with a single value referring to an average or maximum load available across a whole year.

To express the dynamic in question (nr. 1 in the list above), one could also take it a step further then to compute only an average or maximum value in kW, to express the flexibility of a heat pump's load profile. Namely by normalising the value with respect to variations in the outside temperature. Or more precisely, by considering the variations in the difference between the set-point for the inside temperature (e.g. 21°C) and whatever the outside temperature is at a given moment. The concrete parameter in this case could for example be "the amount of kW available for every degree of difference between 21°C and a given outside temperature". If the value of such a parameter would for example be 1 kW/t_{delta}, then one would expect "5 kW of heat pump flexibility" for a specific situation and time period in which both a setpoint of 21°C and an outside air temperature of 16°C are known. The value of such a parameter may lie in its useability as a quick way to get a sense of the expected amount of flexibility, given these two important boundary conditions of in- and outside temperature.

If we were only interested in heat pump flexibility for a very short duration, for example 1 hour or less, then it would be of limited importance to study *how long* a decrease in a heat pump's load could be maintained. However, longer durations are certainly of interest to both the user as well as the broader electricity system itself. The individual owner of a heat pump may be interested in being able to avoid consuming a lot of electricity during a sustained period of high electricity prices (e.g. from 16:00 to 22:00), while the broader system may similarly be interested to reduce demand for extended periods of time in order to deal with a lull in renewable electricity generation, which can easily last four to eight hours or even longer.

The question then becomes how to capture and quantify this dynamic (the 2nd one from our list above) in a concrete parameter. Obviously one possibility is to simply quantify precisely how the kW-values change in time (e.g. from one hour to the next), which can result in a timeseries of 10 or more values for every individual heat pump flexibility intervention. Each value would show what the reference consumption profile of the heat pump *would have been*, if there had been no flexibility intervention. Depending on whether or not the reference profile for the time period considered is flat or not, these values will (or won't) fluctuate heavily. Such an approach of quantifying the duration-effect of a flexibility intervention on the 'available' amount of load is precise, but lacks in terms of simplicity and useability. It would be hard to easily compare the amount of heat pump flexibility in one building with the amount in another, when using complicated time series as a metric.

Another possibility is to try to capture the duration-effect by computing a kWh value in addition to a kW value. Together, these two values would indicate not only what the maximum load decrease would be if a heat pump is 'activated', but also what the total energy would be that could be reduced (in kWh). However, there are many ways to reduce load by a total of x kWh's. The ability to perform a 5-hour long load reduction of 1 kW would be equated to the ability to perform a 1-hour long reduction of 5 kW. Given the fact that a kWh value is so abstract, ignoring the underlying reality with respect to the building physics and the heat pump's reference consumption profile, using such an energy-based parameter is deemed to be too much of a simplification for the purposes of this report. Kilowatts and kilowatthours of heat pump load cannot simply be shifted at will, from one hour to another, as they can in an electrochemical battery. Conceptualising heat pump flexibility in this way is potentially misleading, and could lead to an overestimation of the actual amount of flexibility available, by insufficiently taking into account how the shifting-around of kilowattshours is constrained in practice.

The third dynamic to be captured by parameters when quantifying an "amount of heat pump flexibility", is the fact that a reduction in heat pump load at one point in time (compared to the reference load) leads to an increase in load at a later point in time – and vice versa. As explained previously, turning off a heat pump and letting a building cool down to a temperature below the user's set-point, obviously leads to an increase in electricity demand when the flexibility intervention ends and the heat pump is activated to restore the temperature back to the set-point. However, the net energy balance of the overall operation can be difficult to predict, as it can be affected by a range of factors, some of which have a specific timing-aspect to them as well:

- The desired 'speed of recovery', meaning how fast the heat pump should attempt to restore the indoor temperature to the set-point after being reactivated. When a building was allowed to cool down below the set-point during a flexibility intervention, heating back to the set-point in a calm and patient manner tends to be more energy efficient then 'rushing' this process by ramping up the flow-temperature being fed to the heating system.
- The evolution of outside air temperatures during the entire timespan of the operation. If the outside temperature happens to increase as the heat pump is trying to recover the indoor temperature back to set-point, this can affect the net energy balance.
- Changes in the difference between the inside and outside temperature caused by flexibility intervention itself. Because of the fact that the building is temporarily heated less, temperature differential between the building and its environment is reduced, leading to lower heat losses and therefore increasing the likelihood that the net energy balance of the operation in its entirety will be beneficial. The opposite takes place when a building is pre-

heated in anticipation of a flexibility intervention, temporarily raising the indoor temperature above set-point.

- Changes in the flow temperature of the heat pump, caused by the need to restore the indoor temperature back to set-point. A heat pump may need to work 'harder', raising the temperature fed to the underfloor heating system or radiators, in order to raise the indoor temperature back to setpoint in quick enough manner. How quickly is quick enough, depends on assumption with respect to what is acceptable from a comfort perspective.
- The reference heating regime set up by the user, dictating how the set-point itself evolves over time – including throughout the duration of the entire flexibility intervention.
- Heat gains as a result of solar radiation through the building's windows, which may for example significantly aid the process of recovering the indoor temperature to the set-point, depending on the timing of the operation.
- Heat that is emitted by the user's household members themselves – also called internal heat gains –, dependent on whether the households members are at home or not.

A parameter that could be quantified to capture this dynamic, is a so-called 'round-trip efficiency' (RTE), which is a percentage indicating the relative sizes of the load reduction- and load increase-parts of a heat pump flexibility intervention. This term is more typically used in the context of traditional energy storage, for example in the case of pump-hydro energy storage, or a standard lithium ion battery. When water is pumped up a hill to be stored in an elevated reservoir, in order to generate electricity at a later point in time by flowing the water downhill again, 30% of the energy consumed in this process may be lost – pointing to an overall RTE of 70%. Similarly, a lithium ion battery may have a 90% RTE, indicating that only 10% of energy is lost in the charging and discharging processes. However, in the context of heat pump flexibility, computing an RTE value for each individual intervention can be a highly cumbersome process.

One reason for this is the complex reality in terms of building physics, as indicated in the list above. Another reason is the fact that – when a flexibility intervention occurs – deviations from the reference electricity consumption profile do not only occur in the initial hours, but can keep occurring for many days after the heat pump was originally turned off. Even long after the heat pump was turned back on again, the different 'trajectory' it was put on by having the flexibility intervention take place, can be rather complex and long-lasting. Because of this, determining what the 'end point' of a flexibility intervention is becomes at least partially arbitrary. Especially in the case of heating regimes in which the setpoint temperature is not maintained 24/7. Given this fact, calculating an RTE value is not always possible. Or at least not without making additional assumptions about what you arbitrarily decide is the 'end-point' of a flexibility intervention.

The fourth dynamic worth capturing in principle is the fact that the a heat pump can remain turned off for a longer period of time if the building has been consciously pre-heated above set-point in anticipation of the flexibility intervention. A potential parameter that could be computed to capture this dynamic, would be "how much longer the heat pump can remain turned off for each additional degree of pre-heating". Alternatively, one could use parameters to express the changes in the amount of kW's and kWh's of flexibility that are available during the heat pump intervention – again, for every additional degree of pre-heating that took place.

The fifth and final dynamic is the fact that both the total frequency of individual heat pump flexibility interventions within a given time period (e.g. one day or one week) and the amount of time in between individual interventions are both constrained somehow. Notably, in the context of this report, this dynamic refers purely to the technical aspects of heat pump flexibility that can act as constraining factors. Not the additional ways in which user behaviour and preferences may impose constraints on this front. A user may only have an appetite for a certain number of interventions per day, week or month, and a preference about the amount of time in between two consecutive interventions. Such matters are researched elsewhere in the FlexSys project, but are out of scope in this report.

The purely technical constraint associated with this dynamic is the fact that a single intervention can take a considerable amount of time to complete. Especially when outside temperature are on the milder side, the speed at which the building cools down when the heat pump is turned off can be rather slow. If on top of that the recovery period is also lengthened because a patient and therefore energy efficient re-heating process is allowed, then the total timespan of a single intervention including recovery can be several days long. A potential parameter to capture this dynamic would be to compute a type of "cooldown times", which would express the minimum amount of hours that should be left in between two consecutive moments of turning off the heat pump for a flexibility intervention. The value of such a parameter would be highly dependent on the timing of the interventions in question, with large differences between the coldest winter-weeks and the mildest weeks of spring or autumn. Normalising the parameter with respect to the outside temperature could therefore be considered, meaning that the 'cooldown time' would be expressed as a function of how cold it is outside (e.g. per degree difference between the indoor set-point and the outdoor temperature). However, simply taking a closer look at how the indoor temperature tends to evolve throughout flexibility interventions should already give an intuitive understanding of the constraints related to the dynamic in question.

The two chosen indicators

To quantify the "amount of flexibility" observed in the simulations performed for this report, we chose to focus on a set of two parameters. The first is the **duration** of flexibility interventions, which is the amount of time – expressed in a number of hours – that it takes for a building to cool down to the predefined 'threshold temperature' (e.g. 18°C) after the heat pump was turned off. The second is the **load reduction** made possible by flexibility interventions, which is expressed in Watt. For this parameter, we compute the value for several time horizons, namely 1h, 2h, 4h, 8h and 24h. For each time horizon, the value represents the amount of Watt by which the heat pump's load can be reduced (compared to the reference consumption profile), for the amount of time indicated. For example, when we speak of the "4 hourly load reduction", what we mean is the load reduction *that can be maintained for four hours* after the heat pump was originally turned off. A more detailed discussion on these two parameters and the values that were computed – which make out the main results of this report – can be found in sections 3.3, 3.4 and 3.5.

As discussed above, a whole range of parameters could hypothetically be defined and computed to capture every possible dynamic related to heat pump flexibility in a detailed and comprehensive manner. However, we simplify our approach here to the chosen set of two easy-to understand parameters for the sake of keeping the results of this report as understandable and useable as possible for a broader audience. We want out results to not only be accessible for building physics experts, but also to players like electricity grid operators, companies that aggregate flexibility across millions of diverse assets, and policy makers.

Moreover, the way in which the simulations for this report were ultimately set up – as discussed in more detail later on – meant that not all parameters that could in theory be quantified were able to be computed. Trade-off's needed to be made in terms of computational complexity and prioritisation of certain aspects of heat pump flexibility which we found most important in the context of the FlexSys project. For example, the nature of the project's main research question – which is what the potential contribution is of residential flexibility to Belgium's security of supply – naturally creates a focus on the 'load reduction' dynamic and the associated parameter. In future research, different trade-off's and choices related to flexibility parameterisation could be made.

Simplified visualisation

To close this section on the indicators of heat pump flexibility, it is useful to visualise the essence of how we conceptualise a flexibility intervention in this report. This not only allows us to clarify what happens – broadly speaking – in the detailed building simulations that were performed, but also to highlight the two parameters of interest, which were ultimately chosen to quantify the "amount of heat pump flexibility".

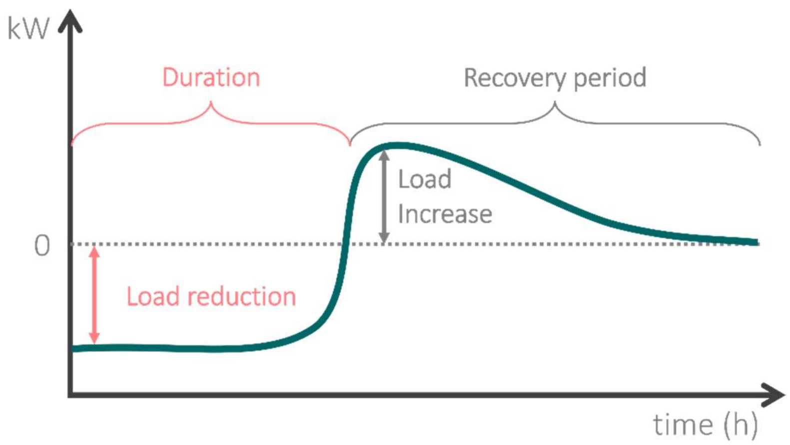


Figure 13: Simplified visualisation of heat pump flexibility as conceptualised in this report

Figure 12 shows how the electricity consumption profile of a heat pump deviates during the hours of a flexibility intervention, compared to its reference consumption profile. When the heat pump is turned off, it obviously consumes less electricity compared to when it remained 'undisturbed', continuing to keep the indoor temperature at the user's set-point. How much lower the electricity consumption is, depends on the hight and shape of the reference consumption profile (not shown on the figure).

During the hours in which the flexibility intervention takes place, the counterfactual reference profile *could* be flat – if the heat pump would have happened to be consuming a constant amount of electricity in this particular period – or it could have another more volatile shape. Depending on the evolution of the outdoor temperature and solar irradiation during these hours, as well as the user's heating regime (the evolution of the set-point), the reference profile itself could be quite volatile. It could also have a value of zero, if the specific set of boundary conditions result in the heat pump no longer being needed (for a few hours) to maintain the setpoint temperature. Therefore, it is important to note that the exact shape of green curve shown in Figure 12 can be quite different in actual building simulations.

As the figure indicates, a period of **load reduction**, is always associated with a certain **duration** – the two main heat pump flexibility parameters of interest in this report. This is followed by a “recovery period”, during which a load increase takes place. However, as explained in more detail in the earlier part of this section, we do not focus on this aspect of heat pump flexibility.

To further illustrate the value of quantifying the load reduction for various time horizons – as we do in this report –, Figure 14 below shows how this can already provide a good indication of how the negative part of the curve ‘evolves’. The benefit of describing this evolution through a limited series of computed load reduction values (1h/2h/4h/8h/24h) is that it roughly describes the potentially complicated shape in a way that is still sufficiently easy to understand. More complicated and potentially confusing options like describing the exact ‘path’ of the load reduction observed in the building simulations through a series of functions or statistical regressions are avoided this way.

It should be noted however that in the case of individual heat pumps, the typical shape of the load reduction part of the curve is flat for a certain amount of time and then suddenly shooting up as the heat pump reactivates and the recovery period is initiated. Therefore, using the load reduction parameters for the different time horizons to “describe the shape of the curve” is primarily intended for curves that represent an aggregation of buildings at the national building stock level. This part of our work is presented in the D1.3 report, but for the parameter values to be available for aggregation in that part of our project’s work, they first of all need to be computed at the individual building level – hence their inclusion in this report.

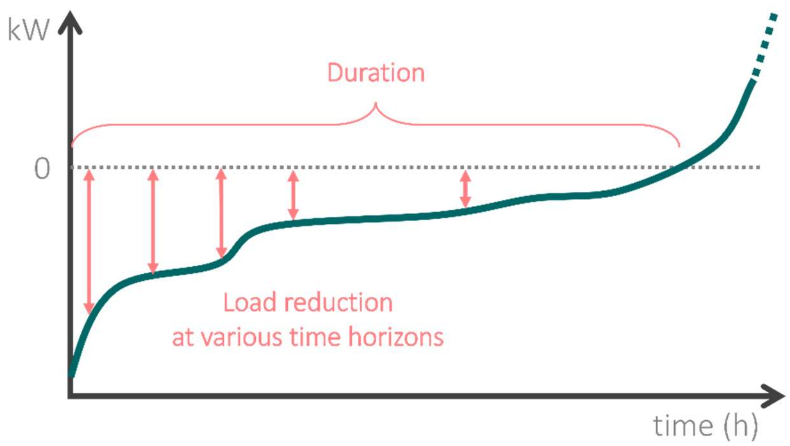


Figure 14: Load reduction parameter variations conceptualised in this report

3.2.3. Parameter variation

The flexibility indicators we focus on in this report are affected by two groups of parameters.

The first group consist of building properties and user profiles: building geometry, building insulation level, heat pump type, heat emission system and heating schedule. In this study, the Belgian building stock is broken down into clusters with a unique combination of these properties. In a next part of the project (Deliverable 1.3), we will estimate the amount of buildings in each cluster, and aggregate the individual results.

The second group of parameters can be used in a sensitivity study, where the minimum temperature threshold and outdoor climate can be varied.

Geometry

Eleven different building geometries are used. Both detached, semi-detached and terraces houses are studied, as well as apartments. For the single family houses, a small, average and large house is selected. For the apartments, both a middle apartment and a roof apartment is selected. These geometries are adopted from the online EPC-simulation tool provided by the Flemish Government [23]. The geometries represent buildings from the EPC-database, where the small, average and large buildings correspond to the 25th, 50th and 75th percentile off the conditioned floor area.

Table 1: Original geometrical properties

geometry	conditioned floor area [m²]	volume [m³]	ground floor area [m²]	facade area [m²]	roof area [m²]	window area [m²]	door area [m²]	total heat loss area [m²]
detached small	146	460	90	167	115	29	3	404
detached average	198	622	126	192	142	35	8	503
detached large	277	798	145	236	179	44	12	617
semi-detached small	131	469	82	144	89	25	2	342
semi-detached average	178	518	96	133	112	23	9	373
semi-detached large	234	643	98	170	118	31	10	427
terraced small	126	437	59	83	76	22	2	241
terraced average	160	475	54	128	55	33	9	280
terraced large	199	547	75	112	91	29	10	316
apartment middle	100	300	0	25	0	25	0	50
apartment roof	100	300	0	34	100	16	0	151

Our simplified EnergyPlus model – as discussed later in 3.2.4 – employs a basic cuboid geometry, requiring modifications to the dimensions listed in Table 1. To adjust, we relied on the conditioned floor area, volume, and total heat loss area. We presumed single-family houses span two floors, whereas apartments occupy just one. Table 2 shows the final geometrical properties used in our energy simulations. It's important to note that some geometries may underestimate ground floor and roof areas while overestimating façade areas. Conversely, other geometries present the opposite pattern.

Table 2: Definitive geometrical properties

geometry	conditioned floor area [m²]	volume [m³]	ground floor area [m²]	facade area [m²]	roof area [m²]	window area [m²]	door area [m²]	total heat loss area [m²]
detached small	146	460	73	226	73	29	3	404
detached average	198	622	99	262	99	35	8	503
detached large	277	798	139	283	139	44	12	617
semi-detached small	131	469	66	183	66	25	2	342
semi-detached average	178	518	89	163	89	23	9	373
semi-detached large	233	642	117	153	117	31	10	427
terraced small	126	437	63	92	63	22	2	241
terraced average	160	475	80	77	80	33	9	280
terraced large	199	547	99	78	99	29	10	316
apartment middle	100	300	0	25	0	25	0	50
apartment roof	100	300	0	34	100	16	0	151

Insulation level

Six insulation levels are defined which represent typical values for buildings with EPC-label A to F. Note that the EPC-label takes into account others aspects of the building besides the building envelope, such as HVAC systems or PV panels. For label A, the most recent maximum U-values are used, which were introduced in Flemish EPBD regulation in 2016. For label B, the maximum U-values at the introduction of the Flemish EPBD regulation in 2006 are used. For label C to F, typical values from the TABULA study were used [24]. For every insulation level, an estimation of the air leakage is included as well. An overview of the selected U-values and air leakage values is shown in

Table 3: Building envelope properties

insulation level	U-value windows [W/(m².K)]	U-value roof [W/(m².K)]	U-value wall [W/(m².K)]	U-value floor [W/(m².K)]	U-value doors [W/(m².K)]	v_{50} [m³/(h.m²)]
A	1.50	0.24	0.24	0.24	2.00	3.2
B	2.50	0.40	0.60	0.40	2.90	4.0
C	3.00	0.80	0.60	1.50	3.50	6.0
D	3.50	1.20	1.40	2.10	3.80	8.0
E	3.60	1.30	1.90	2.70	4.00	10.0
F	5.00	1.90	2.20	2.80	4.00	12.0

Heat pump type

For individual building simulations, we solely assess air-water heat pumps. When extrapolating to the building stock level, COP corrections will be implemented to reflect the results for geothermal heat pumps and air-air heat pumps.

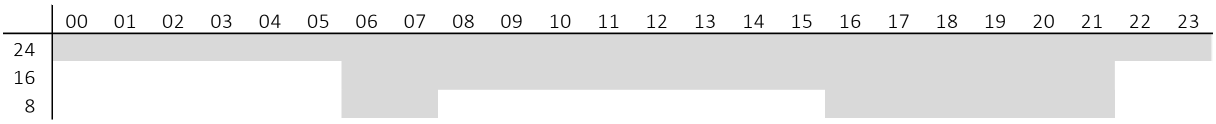
Heat emission system

Both underfloor heating and radiator heating are evaluated.

Heating schedule

We've established three heating schedules, with the specific heating hours outlined in Table 4. For the 8h heating schedule, the specified hours apply to weekdays, while weekends follow the 16h schedule. During heating hours, a heating setpoint of 21°C is defined. Outside heating hours, a minimum temperature of 17°C is maintained. It's worth noting that our approach uses a single-zone model, where the building is kept at the uniform temperature.

Table 4: Heating schedules



The 8h heating schedule is not the most realistic scenario for a slow-reacting heating system such as underfloor heating. Since thermal comfort will not be guaranteed during the 2-hour heating period in the morning, this combination is not used in the building stock analysis in D1.3 report. However, for consistency and completeness we will evaluate this scenario in this report.

To assess the impact of pre-heating a building, we introduced a forth heating schedule, where the building is kept at a constant temperature of 23°C.

Minimum threshold

Three minimum temperature thresholds have been selected to determine when the heating system is reactivated after a flex event: 16°C, 18°C, and 20°C.

- The 18°C threshold is viewed as a realistic comfort minimum that residents would typically accept in their homes.
- At 16°C, this threshold represents a more extreme value. Some residents might tolerate this cooler setting if there's adequate financial incentive to compensate for the decreased comfort.
- Conversely, a drop to the 20°C threshold is subtle enough that most residents may not notice and would likely accept without significant compensation.

Climate

We selected three recent years of historical climate data for the city of Uccle, to represent cold (2010), average (2005) and warm (2014) conditions. Doing so allows us to use the results of the flexibility study in the D1.4 part of the project, where we model the balance of Belgium's electricity grid based on historical wind and solar data to determine electricity generation. By syncing wind and solar data with the outdoor temperatures in our simulations, we ensure a more cohesive and realistic approach.

Given that our flexibility indicators fluctuate significantly across seasons, computing average values for an entire year isn't practical. Our main focus is on the winter months, when electricity demand for heat pumps peaks, which presents the greatest energy flexibility potential. Calculating the average temperature for the winter months December, January and February returns an 3.7°C temperature. As this corresponds to the typical temperature for December in an average year, we will centre our analysis on this month in the report.

Table 5: Monthly average temperatures

	cold [°C]	average [°C]	warm [°C]
jan	0.1	5.0	6.1
feb	2.5	2.5	6.6
mar	6.7	7.3	9.3
apr	10.3	10.6	12.4
may	11.2	13.3	13.5
jun	17.4	18.2	16.5
jul	20.5	18.3	19.3
aug	17.1	16.7	16.2
sep	14.2	16.6	16.5
oct	10.6	14.2	13.6
nov	6.1	6.3	8.9
dec	-0.7	3.7	4.3

3.2.4. Building model

In this study, we investigate the influence of a large set of parameters on the building's ability to shift energy demand to a later moment in time. For this purpose , the dynamic simulation model for each building with its unique combination of parameter values must be mathematically simple.

Grey-box models

To this end, we've selected the grey-box modelling approach using resistor-capacitor (RC) models. Grey-box modelling offers flexibility; it allows for tailoring model complexity based on the specific application at hand, and simplifies many modelling tasks. However, ensuring the model's accuracy remains a manual task.

Two predominant strategies characterize grey-box modelling: forward and inverse modelling. The forward method resonates with physics-oriented models, where parameter values stem from the physical properties of buildings, albeit with some simplifications [17]. Conversely, inverse grey-box modelling aligns more with data-driven models, where parameter values are derived from a training data set. In contrast to black-box modelling, the structure and mathematical construct of the model in grey-box remains consistent throughout the parameter estimation phase.

To simplify, the essence of inverse grey-box modelling lies in training models using a dataset of system inputs (boundary conditions) and system outputs, sourced either from direct measurements or detailed simulation data. Subsequently, the RC model is used to replicate the system's behaviour, particularly in the face of system inputs distinct from the training set. The inverse grey-box modelling approach is represented in Figure 15.

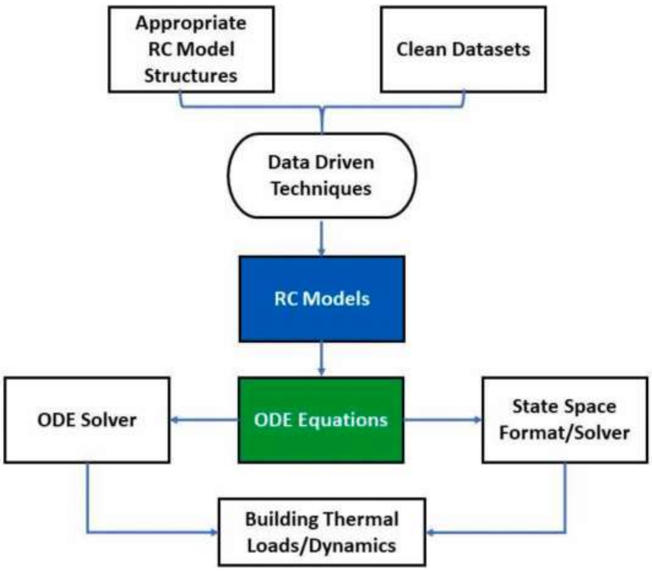


Figure 15: Flow chart of inverse grey-box modelling approach [17]

RC model architecture

The selection of the model architecture is influenced by multiple considerations such as the model's intended use, the acceptable level of mathematical complexity and accuracy, and the characteristics of the building. Determining the most suitable model architecture often becomes a significant part of the modelling task. The configuration and quantity of resistors and capacitors can profoundly affect the results, either marginally or substantially. However, for this study, we opted for a generic model structure based on findings from prior research [15][16][20]. We selected a single-zone model, incorporating 5 capacitors and 8 resistors, as depicted in Figure 10.

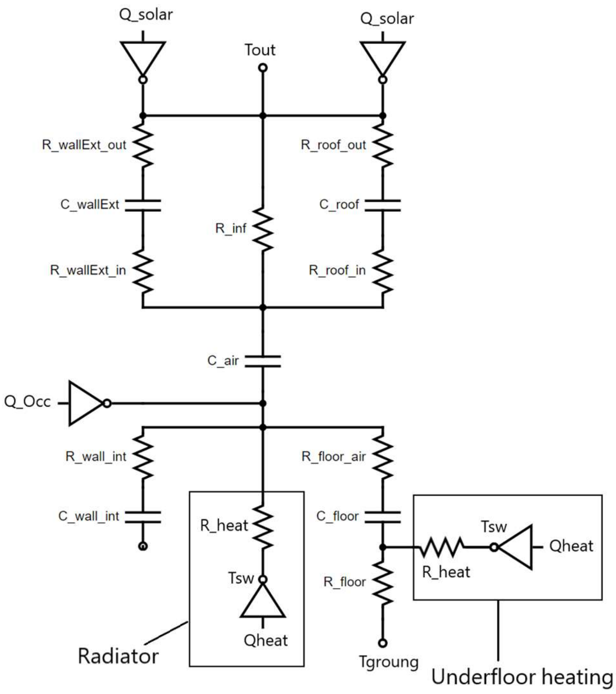


Figure 16: Resistor-capacitor model architecture used in this study

While grey-box models aren't designed to provide precise physical interpretations, the inclusion of resistors and capacitors can be conceptually tied to building physics principles. As depicted in Figure 16 , capacitors, also referred to as thermal nodes that account for specific states, are associated with external and internal walls, the roof, floor, and indoor air. Resistors, on the other hand, are employed to characterize the temperature differential between these capacitors or nodes. Solar gains are directed into the capacitors of external walls and the roof.

Radiators, known for their quick response times, are not assigned a capacitor in the model. In contrast, the underfloor heating system, with its slower response, includes the floor's thermal capacity. For underfloor heating, the entirety of the heat is assigned to the floor's capacitor. Meanwhile, when considering radiators and the heat transfer mechanisms involved, 70% of the heat goes to the indoor air capacitor due to convection, 20% is directed to the internal walls' capacitor, and the remaining 10% is evenly distributed between the floor and ceiling capacitors

Heat pump model

The heating systems, whether radiators or underfloor systems, are powered by a heat pump. In this study, we employ a black-box model to represent the behaviour of the heat pump. The model is regressed on the catalogue data for an air-water heat pump type Daikin Altherma ERLQ-011-CV3. The COP for various outside temperatures and supply water temperatures is depicted in Figure 17. The COPs calculated account for efficiency reductions during defrosting cycles. Our model assumes the heat pump operates at full load, while it's important to remember that in real-world conditions, a heat pump typically functions under part-load situations. It is presumed that the heat pump's capacity is as large as needed to meet the building's full heating demand.

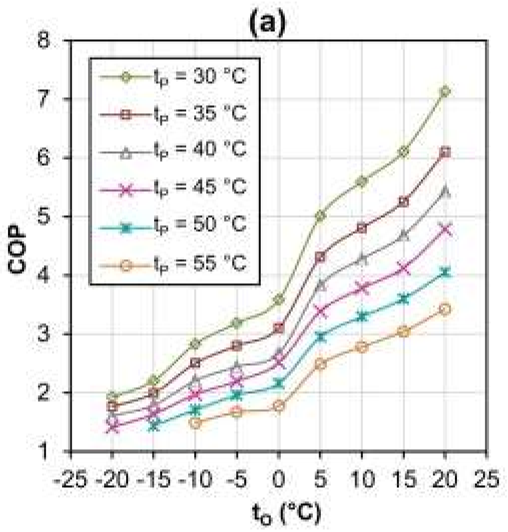


Figure 17: COP as a function of outdoor temperature (t_O) and water production temperature (t_P) [18]

The heating curve establishes a relation between outdoor temperature and the supply water temperature to provide efficient heating with the heat pump. Figure 18 illustrates how different heating curves are used for underfloor heating and radiator heating, as higher supply water temperatures are required in the latter since the heat emitting surface is much smaller compared to underfloor heating.

In our approach, a case specific heating curve is used for every building simulation. The heating curve is calculated using the methodology developed by Sharifi et al. [19]. In their method, the required supply water temperature is simulated for a range of outdoor temperatures. Subsequently, the calculated supply water temperature is related to the outdoor temperature and a regression line is derived.

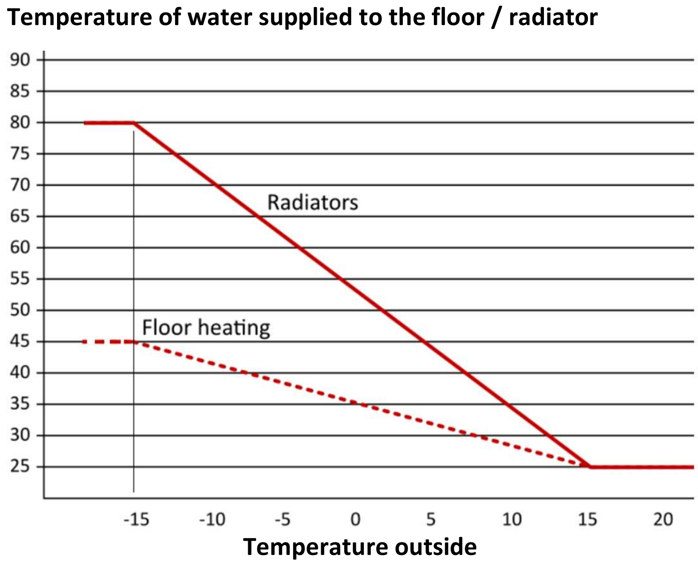


Figure 18: An example of heating curve for a heat pump

Parameter estimation

The parameter values of the R-C model must be estimated for each building individually. However, these values cannot be estimated only using their physical characteristics, as they do not exactly correspond to a building physical attribute. For example, the combined thermal mass of a building's internal walls is represented as a single capacitor, a simplification compared to the actual structure.

In the model training step, the parameter values are estimated [20]. Due to the absence of measurement data for model training, a white-box model is used to execute a dynamic building simulation, generating the necessary data. A white-box model is created for each building with a unique combination of geometry and insulation level, as detailed in 3.2.3.

The EnergyPlus software was used to run the building simulations [21]. As already touched upon in 3.2.3, the original building geometries are translated to a simplified model of a cuboid, representing a single zone model of the building. The boundary conditions of the cuboid’s sides are adjusted based on the geometries to represent different building types: detached, semi-detached and terraced houses or middle and roof apartment. Windows are assumed to be uniformly distributed across all outdoor walls.

The simulation is run for one year to calculate the indoor temperature in response to a randomly generated heating power input. Subsequently, the CTSM tool, which is implemented in R, is used for parameter estimation [22]. CTSM is favoured in many applications because of its straightforward problem formulation and rapid computation capabilities.

3.3. Results

The energy flexibility a building can offer is intrinsically tied to its energy consumption. Hence, we begin by examining the influence of our building parameters on energy use during the reference heat pump operation. We explore the building's heat demand, the supply water temperature, the corresponding COP and the consequent electrical energy consumption of the heat pump.

Following this foundational analysis, we delve into the flexibility assessment, focusing on the duration of the flex events and the associated load reductions and increases arising from these events.

3.3.1. Reference heat pump operation

Heat demand

Our energy analysis starts with the an overview of the total heat demand for the heat pump in December in the average climate year. As previously highlighted, our primary focus is on this month, since it’s a representative winter month. The heat demand represents the energy delivered by the heat pump to the heating system to ensure a comfort temperature of 21°C. This metric omits the efficiency of the heat pump, but provides insight into the variances between building types and insulation levels.

Table 6: Total heat demand in December

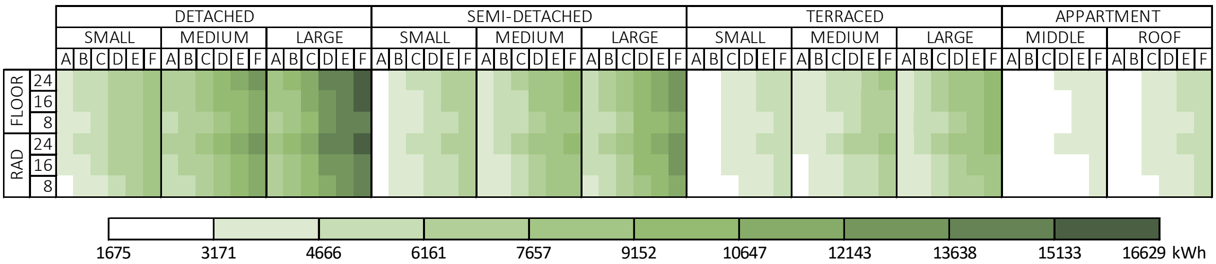


Table 6 presents the total heat demand across all parameter combinations. We observe that:

- Buildings with superior insulation levels require less energy for heating.
- More compact building typologies, such as apartments and terraced houses, have a reduced heating demand.
- The heat demand for underfloor heating and radiator heating is nearly identical
- The intermittent heating schedules (16h, 8h) require less heat compared to the constant heating schedules (24h), but the difference is limited. This effect may be attributed by our simulation parameter assumptions and relatively long simulation time-step of 1 hour.

In order to provide context for the monthly average values for the month December, we study the distribution of the heat demand during the year in Figure 19. Using a medium terraced house with insulation level A, underfloor heating, and a continuous heating regime as a case study, it's evident that the heat demand surges during the colder months. It's important to note that the energy use is quite substantial, as we are examining a building that is presumed to be fully heated.

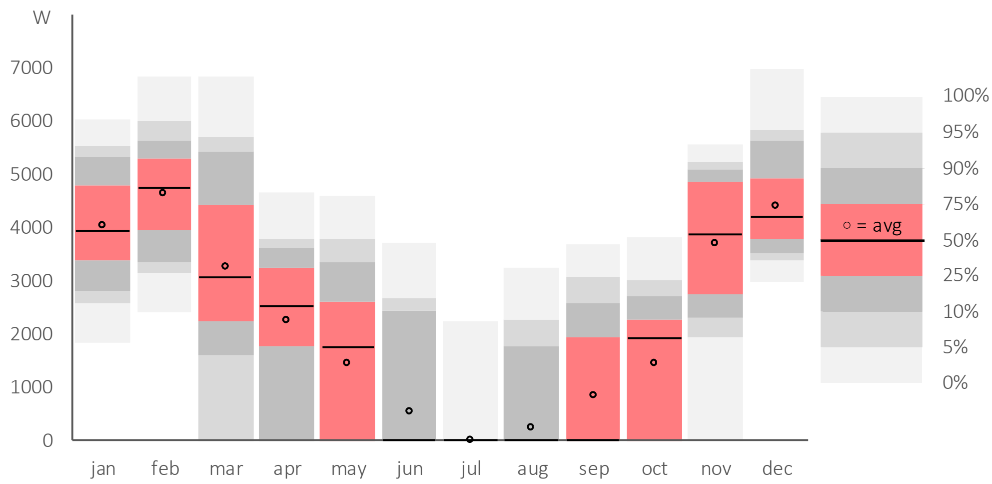
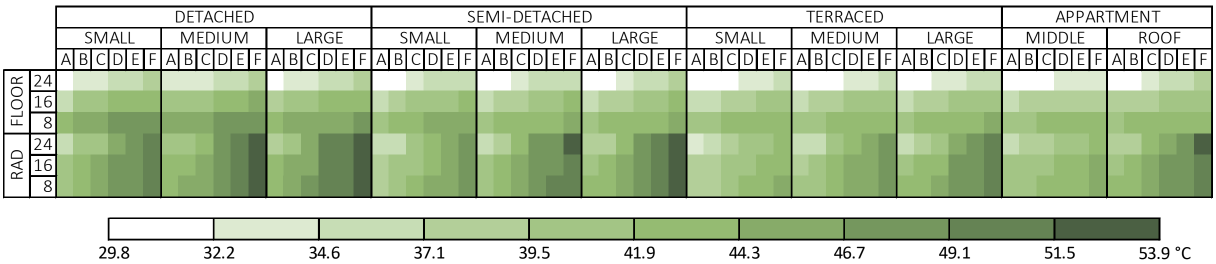


Figure 19: Distribution of hourly heat demand
(medium terraced house / insulation level A / underfloor heating / continuous heating regime)

Supply water temperature

Next, we outline the average supply water temperature needed in the heat emission system to ensure the desired indoor temperature.

Table 7: Average supply water temperatures in December



From Table 7, we learn that:

- Buildings with a better insulation level require lower supply water temperatures.
- Building typologies with a better compactness, such as apartments and terraced houses, require lower temperatures.
- Underfloor heating operate at lower temperatures compared to radiator heating.
- The continuous heating schedules (24h) requires lower temperatures compared to intermittent schedules (16h, 8h).

To delve deeper, we explore the medium terraced house's supply water temperature throughout the year. Figure 20 highlights increased temperatures during winter months, resulting form the heating curve implemented in our building model.

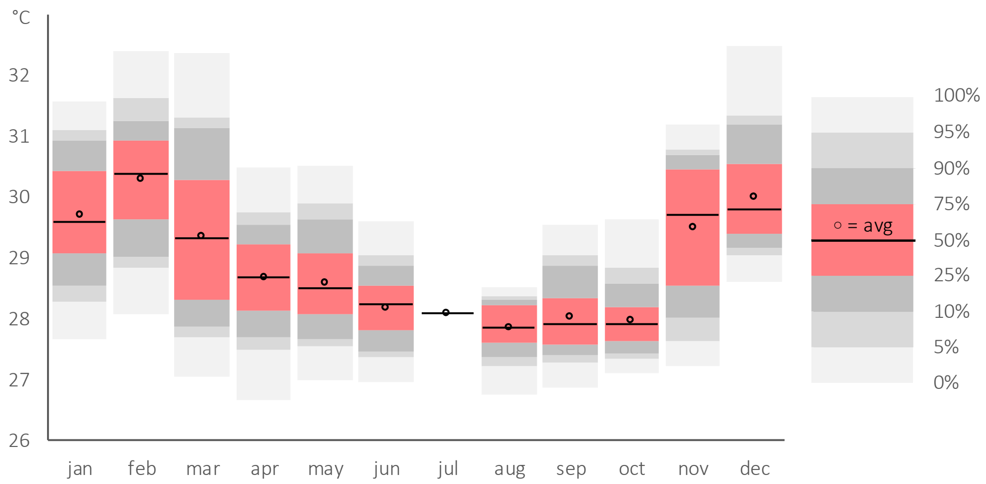


Figure 20: Distribution of supply water temperature
(medium terraced house / insulation level A / underfloor heating / continuous heating regime)

COP

In our building model, the COP of the air-water heat pump is derived based on the supply water temperature and the outdoor temperature. Consequently, the observations from the COP analysis mirror those previously mentioned.

Table 8: Average COP of the air-water heat pump in December

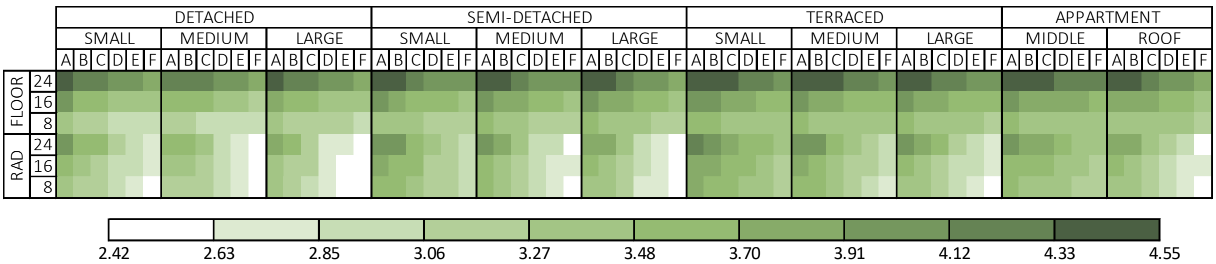


Table 8 illustrates that:

- Buildings with superior insulation levels have higher COPs.
- Compact building types, such as apartments and terraced houses, are related to higher COPs.
- Underfloor heating results in a higher COP compared to radiator heating.
- The constant heating schedule (24h) tends to have higher COPs compared to the intermittent ones (16h, 8h).

A closer look at the medium terraced house in Figure 21 reveals that the lowest COPs occur during winter. This is attributed to the necessity for elevated supply water temperatures to ensure optimal comfort. It's noteworthy that the COP is at its lowest, precisely when heating is most needed.

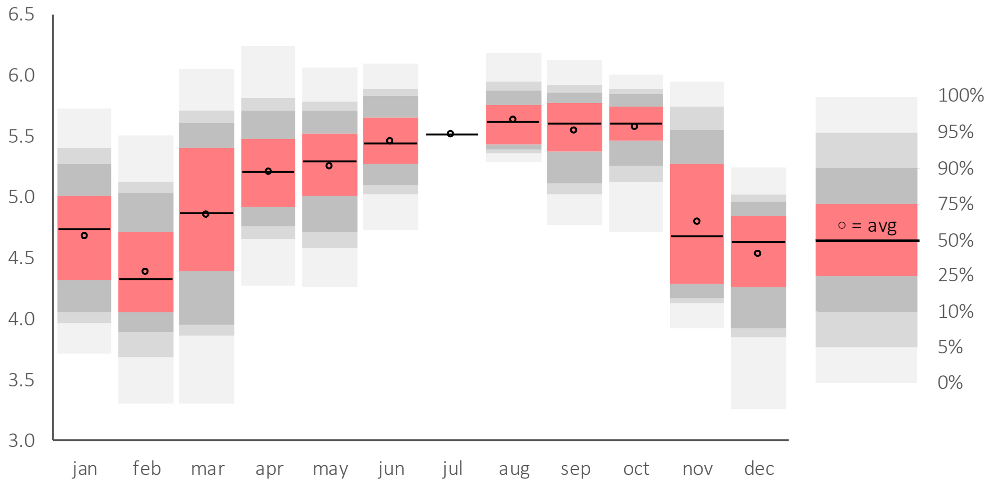


Figure 21: Distribution of COP
(medium terraced house / insulation level A / underfloor heating / continuous heating regime)

3.3.2. Flexibility

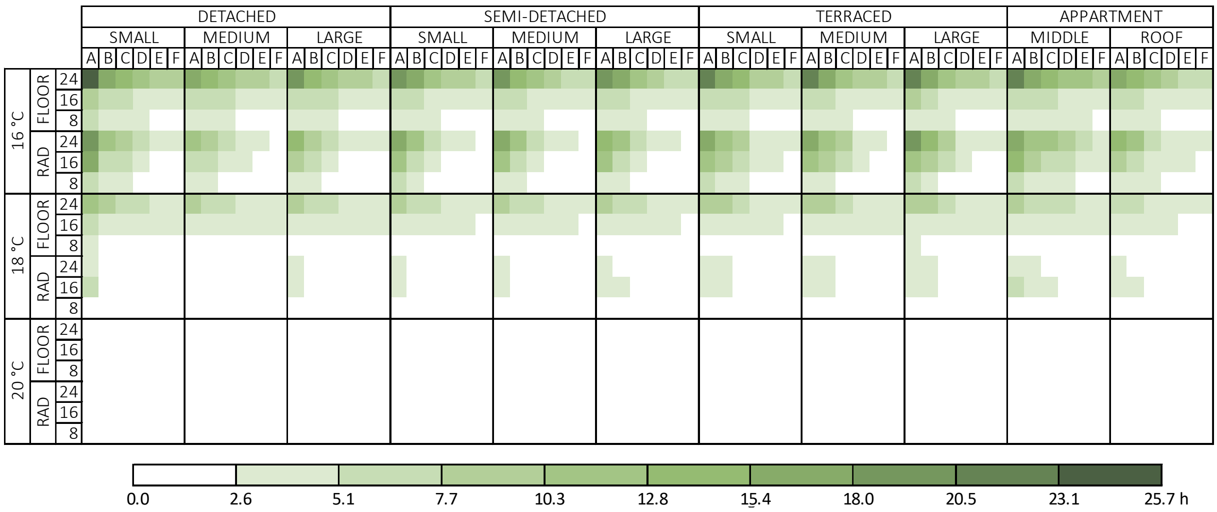
3.3.2.1. Duration

The duration is defined as the time it takes for a building to reach the threshold temperature after the heating system is deactivated in case of a flex event. After reaching the threshold, the heating system resumes normal operation and heats the building back to the original setpoint, being 21°C during heating times, and 17°C during non-heating times.

Overview

We once again delve into the analysis for the month of December in a typical climate year and study the average duration which can be expected.

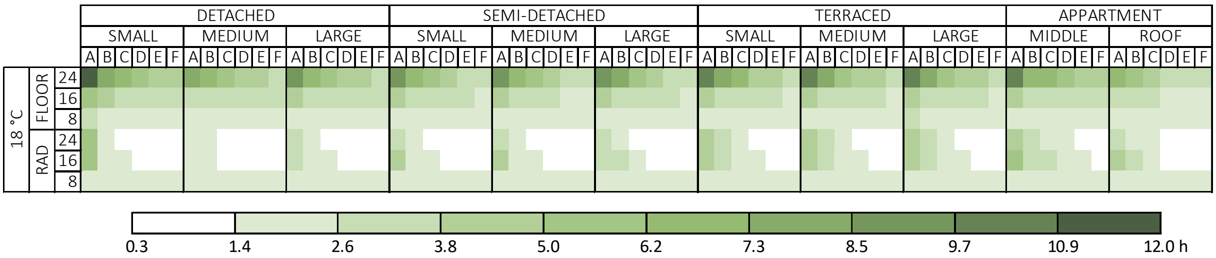
Table 9: Duration in December



From an examination of Table 9, it's clear that the minimum temperature threshold is the most critical parameter. A threshold of 20°C provides limited flexibility, whereas achieving the 16°C mark can require a significantly longer duration.

To better discern the influence of other parameters, we centre our attention on the results for the 18°C threshold. We consider this threshold our base scenario, since it offers a good trade-off between a high flexibility potential and an acceptable comfort loss.

Table 10: Duration in December for the 18°C threshold



We can learn from Table 10 that:

- Buildings with superior insulation levels have a higher duration in terms of heat pump flexibility.
- Building typologies with superior compactness, like apartments and terraced houses, generally correspond to longer flex events. However, the impact is somewhat obscured in the table, as other parameters, such as the percentage of glazing in a building, also influence the results.
- The presence of underfloor heating contributes to longer flex durations as the floor continues to radiate heat even after the heat pump is switched off.
- The intermittent schedules (16h, 8h) present a reduced average monthly duration compared to continuous heating (24h). During periods with no heating demand, the duration is considered to be 0, consequently bringing down the average value on a monthly basis.

In alignment with the energy findings, we present the annual distribution of the 16°C threshold duration for a medium terraced house characterized by insulation level A, underfloor heating, and a continuous heating schedule. Figure 22 illustrates that the duration is inversely related to the outdoor temperature: during colder months, the duration of the flex events tends to be shorter. From June to October, no result is displayed for the duration of the flex event. Yet, in the results for the reference heat pump operation, we observed a limited energy use during these months. This phenomenon can be explained by our decision to adopt a 48-hour observation window post flex event. Apparently, for this energy-efficient building and relatively mild outdoor conditions, the indoor temperature does not reach the 16°C limit within a 48h period.

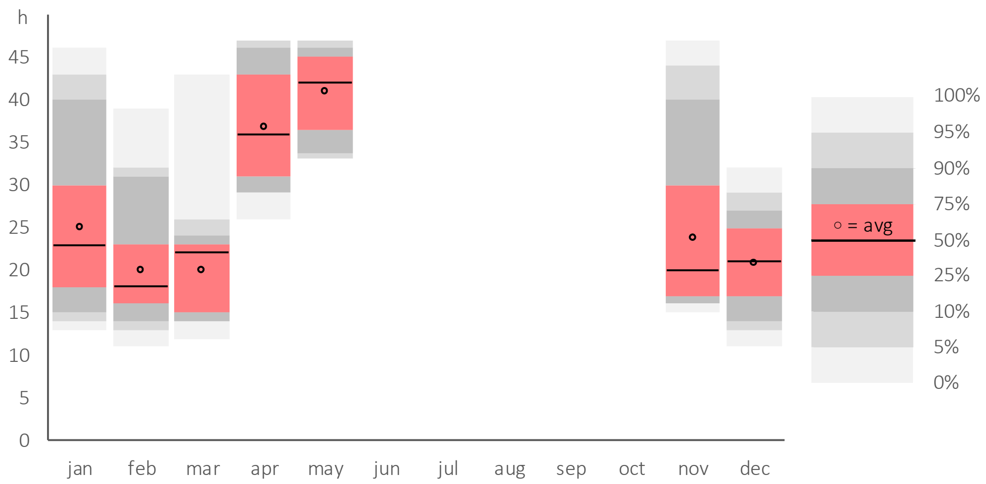


Figure 22: Distribution of the duration
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

Detailed analysis

In a more detailed analysis in Figure 23 and Figure 24, we analyse the temperature response of the medium terraced house during a flex event for underfloor heated and radiator heated buildings, respectively. The event takes place at midnight on the 1st of December in the average year. The average outdoor temperature in the 48 hour period observed in the charts is 3.6°C.

The graphs highlight that buildings with a superior insulation level exhibit a more gradual cooling rate. Additionally, a faster temperature drop is evident in buildings equipped with radiator heating compared to those with underfloor heating.

As previously highlighted, the floor's thermal mass accounts for the distinction between underfloor and radiator heating. Also, with underfloor heating, the heat is emitted to the building as radiative heating, warming up the walls and ceilings of the building. With radiator heating on the contrary, around 70% of the heat is emitted as convective heat to the indoor air. Given the indoor air's low thermal capacity, we see a pronounced temperature drop right after a flex event. Due to the same reasons, we see a faster temperature recovery with radiator heating after reaching the minimum threshold.

Observing the charts, it becomes evident that the 16°C minimum temperature is never touched. This phenomenon can be attributed by the 1-hour timestep in our building simulations. Had we allowed the building to cool down for an additional hour, the temperature would have dropped below 16°C.

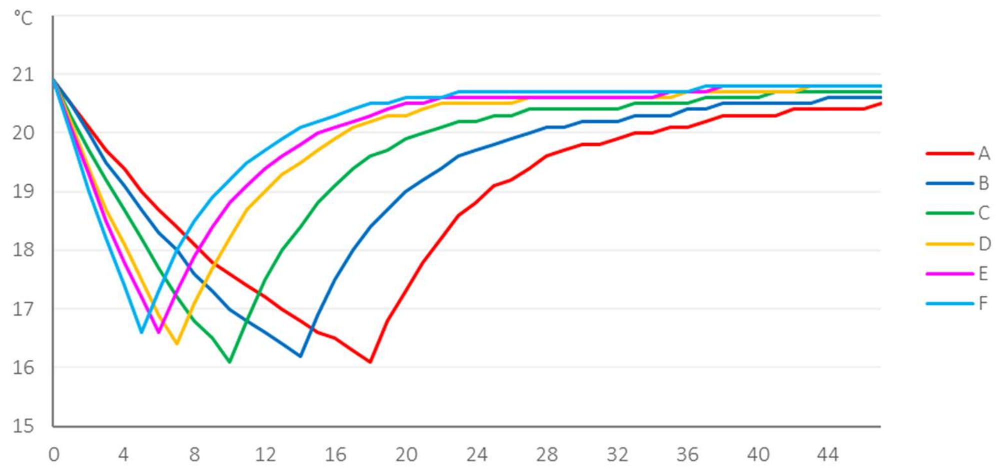


Figure 23: Temperature reaction during a flex event
(medium terraced house / all insulation levels / underfloor heating / continuous heating regime / 16°C threshold)

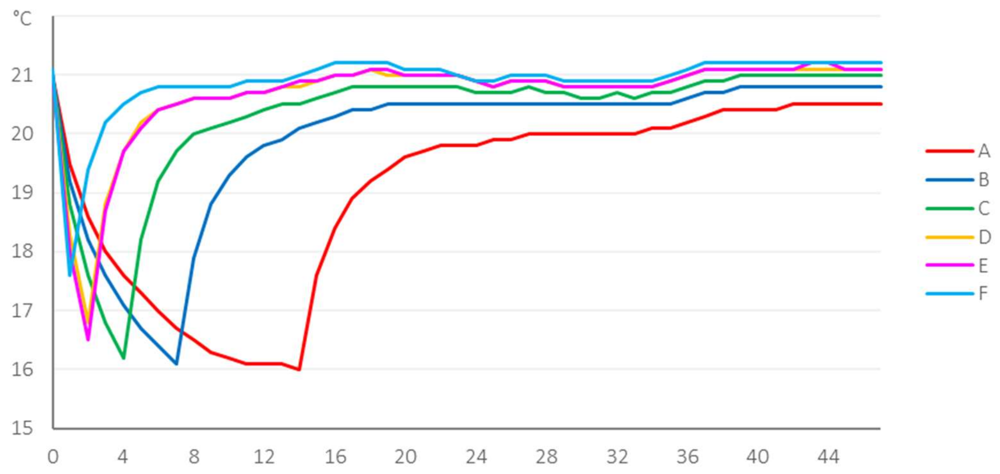


Figure 24: Temperature reaction during a flex event
(medium terraced house / all insulation levels / radiator heating / continuous heating regime / 16°C threshold)

In Figure 25 and Figure 26, we observe the temperature response for underfloor heating and radiator heating across various building types, showcasing medium sized single family houses alongside a enclosed apartment. It's evident once more that the more energy-efficient building types exhibit a reduced rate of cooling.

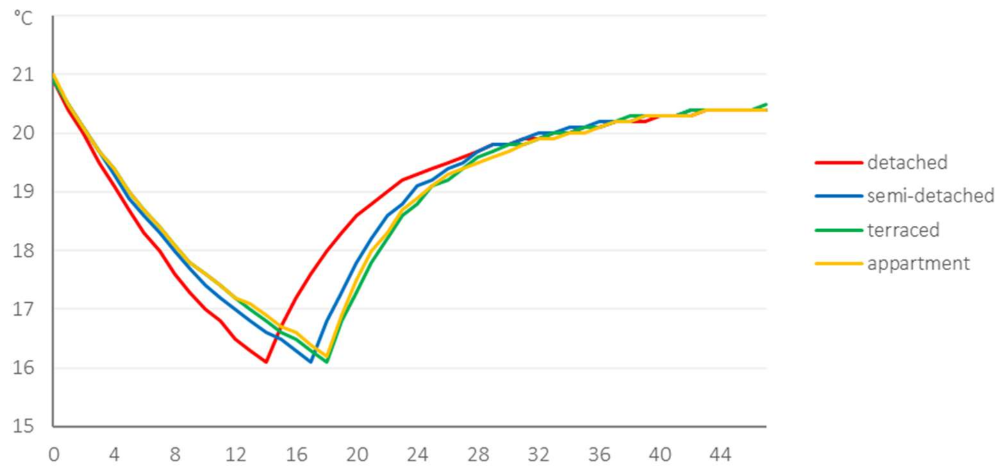


Figure 25: Temperature reaction during a flex event
(4 building types / insulation levels A / underfloor heating / continuous heating regime / 16°C threshold)

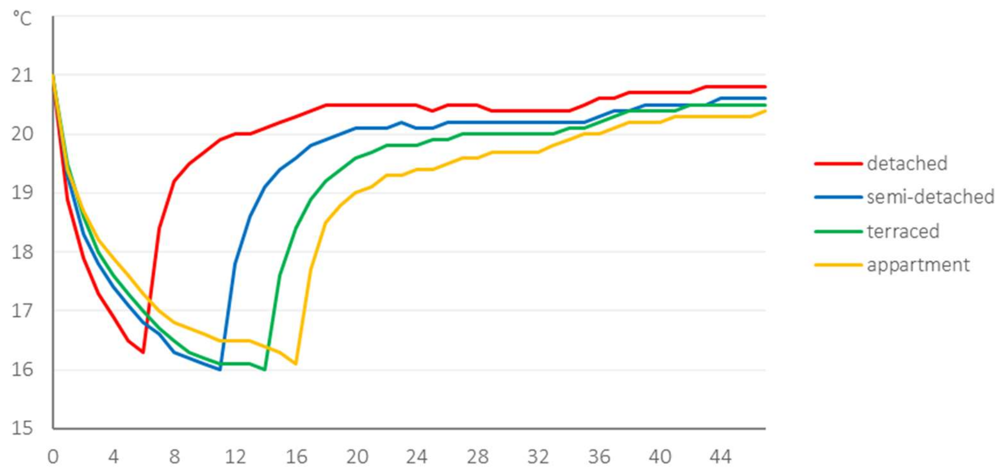


Figure 26: Temperature reaction during a flex event
(4 building types / insulation levels A / radiator heating / continuous heating regime / 16°C threshold)

Preheating

In the FlexSys project, we assess the impact of preheating the building by examining the duration after a flex event. Specifically, we compare the continuous heating schedule with a setpoint of 21°C against one with a 23°C setpoint.

Table 11: Duration in December for the 21°C and 23°C setpoint

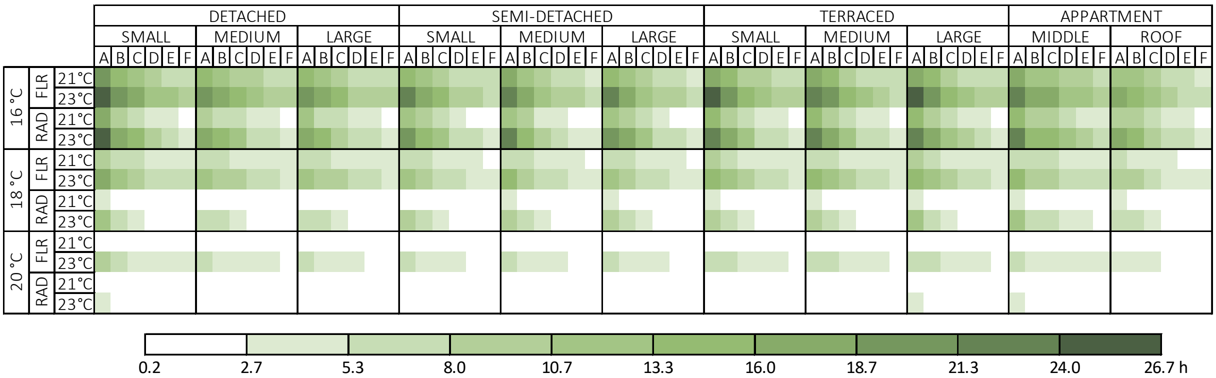


Table 11 clearly highlights a notable increase in duration due to preheating. To delve deeper into the effects of various simulation parameters, we specifically concentrate on the 18°C threshold.

Table 12: Duration in December for the 21°C and 23°C setpoint and 18°C threshold

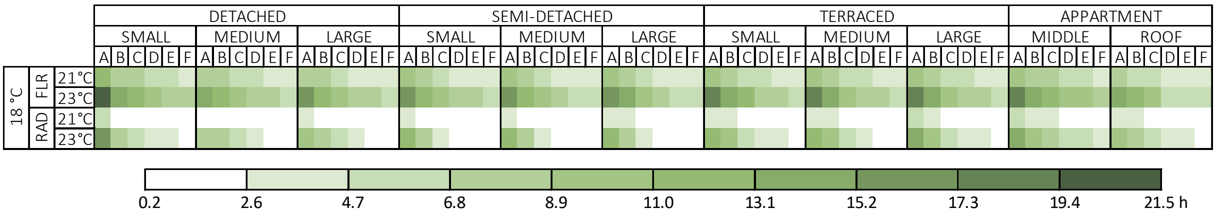


Table 12 indicates that:

- Preheating has a similar relative impact on the duration of the flex event for all insulation levels and building types.
- For buildings equipped with underfloor heating, the flex event duration, beginning at 23°C and ending at an 18°C threshold, is approximately twice as long as when starting from a 21°C baseline.
- In contrast, buildings with radiator heating see their flex duration triple with the preheating setpoint. This phenomenon is attributed to the fast initial decrease in indoor air temperature, a point previously mentioned. Following this swift initial decline, the temperature's rate of decrease moderates. In the standard scenario, the temperature's first 3°C drop is rapidly achieved. Whereas the additional 2°C drop in the preheating scenario takes relatively longer.

3.3.2.2. Load reduction

The load reduction during a flexibility event is defined as the amount of electricity which can be temporarily avoided by deactivating the heat pump until the indoor temperature reaches the minimum threshold. We examine periods of 1h, 2h, 4h, 8h, and 24h after a flex event, quantifying the load reduction as the minimum amount of electricity which can be avoided during every hour of this period.

Overview

For consistency with prior sections, we focus our analysis on the month of December in an average year. Table 13 to Table 17 present the average load reduction which can be guaranteed during periods of 1h, 2h, 4h, 8h, and 24h, respectively.

Table 13: 1h load reduction in December

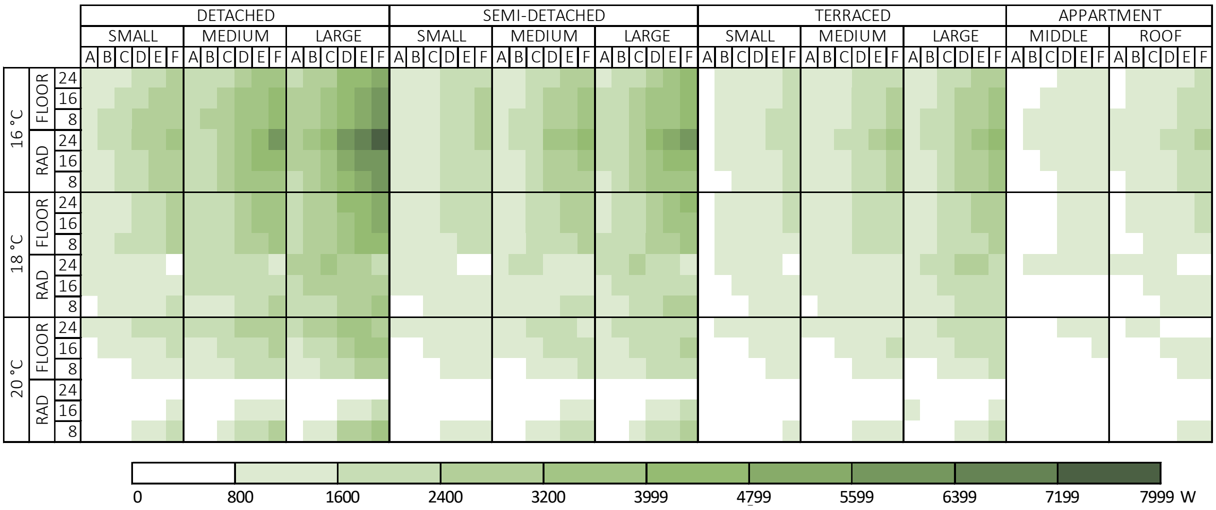


Table 14: 2h load reduction in December

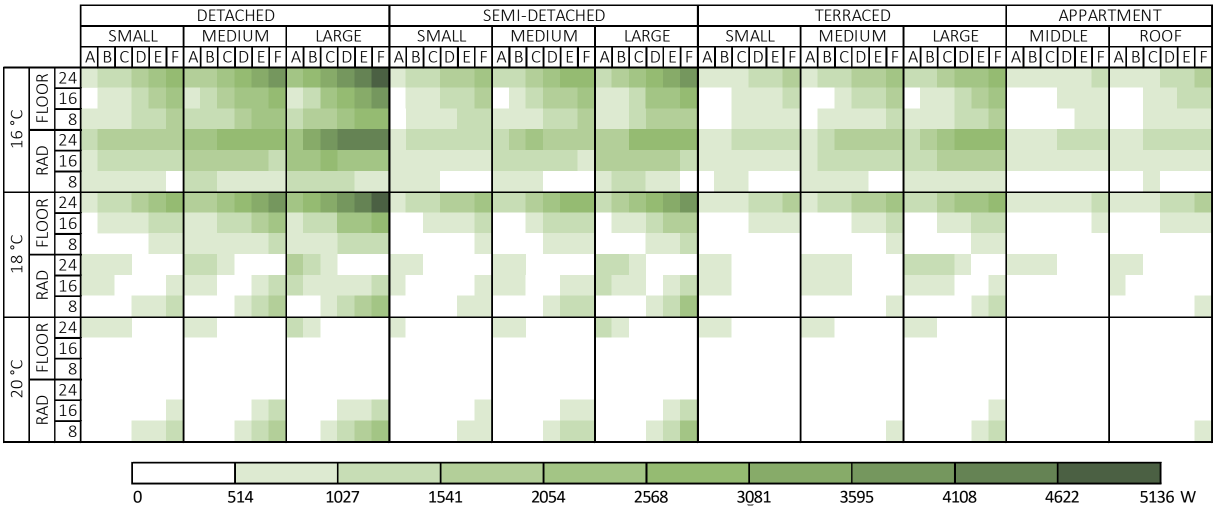


Table 15: 4h load reduction in December

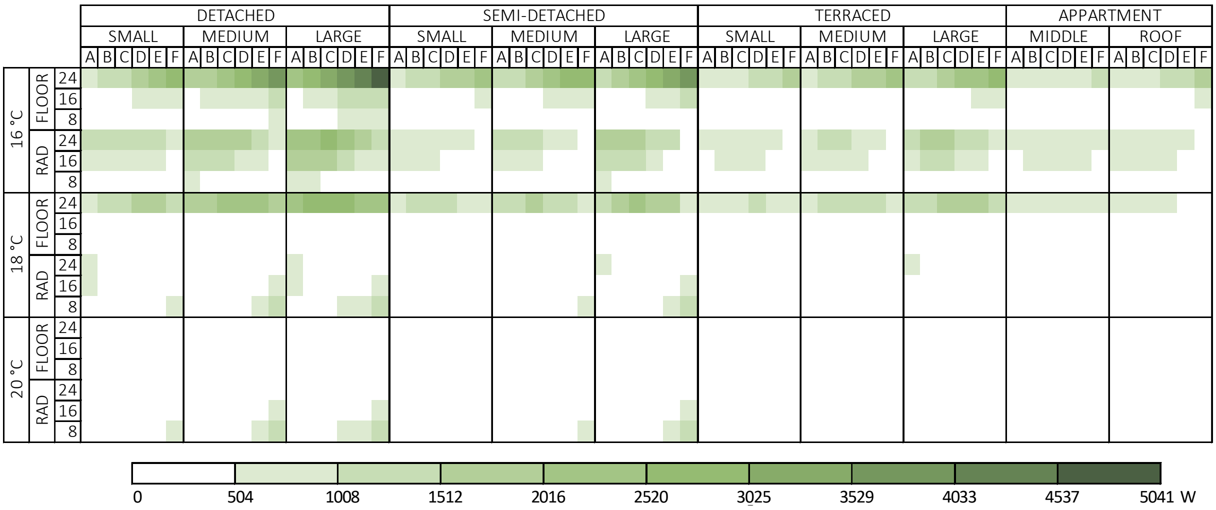


Table 16: 8h load reduction in December

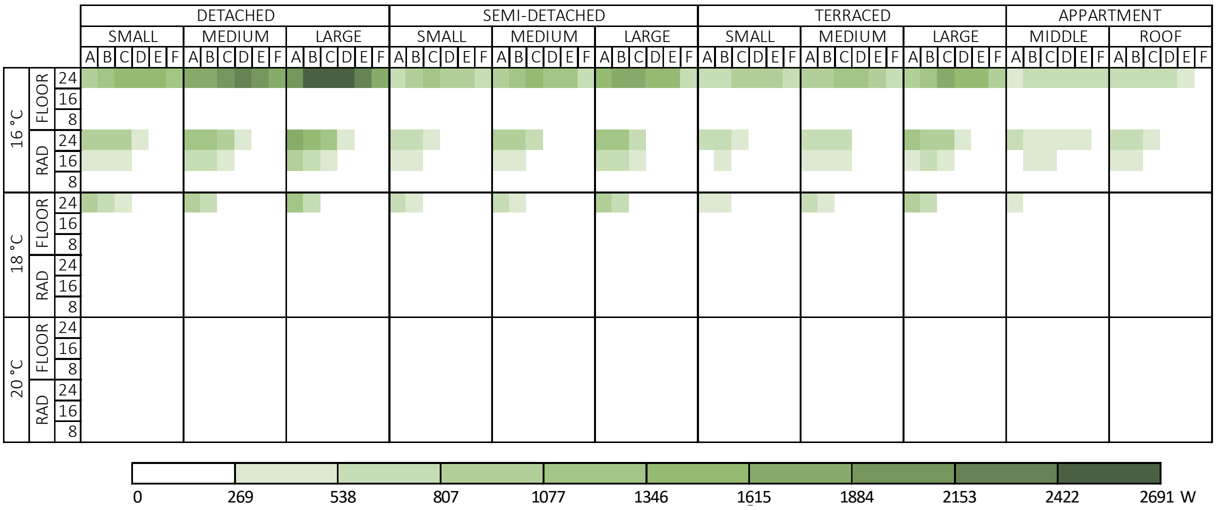
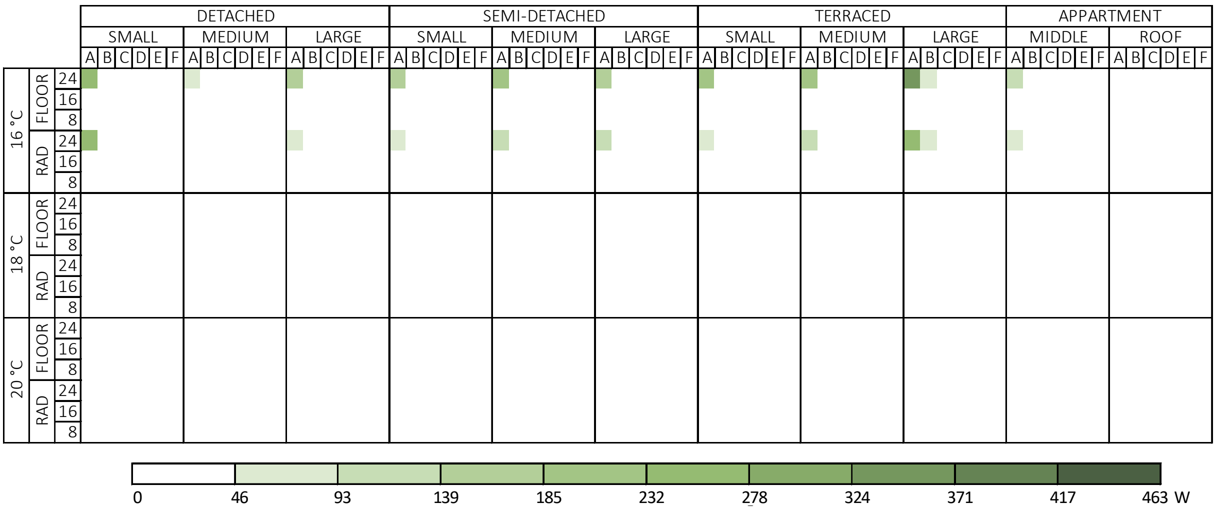


Table 17: 24h load reduction in December



From the aforementioned tables, we draw the following conclusions:

- Shorter periods offer a higher load reduction compared to longer periods.
- The 20°C threshold offers minimal load reduction, whereas the 16°C threshold presents the most potential.
- The 24h load reduction is constrained to specific scenarios with continuous heating for the 16°C threshold. In terms of absolute figures, the load reduction is minimal.

To better understand the influence of our simulation parameters, we once again zero in on the results for the 18°C threshold.

Table 18: 1h load reduction in December for the 18°C threshold

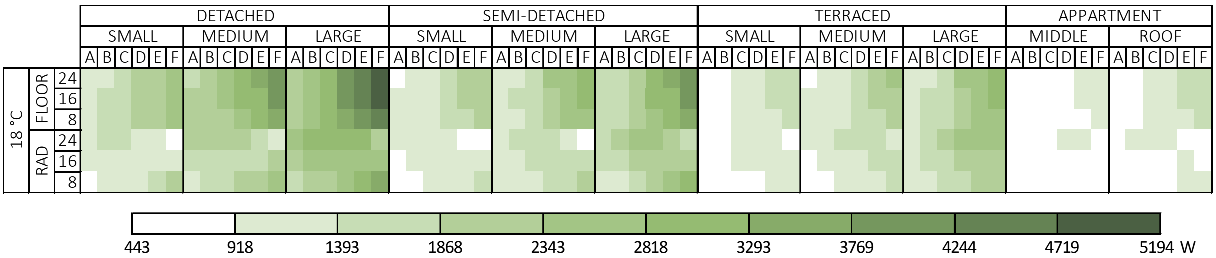


Table 19: 2h load reduction in December for the 18°C threshold

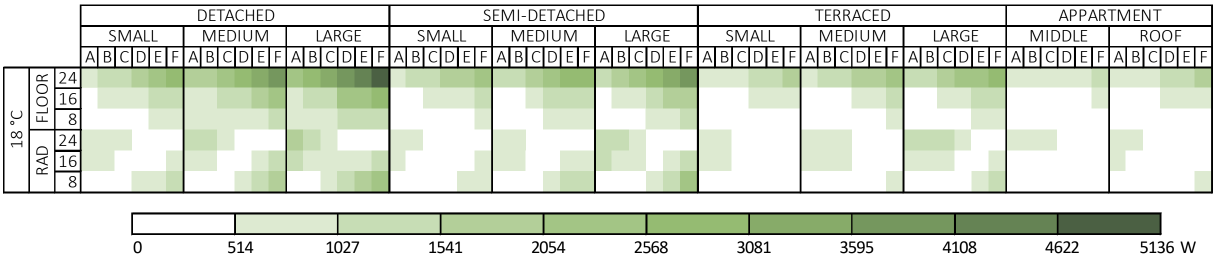


Table 20: 4h load reduction in December for the 18°C threshold

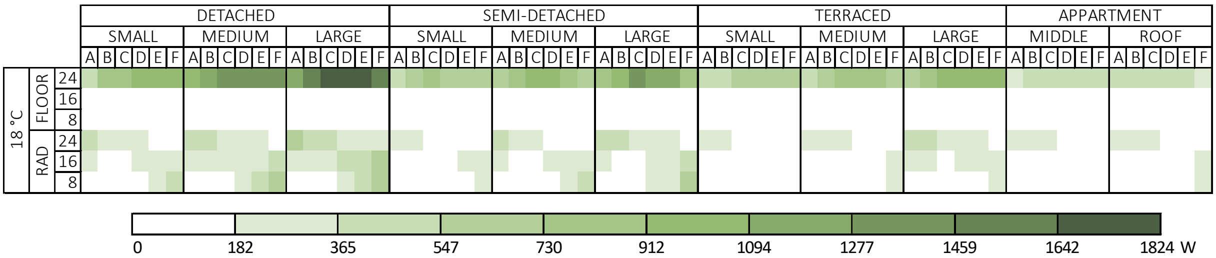


Table 21: 8h load reduction in December for the 18°C threshold

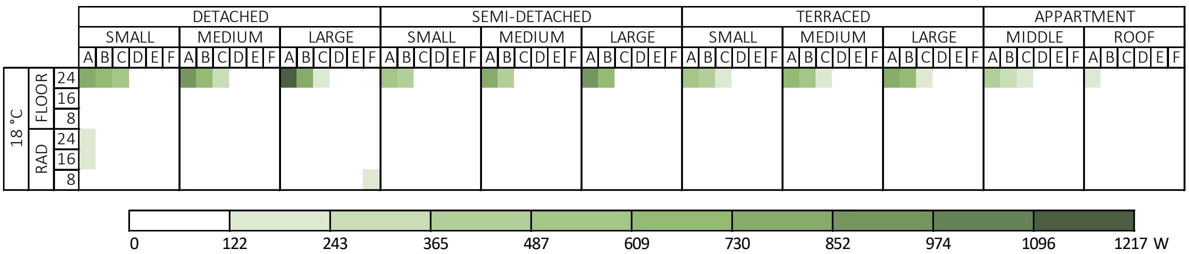


Table 22: 24h load reduction in December for the 18°C threshold

			DETACHED			SEMI-DETACHED			TERRACED			APPARTMENT	
			SMALL	MEDIUM	LARGE	SMALL	MEDIUM	LARGE	SMALL	MEDIUM	LARGE	MIDDLE	ROOF
			A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F	A B C D E F
18 °C	FLOOR	24											
		16											
		8											
	RAD	24											
		16											
		8											

0 0 0 0 0 0 0 0 0 0 0 W

From Table 18 to Table 22, we deduce the following insights:

- Better insulated buildings demonstrate a relatively limited load reduction over shorter periods due to the lower electricity demand of the heat pump. On the other hand, their load reduction is enhanced over extended durations because the temperature decrease is more gradual than in buildings with inferior insulation.
- Similar conclusions are drawn for more energy efficient building types.
- Underfloor heating offers a higher load reduction compared to radiator heating for the longer timeframes.
- For shorter timeframes, such as the 2h load reduction, the values for the 18°C and 16°C thresholds are nearly identical, as only a few buildings hit the 18°C minimum within two hours.

To offer a comprehensive understanding of the load reduction throughout the year, we illustrate the yearly distribution for a medium terraced house with insulation level A, equipped with underfloor heating and following a continuous heating pattern. As observed in Figure 27 to Figure 31, the colder months generally present more flexibility, resulting from a higher electricity use of the heat pump. This effect is somewhat tempered for the longer timeframe flexibilities since the potential is constrained by the faster temperature drop. It's noteworthy to highlight that the outcomes for the 1h, 2h, 8h and 4h load reductions bear strong similarities, as it's a rarity for the building's temperature to fall below the 16°C threshold within a eight-hour span.

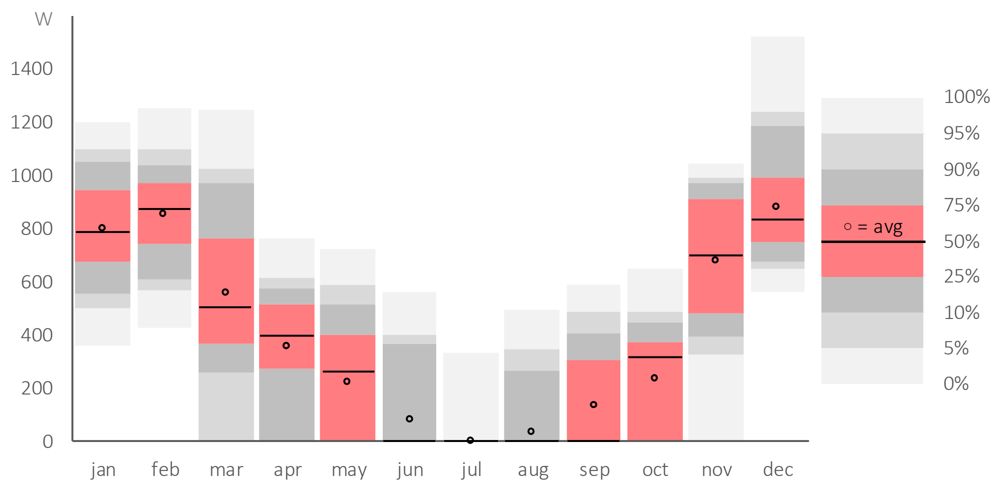


Figure 27: Distribution of the 1h load reduction
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

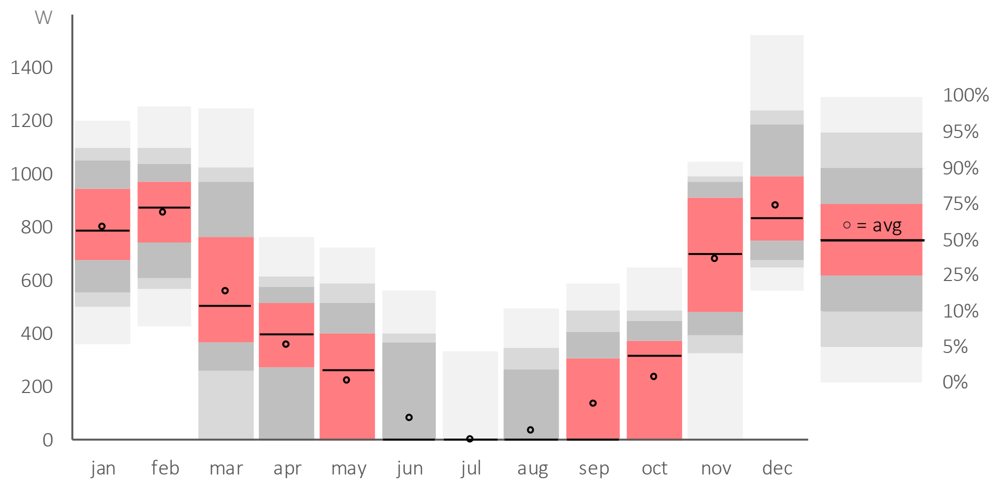


Figure 28: Distribution of the 2h load reduction
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

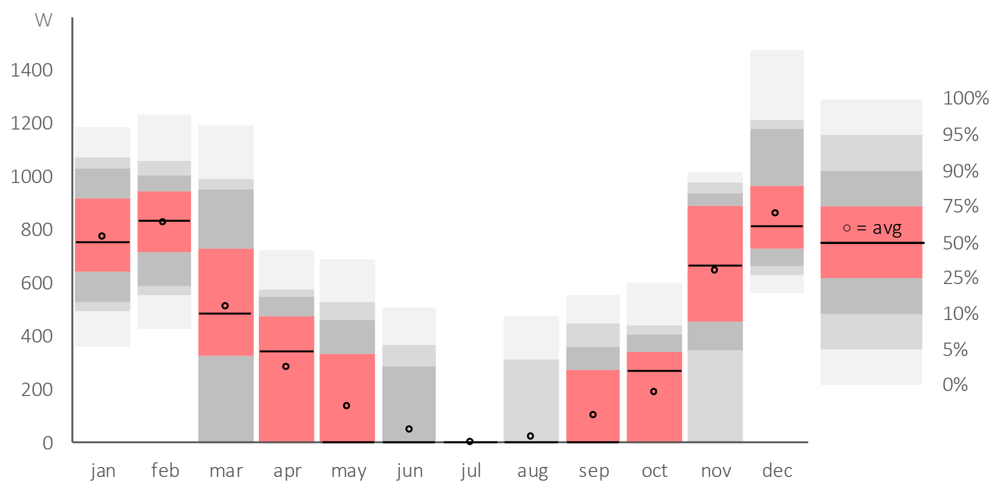


Figure 29: Monthly distribution of the 4h load reduction
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

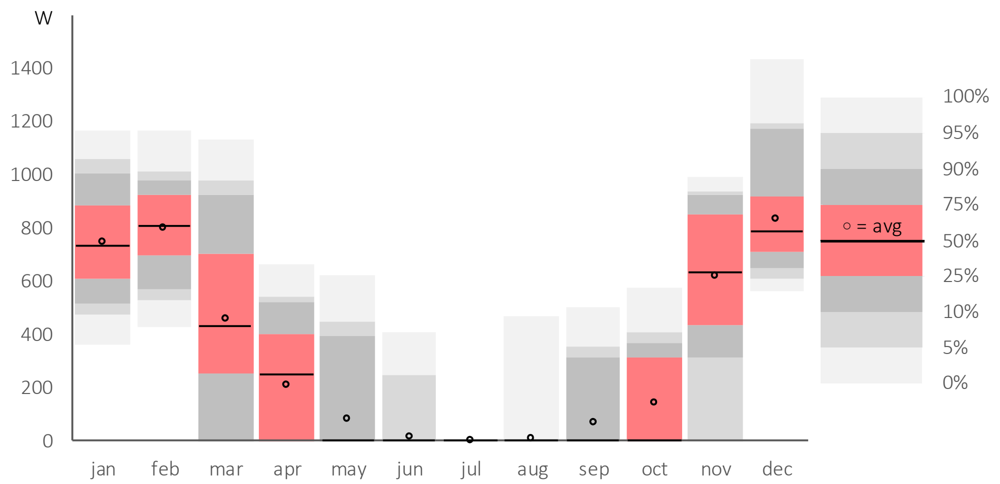


Figure 30: Distribution of the 8h load reduction
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

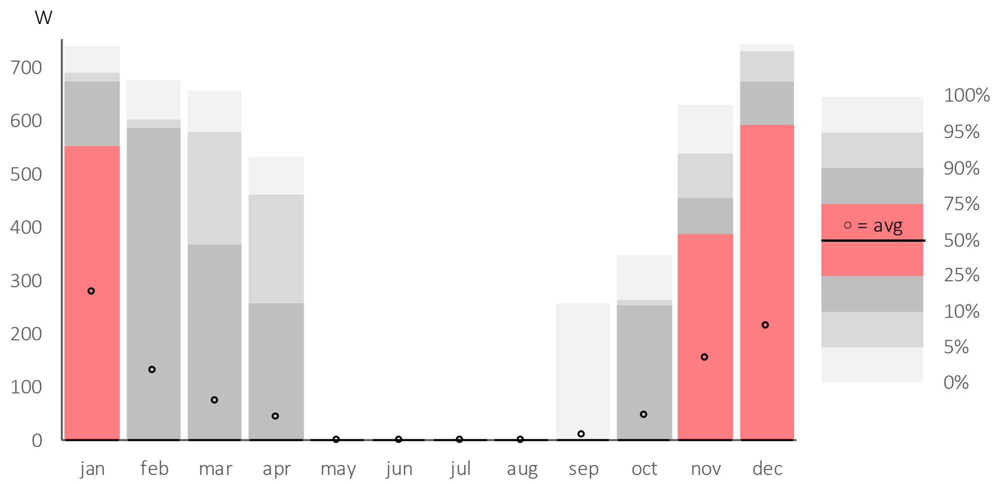


Figure 31: Distribution of the 24h load reduction
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

Detailed analysis

To gain a clearer insight in how the building reacts during a flex event, we examine both the initial load reduction as well as the load increase after the minimum threshold temperature is achieved. Our focus remains on an event starting on the 1st of December at midnight. Figure 32 and depict the outcomes of these flex events for a medium terraced house equipped with underfloor and radiator heating across varying insulation grades.

For the underfloor heating, we observe a relatively extended load reduction period, followed by sharp load increase as lot of energy is required to bring the floor back up to temperate. Buildings with superior insulation levels exhibit extended load reduction durations.

For radiator-heated buildings, a distinct pattern emerges. Following the initial load reduction, there's a relatively gentle and consistent load increase, which in some cases persists beyond the 48-hour period we're analyzing. This divergence can likely be attributed to the inherent operational differences between underfloor and radiator heating. With radiator heating, the convective heat quickly brings the indoor air to the desired temperature without requiring an exceptionally high power output. This process indirectly heats the building's thermal mass, including the walls, floor, and ceiling, through the elevated temperature of the indoor air. Consequently, reheating the building's thermal mass is a more prolonged affair, leading to extended, gradual load increases.

The duration of the flex events is deducted from this chart as the moment in time where the buildings transition from a load reduction to a load increase. The charts illustrate a shorter duration for buildings with inferior insulation.

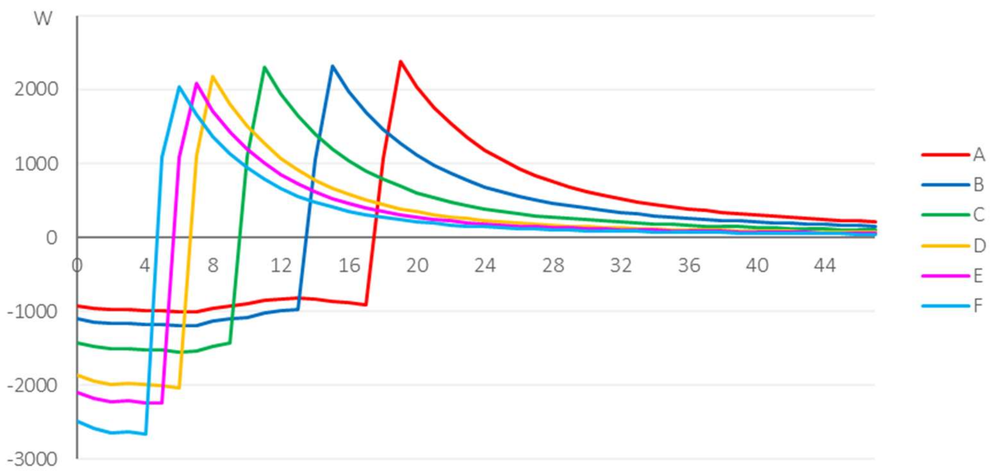


Figure 32: Load reduction and load increase during a flex event
(medium terraced house / all insulation levels / underfloor heating / continuous heating regime / 16°C threshold)

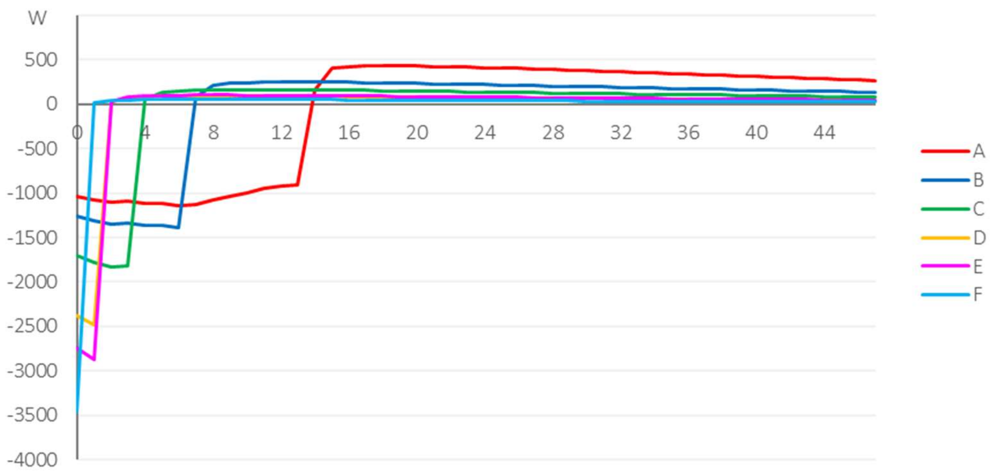


Figure 33: Load reduction and load increase during a flex event
(medium terraced house / all insulation levels / radiator heating / continuous heating regime / 16°C threshold)

In Figure 34 and Figure 35, we study the building's response for underfloor heating and radiator heating across various building types. The selection of buildings is consistent with the previous section as in the previous sections, and observe again how energy-efficient building types exhibit characteristics akin to those with higher insulation grades.

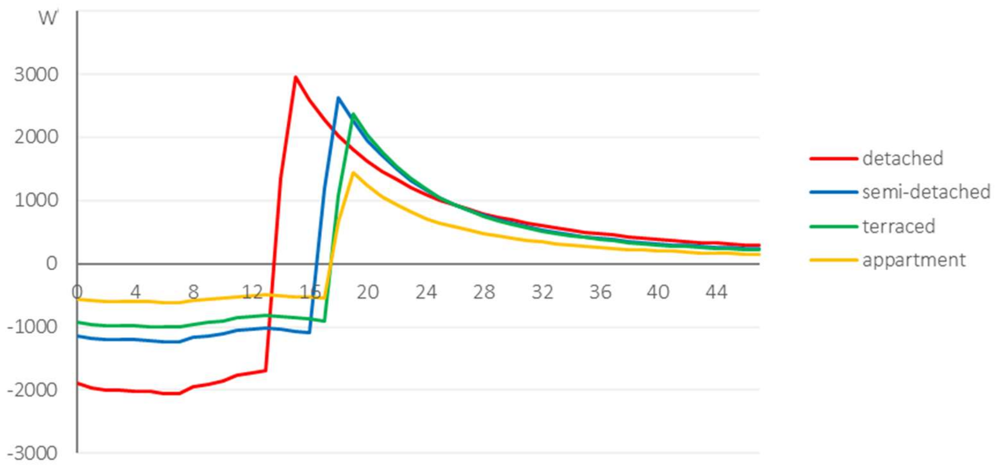


Figure 34: Load reduction and load increase during a flex event
(4 building types / insulation levels A / underfloor heating / continuous heating regime / 16°C threshold)

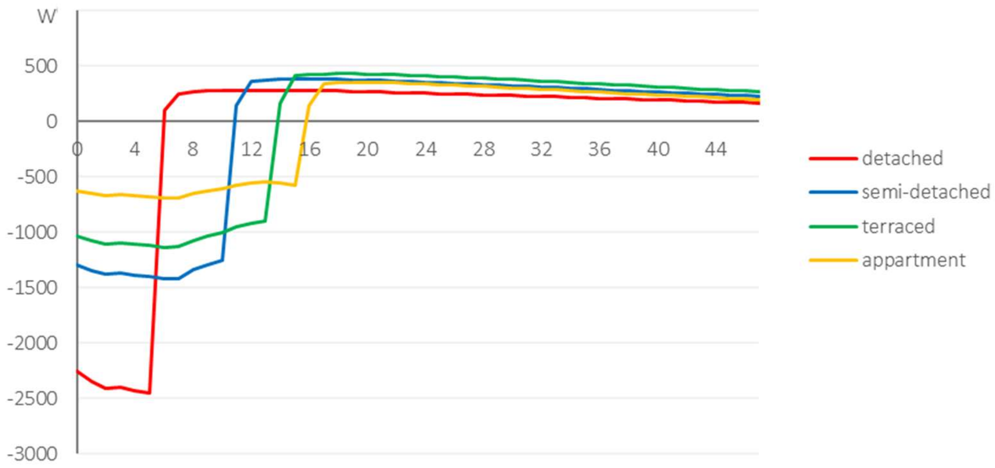


Figure 35: Load reduction and load increase during a flex event
(4 building types / insulation levels A / radiator heating / continuous heating regime / 16°C threshold)

The prior graphs provide a focused view of specific flex events under defined outdoor temperature conditions, but they don't paint a comprehensive picture of expected outcomes over an extended period with fluctuating temperatures. To grasp how the building might behave throughout December, we assess all possible flex events initiated hourly throughout the month, totalling 744 hours. For each flex event, we compute the load shift (reduction or increase) for up to 48 hours post-event. We then determine the distribution of these results for every hour after the flex event, culminating in a flexibility curve.

In Figure 36, we display the flexibility curve for a medium terraced house outfitted with A-level insulation and an underfloor heating system. Conversely, Figure 37 presents the curve for the same house, but with D-level insulation.

To illustrate, looking at Figure 36, we initially notice a consistent load reduction for the first 12 hours after the flex event, ranging from a 750W to a 1500W drop. From the 13th to the 30th hour, we see mixed outcomes: in some instances, there's still a load reduction, while in others, we observe load increases reaching up to 2500W. Beyond the 30th hour, load increases dominate. The chart's coloured areas denote percentile distributions, providing insight not just into the extreme ends but also for example in the core outcomes between the 25th and 75th percentiles, highlighted in cyan. The average results are denoted by a series of dots.

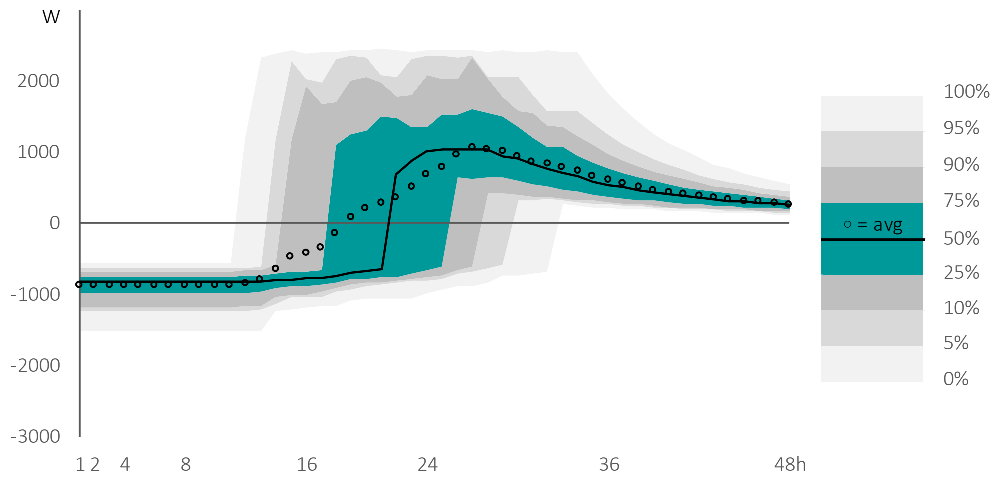


Figure 36: Flexibility curve December
(medium terraced house / insulation level A / underfloor heating / continuous heating regime / 16°C threshold)

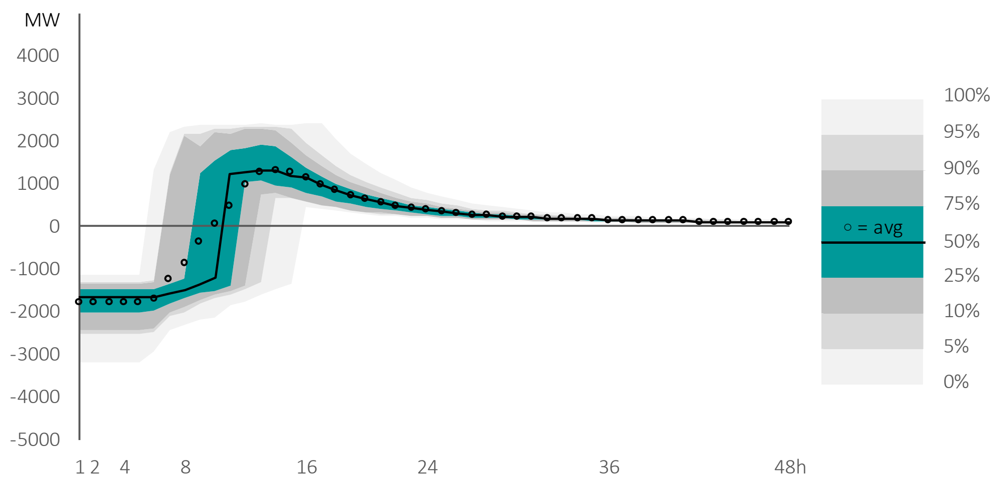


Figure 37: Flexibility curve December
(medium terraced house / insulation level D / underfloor heating / continuous heating regime / 16°C threshold)

Comparing both charts, we deduce the following:

- In the initial stages of a flex event, there's a reduced electricity consumption by the building's heat pump in comparison to the standard baseline scenario without a flex event. This is the load reduction we studied earlier and is depicted as negative values in the chart.
- Once the building hits its threshold temperature, there is a recovery phase, where we observe a load increase relative to the baseline scenario, represented by positive values.
- The nature of the dynamic building simulations results in complex interactions between the flex scenario and the baseline scenario, resulting in a prolonged 'tail' of positive values in the charts.
- The better insulated building exhibits a reduced load reduction and load increase, as it requires less energy for heating.
- The building with superior insulation showcases a longer period with negative values, since the building cools down slower.

The flexibility curves discussed earlier shed light on the distribution of load reductions and increases over a month. However, these curves don't facilitate direct comparisons across our simulation parameters. To address this, we extracted the average values from these flexibility curves. Figure 38 and Figure 39 illustrates the average flexibility curves for December across various simulation parameters for both underfloor and radiator heating. It's evident that underfloor heating extends the duration of the flex event compared to radiator heating, resulting from a slower cooldown to the threshold temperature. We observe again that better insulation levels are related to lower load reductions, but longer flexibility periods.

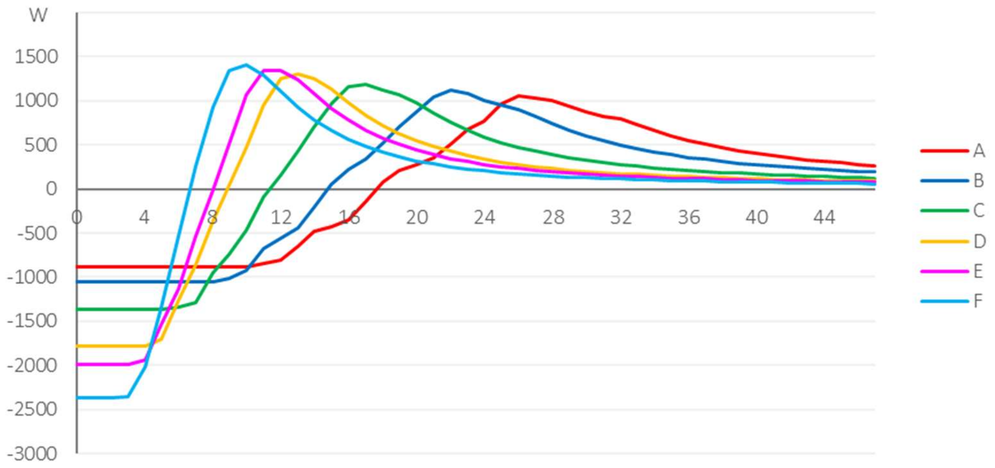


Figure 38: Average flexibility curve for December
(medium terraced house / all insulation levels / underfloor heating / continuous heating regime / 16°C threshold)

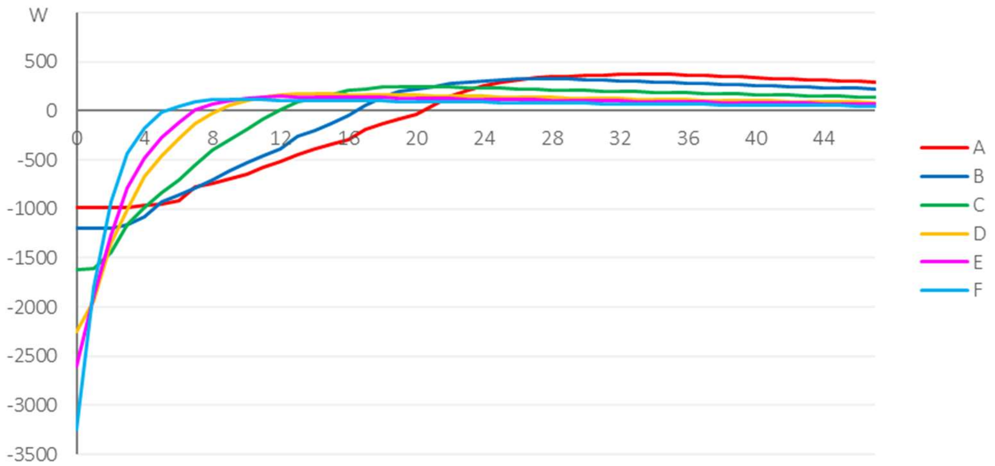


Figure 39: Average flexibility curve for December
(medium terraced house / all insulation levels / radiator heating / continuous heating regime / 16°C threshold)

Figure 40 and Figure 41 present the flexibility across different building types for underfloor heating and radiator heating, respectively. Similar effects are in play as discussed in the previous charts: more energy efficient building types offer lower flexibility values, but sustain flexibility over a longer period.

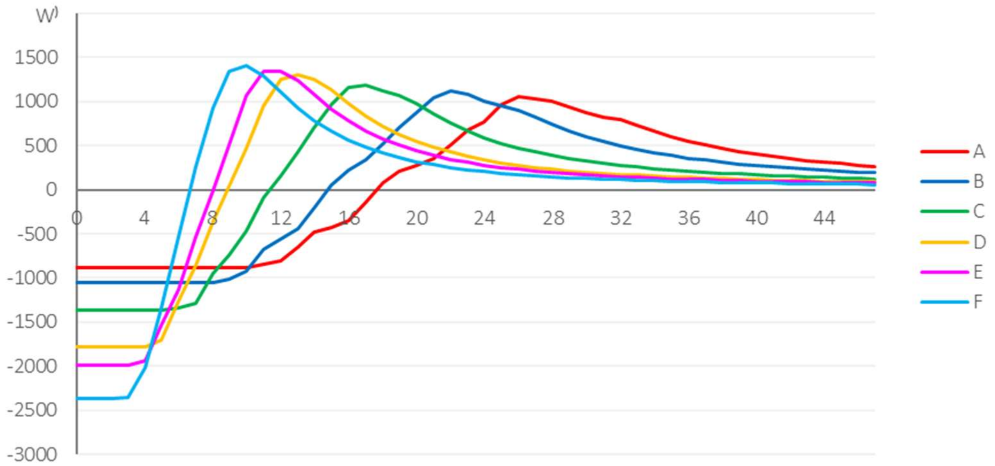


Figure 40: Average flexibility curve for December
(4 building types / insulation levels A / underfloor heating / continuous heating regime / 16°C threshold)

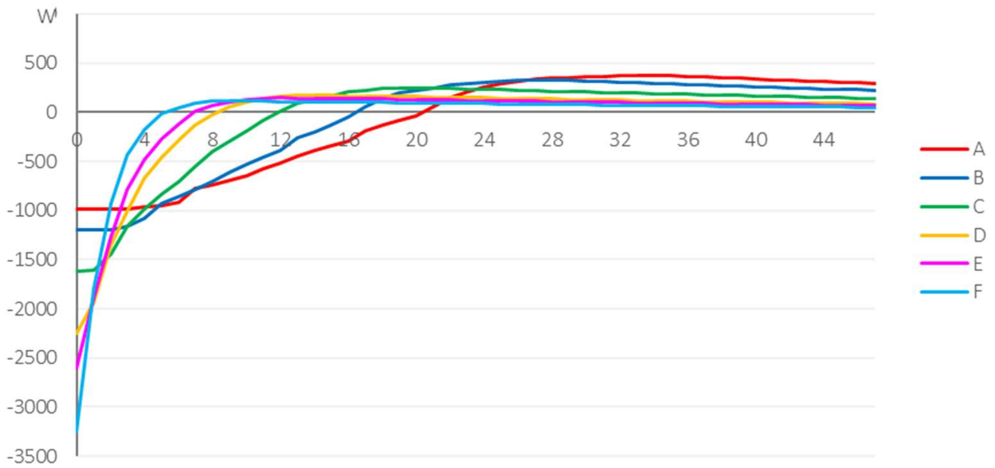


Figure 41: Average flexibility curve for December
(4 building types / insulation levels A / radiator heating / continuous heating regime / 16°C threshold)

3.4. Conclusions

The flexibility potential of heat pumps in residential buildings was the focal point of this research. By employing basic dynamic models and a diverse array of simulation parameters, we were able to evaluate the flexibility for buildings with different attributes. We studied buildings with different geometries, insulation levels and heat emissions systems, and we analysed the impact of heating schedules, minimum threshold and outdoor temperatures.

We evaluated the technical flexibility potential of heat pumps under standard operation by deactivating the heating system until a specified minimum threshold temperature was achieved. Our focus was on understanding the load reduction after a flex event's initiation and the subsequent load increase required after hitting the threshold to restore the building's temperature to its initial setpoint.

Throughout the project, the influence of our simulation assumptions on the results became increasingly evident. The RC-model we employed for the building energy simulations was particularly sensitive to the chosen C-values. Given the absence of real-life measurement data for all buildings to calibrate our models, the accuracy of our results could not be fully confirmed. Therefore, the emphasis of this study should be on the relative differences in performance between building attributes, rather than the absolute numbers provided. It's important to understand that these challenges are common in building simulation studies, and the absolute figures in similar research should always be viewed with a degree of caution.

The key parameters we observed in determining the energy flexibility of a building are:

1. **Temperature Threshold**:
   - The lower temperature limit set for buildings during a flex event serves as a crucial determinant for the event's duration.
2. **Insulation Quality:**
   - Buildings with high-quality insulation demonstrate limited flexibility over extended durations.
   - Conversely, those with less efficient insulation provide significant flexibility, albeit over shorter timeframes.
3. **Building Geometry and Energy Efficiency:**
   - Energy-efficient building types, like apartments and terraced houses, exhibit similar flexibility trends as well-insulated buildings.
   - In contrast, less efficient designs, such as semi-detached and detached homes, align with the flexibility patterns of buildings with poorer insulation.
4. **Heating System:**
   - Underfloor heating-equipped buildings outperform those with radiator heating in terms of flexibility. The prolonged heat emission from the floor after a flex event's initiation contributes to this disparity.
5. **Heating Schedule:**
   - Buildings which are heated 24/7 offer a higher flexibility potential compared to buildings with an intermittent heating schedule.
6. **Seasonal Variations:**
   - Short-term flexibility tends to be heightened in colder months when contrasted with warmer periods.

- The longer-duration flexibility can be higher in less severely cold months since the building cools down slower.

3.5. Limitations and perspectives

Every research project, especially those involving building simulations, has inherent limitations related to its scope and methodology. The FlexSys project is no different. During the study, we had to balance the level of detail with the need to compare a broad range of parameters. Some of the limitations observed include:

- Building model
    - The geometric complexity of a 3D building is represented by a simplified cuboid.
    - The building is treated as a single-zone model with a uniform temperature, overlooking the temperature variations that occur in reality between different floors or rooms with varying functions. This simplification might lead to an overestimation of the building's energy consumption.
    - The RC models, while useful, do simplify certain physical realities, and the choice of R- and C-values significantly affects the outcomes.
    - Some operational aspects of the heat pump, such as part-load operations, are not considered in the heat pump model.
    - The sizing of the radiators is rather large, representing oversized, low-temperature radiators. In reality, radiators might be smaller, necessitating higher supply water temperatures resulting in lower COPs.
    - The simulation’s hourly timestep is rather large to study dynamic building behaviour and temperature control.
- Simulation parameters
    - Real-world buildings and their components exhibit significant variations in thermal capacity. This study did not account for these variations, which could notably impact the flexibility indicators for particular buildings.
    - The study exclusively evaluated air-water heat pumps. Including geothermal and air-air heat pumps would provide a more comprehensive view, given their distinct yearly COP variations.
- Flexibility indicators calculation
    - The study assumes the building retains its original heating curve during a flex event. As a result, the temperature recovers gradually after the minimum temperature is reached. However, occupants might prefer a more rapid return to the original setpoint.
    - The primary focus was on the energy saved during a flex event, with less attention on the increased energy use during the recovery phase, stemming from the aforementioned heating curve assumption.
    - Additionally, when calculating the difference in energy use between a reference and a flex scenario, complex dynamic effects come into play. This can result in energy use differences long beyond the 48-hour period post flex events we studied.
    - Due to these last two points, it is challenging to determine if the flex scenario led to a decreased electricity use (because of reduced heat losses during the colder periods)

  or if it caused a net increase in electricity consumption (due to the higher COPs during the recovery phase).
  - We utilized a heuristic control for our flexibility scenario, simply deactivating the heat pump until a set minimum temperature was met. While this method offers clarity, more advanced scenarios could be employed using model predictive control, which would factor in external signals like price fluctuations or weather predictions. These signals might prompt a preheating phase, yielding added flexibility. Overall, our approach provides a conservative measure of flexibility.
  - As discussed in section 3.2.2, there are many parameters that can be hypothesized in an attempt to comprehensively capture and quantify heat pump flexibility from the perspective of its many complicated and intertwining dynamics. However, pragmatic choices ultimately have to be made about which parameters to actually compute and why. Given the high-level research question of the FlexSys project – with its focus on security of Belgian electricity supply – and given the goal to make the results of this report easily understandable for a relatively wide audience, a conscious choice was made to compute only 'duration' and 'load reduction' parameters. However, future research on heat pump flexibility could obviously make different choices and decide to compute more and different parameters.

These limitation offers some perspectives for a more advanced analysis in further research.

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