Utrecht University

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Master Energy Science

Economic potential of Demand Response for office buildings in the Netherlands

Master thesis

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Abstract

To combat imbalances in the electricity grid and support the integration of renewable energy sources, demand response (DR) is increasingly being looked at as a key solution. Electricity consumers can change their electricity consumption pattern based on dynamic prices to help stabilize the grid and reduce their energy bill. This study focuses on the economic potential of demand response for office buildings in the Netherlands.

A model of an office building has been developed in Matlab, containing a thermal model of the building and models of the Heating Ventilation and Air-Conditioning (HVAC) system, employees' electric vehicles (EVs) and employees' laptops. These assets can be operated flexibly, in reaction to dynamic prices. The office buys its electricity on the Dutch day-ahead market and can subsequently also trade on the automatic frequency restoration reserve (aFRR) markets. Multiple control strategies have been considered: a reference control strategy, a rule-based strategy and a Model Predictive Controller, with the objective of minimizing the electricity costs while maintaining indoor comfort and respecting battery capacity boundaries.

Running yearly simulations with various variations in input, a number of conclusions can be drawn: 1) The economic profitability is highly dependant on the simulation year. Profits of DR are at least ten times higher in 2022 than 2019, due to higher electricity prices and increased variability in the price. 2) The HVAC is best controlled by the MPC, but the MPC leads mainly to energy consumption reduction instead of consumption pattern shifting. This combination can also have high investment costs, although this strongly depends on the HVAC hard- and software already installed in the office. 3) EVs have a lot of DR economic potential for office buldings as investments are low and the electricity consumption is high and easily shiftable. Additionally, the EV penetration level is expected to rise quickly the coming years in the Netherlands. 4) Laptop DR is barely profitable in the day-ahead market, but performs well in the aFRR market. 5) Total electric vehicle DR profit in 2022 is around 7,500 euros, and HVAC DR profits lie at 2,000 euro for a 4,000 square meter office. Considering the revenue of a 4,000 sq. m office is in the millions, the profits are not enormous but there is economic potential and the profits will increase with higher EV penetration.

Contents

List of abbreviations

A	Ampere
aFRR	automatic Frequency Restoration Reserve
AHU	Air Handling Unit
ATES	Aquifer Thermal Energy Storage
BEV	Battery Electric Vehicle
BRCM	Building Resistance Capacitance Model
BTM	Building Thermal Mass
DA market	Day-ahead market
DER	Distributed Energy Resources
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
HP	Heat Pump
HVAC	Heating, Ventilation and Air-Conditioning
ICT	Information and Communication Technology
IT	Communication Technology
MPC	Model Predictive Control
P	Power
PHEV	Plug-in Hybrid Electric Vehicle
PMV	Predicted Mean Vote
PPD	Percentage People Dissatisfied
PV	Photovoltaic
RB	Rule-based
RES	Renewable Energy Sources
RC	Resistance-capacitance
SoC	State-of-charge
TES	Thermal Energy Storage
V	Volt
VRES	Variable Renewable Energy Sources

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1 Introduction

1.1 Problem background

Since the invention of the light bulb by Nikola Tesla in 1879, the world has rapidly electrified, with many households now using electricity-powered fridges, washing machines, televisions, phones, air-conditioners etc. The demand for electricity is ever-growing and The Electrification of Everything is not complete; heating is becoming increasingly electric, just as transportation. Besides this driving factor, global population growth and increasing welfare are causing more and more electricity usage (J. K. Kok, Scheepers, and Kamphuis 2010). Lastly, the need for a sustainable society and reduced greenhouse gas emissions also drives the energy system towards electricity and away from fossil fuels.

The electricity supply has had to grow with the demand through the years, but is now changing. Electricity has traditionally been generated by large, centralized, typically fossil fuel-based power plants. The output of these power plants is adapted continuously to meet the instantaneous demand. This is relatively straightforward, as the output is mainly determined by the amount of fuel the plant is supplied with. With the rise of generation from Variable Renewable Energy Sources (VRES) however, the energy supply is becoming less flexible. The electricity output from photovoltaic (PV) panels and wind turbines is governed by the weather and therefore largely uncontrollable (R. Li et al. 2022). This intermittency of RES causes power balancing problems for grid operators, as the supply cannot be adapted to the demand as easily. Additionally, much of the VRES capacity is spatially distributed instead of centralized. For example, many PV panels are installed on private homes and thus connected to the distribution grid, as opposed to the transmission grid as electricity suppliers usually are (J. K. Kok, Scheepers, and Kamphuis 2010). On sunny days, this can cause overloading of local distribution grids which were not designed for injection of power. Overloading can also happen during high demand, for example around dinner time, when many households use their induction stoves, televisions etc. This problem is called congestion.

To maintain grid stability, supply and demand must be balanced across all time scales. On a short time scale, grid voltage levels and frequency must be kept within safe limits. This is done by a combination of services, for example power generators able to quickly provide extra power in case of a system contingency, or rotating machinery keeping the system frequency stable on a second to minute basis. These ancillary services (AS) have historically only represented a small share of the total electricity market revenue, but due to VRES, ancillary services are taking on an increasing importance in the system. The variability of VRES entails a greater need for AS to balance demand and supply (Franklin et al. 2022, Freund, Hume, and Stekli 2021). An example of a problem is seen in Figure 2. The electricity production from wind energy causes the residual load that has to be matched by power plants to fluctuate strongly and with very steep ramp rates. This makes the balance between demand and supply harder to maintain.

To deal with the balancing problem, flexibility is required. Flexibility can be defined as "the ability of a power system to utilize its resources to respond to changes in net load" (Spiliotis, Ramos Gutierrez, and Belmans 2016). This can be either supply-flexibility or demand-flexibility. Supply-flexibility includes the ability of generation units to ramp up and down quickly to follow changing loads, and the use of ancillary services to balance the grid, see also Figure 1. Supply-side flexibility has traditionally been the main source of flexibility in the power system, but since Variable Renewable Energy Sources (VRES) cannot be controlled to follow demand, the need for flexibility in the power system grows. To cover the extra need, the supply-side needs to operate even more flexibly or demand needs to become more flexible to balance out the fluctuating generation of wind and solar power. The former option involves a rise in system

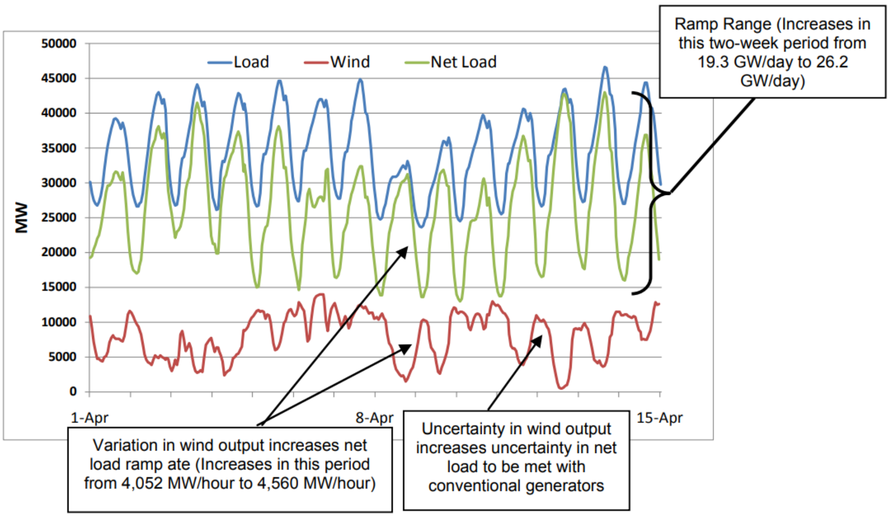

Figure 2: Impact of wind energy on ramping rates in the electricity network. Source: Denholm et al. (2010)

costs as the more flexible units (e.g. gas-fired plants) often have higher variable costs and energy storage is also costly (Taibi et al. 2018). As the share of renewables in the energy mix needs to grow considerably in the coming years, accommodating the resulting intermittency with supply-flexibility would entail high costs.

The second option, demand-flexibility, is therefore increasingly being looked at as an essential part of the transformation of our current energy system to a low-carbon energy system, characterised by intermittent renewable generation (R. Li et al. 2022, Batalla-Bejerano, Trujillo-Baute, and Madlener 2022). Demand-flexibility, or Demand Side Management (DSM) aims to alter consumers' electricity consumption patterns and/or reduce their consumption. The higher objective is to flatten the load curve over time. Reduction of electricity consumption is achieved by *energy efficiency* measures, such as replacing inefficient energy devices with newer, more energy-efficient devices. Changing consumers' consumption patterns is a more challenging issue and is achieved through *demand response (DR)*; demand is changed in response to signals, for example electricity prices. This results in a portion of the energy demand being increased, reduced or shifted for a specific time period. The practice of DR can shift electricity loads from peak moments to off-peak moments, for example from dinner time (when energy demand is high) to noon (when PV production is high). This helps in balancing demand and supply and can relieve congestion by e.g. increasing self-consumption of PV generated electricity. Demand response has proven to be able to minimise operating costs, lower emissions, enhance the reliability and efficiency of power systems and reduce wholesale market prices (Nwulu and Gbadamosi 2021).

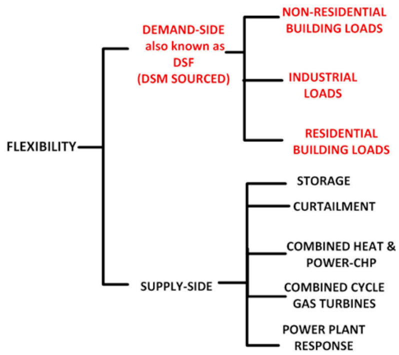

Figure 1: Flexibility source classification. Source: Aduda et al. (2016)

DR can be performed by various types of energy consumers, the opportunities lie mostly in residential housing and the manufacturing and service industries, as seen in Figure 3. Each consumer group has its own advantages and disadvantages for unlocking flexibility. Residential consumers have a hard-to-predict demand pattern and a very small load per household, but can shift operation of their appliances relatively easy. Industrial plants on the other hand are predictable, high energy consumers. Their production processes, however, are often part of a long chain involving many different machines and logistics, therefore deviating from the schedule is impractical for these consumers. Furthermore, the profitability of industrial plants depends on the efficiency they can achieve, so suboptimal operation regarding power and voltage levels quickly translates to monetary losses. Commercial buildings (belonging to the service industry) often have an easier to predict demand pattern compared to households. The demand can be estimated based on weather data, building architecture and operational behaviour. The load in commercial buildings is more flexible than industrial load and therefore more suitable for demand response (Vardakas, Zorba, and Verikoukis 2015). This makes the service industry an attractive sector for unlocking flexibility.

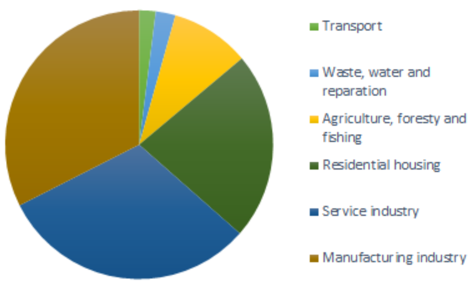

Figure 3: Pie chart of the final electricity consumption in the Netherlands in 2021, by sector. Source: CBS 2021

The service industry as used in Figure 3 consists of hotels, restaurants, ICT companies, publishers, banks, research and consultancy companies, architectural firms, job brokers, schools, hospitals, museums et cetera (Kruiskamp 2022). An especially interesting commercial building type is offices, which comprise a quarter of the non-residential building stock by floor space (Economidou et al. 2011). The Dutch government decided in 2012 that all Dutch office buildings with a surface of more than 100 m^2 should have the energy label classification C or higher by 2023 or they are not allowed to be used until they have taken the appropriate measures to achieve at least label C. Energy labels for buildings are determined based on three indicators: i) the energy requirement in kWh/m^2.y ii) the consumption of fossil fuels in kWh/m^2.y and iii) share of renewable energy in the total consumption (Nederlands Normalisatie Instituut 2022). Additionally, all businesses, which includes offices, restaurants, shops etc., that use over 50,000 kWh or 25,000 m^3 gas per year are legally obligated to implement all energy saving measures with a payback time of five year or less. These measures are given by the Netherlands Enterprise Agency and for offices include the monitoring of the Heating Ventilation Air-Conditioning (HVAC) installations and analysis of their consumption, isolating cavity walls, using time switches to turn off appliances at night, automatically adjusting the heating to outside temperature and more (RVO 2019). These measures can also be taken by office buildings to achieve energy label C. These government bills mean that a) offices are recognised by the government as a type of building that can and should be conscious about their energy use and b) offices will have relatively modern energy systems and monitoring capabilities from 2023 compared to other commercial building types. This makes offices an interesting target for investigation into their potential for demand response.

An additional motivation for focusing on office buildings is the internship organisation this thesis is undertaken at: Sweco. Sweco is an architecture and engineering consultancy firm, and the Sustainable Buildings team this thesis is written at advises real estate owners on how to make their building fleet more sustainable. Therefore, they have considerable knowledge of energy use in the built environment and specifically office buildings.

1.2 Existing literature and research gap

In the scientific citations and abstract database Scopus, the first article with 'demand response' in the title, abstract or keywords was published in 1969 in the American Journal of Agricultural Economics. Unfortunately, this article does not discuss demand response as defined in the previous section, but analyses the negotiations and bargaining tactics between tomato farmers in Indiana and Ohio during the 1966 growing season (Babb, Belden, and Saathoff 1969). The first article (as recorded in Scopus) dealing with demand response to electricity prices, instead of to tomato prices, was published a decade later in Elsevier's journal 'Energy' (Cohn 1980). Demand response was mentioned little the next 25 years, but around 2005 the interest quickly started to rise, as seen in Figure 4. By now, 1400 papers and articles are published per year on the topic. Narrowing it down to 'built environment' or 'buildings', 700 papers and articles per year remain.

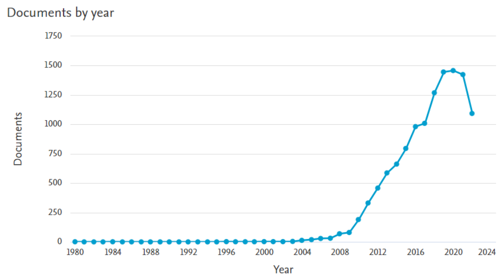

Figure 4: Number of published articles and papers per year up til 2022 as recorded in Scopus, by searching for 'demand response' and ('grid' or 'electricity') in titles, abstracts and keywords.

Considerable research has been done on demand response and related concepts such as smart grids and their Information and Communication Technology (ICT). DR requires intelligent control of appliances and many ICT solutions have been proposed. Much cited surveys on these topics are Palensky and Dietrich (2011), Vardakas, Zorba, and Verikoukis (2015) and Gungor et al. (2013). Vardakas, Zorba, and Verikoukis (2015) provides an extensive review of DR programs and relevant control mechanisms, whereas Gungor et al. (2013) gives an overview of possible applications of smart grid architecture, and communications requirements needed for flexible, reliable smart grid operation. The smart grid is "a sophisticated system integrating an information and communication technology infrastructure to the existing power system infrastructure and the new distributed generation system, in order to fully exploit the use of renewable energy systems and to maximize energy efficiency of the whole power system. (ibid.)". Smart grids are often seen as a prerequisite for effective demand-side management to handle data flows. Palensky and Dietrich (2011) gives an overview of DSM taxonomy and measures, two DSM demonstration projects and an outlook on the technology.

When replacing 'built environment' or 'buildings' in the search with the more specific 'residential' OR 'households', 320 papers or articles published per year (in the past four years) still remain. Replacing it with 'commercial' however, only 80 remain. About 'office' or 'offices' in conjunction with 'demand response' and ('grid' or 'electricity') only 40 articles and papers are published per year. This shows that DR research is focused on residential application and commercial application is likely overlooked.

The most influential articles and papers on demand response in offices are on predicting electricity consumption profiles. Rahman, Srikumar, and Smith (2018) does this with a neural network and Y. Chen et al. (2017) with "Support Vector Regression". Control algorithms are developed by Ma et al. (2012) proposing a Model Predictive Control technique for HVAC control in offices and Thomas, Deblecker, and Ioakimidis (2018) using mixed-integer linear programming to optimise PV output and Electric Vehicle charging in offices. Hao et al. (2014) and Lin et al. (2015) study the technology of HVAC fans performing frequency regulation (a type of ancillary service). Not all papers can be summarised here, but the remaining papers tend to focus on operation of office (or commercial) buildings for demand response. Many control and optimization algorithms are developed and/or tested for different energy assets and markets. HVAC systems are a popular subject (in the studies mentioned above and for example by Klein et al. (2017) and Mäki, Jokisalo, and Kosonen (2019)), though PV panels, EV and storage are also considered. The research tends to focus on one control algorithm, a limited number of energy assets and one type of market (if considered) at the same time. This gives detailed insight into how one type of appliance could participate optimally in one type of electricity market. Studying this existing literature, it is apparent there is a body of work on technical potential of various methods of DR in office buildings. There is, however, little research into economic potential of DR for office buildings using a more holistic view.

Higher-level studies on economic potential do exist beyond the office scope. However, economic studies into DR often take the form of designing flexibility markets, negotiation and optimization problems between utility companies and end users (N. Li, L. Chen, and Low 2011, Maharjan et al. 2013, Kornrumpf et al. 2016) or studies into economic benefits on the grid level (Klaassen et al. 2017). There is a lack of economic analyses that are building-centric and examine revenues of DR for participants in detail, also taking various DR set-ups into account. Nolan and O'Malley (2015) also recognises the uncertainty around the potential revenue for DR program participants and sees this as a barrier to widespread deployment of DR programs.

A study into the economic potential of DR for office buildings would therefore be a valuable contribution to the field of energy science. This study would need to take a holistic view on the problem, considering different control strategies, multiple markets and all relevant (office-specific) energy assets, to overcome the limits identified in the existing literature.

1.3 Research aim

The main research aim in this study will be:

To gain insight into the economic potential of demand response for office buildings in the Dutch market.

This research objective follows from the research gap identified in Section 1.2. The Dutch market will be used to narrow the spatial scope.
Insight will be gained by answering the following five research questions:

1. Which energy assets in office buildings are available for unlocking flexibility?
   This concerns energy assets relevant for electricity consumption/production.
2. Which operational modifications need to be made to run an office building flexibly?
   DR requires more advanced operation of buildings in terms of control and ICT.
3. What is the current (theoretical) profitability of demand response for office buildings?
   The profitability of DR in various existing markets needs to be known to assess economic potential. This question concerns office buildings that currently exist in the Netherlands, and how they could perform DR with the assets they already have.
4. Which building technological/structural modifications can be made to increase the capacity for demand response?
   Technological modifications are changes in installed appliances, structural modifications concern changes in walls, windows etc.
5. How could profitability of DR for office buildings develop under future electricity prices/DR programs?
   Future profitability is also of interest to assess economic potential.

2 Theoretical background

This section will describe various concepts relevant to this study. More specifically, this section covers the electricity market, demand response programs and load flexibility.

2.1 Electricity market

There are multiple electricity markets, each dealing with balancing demand and supply on a different time-scale. The process starts with determining demand. Electricity suppliers create expected accumulated load profiles of all customers. Based on this load profile the base load, needed throughout the entire day, and the 16 and 12 hour peak loads can be determined. These are quantities that are often bought in advance on future markets, four years to a month ahead of delivery. An example of such a profile is shown in Figure 5. On the day-ahead (DA) market, participants can buy and sell electricity in an auction that cleares at 12 pm the day before. Hourly prices are then set based on the demand and quantity offered, all parties receive/pay these set prices. These day-ahead prices often referred to as 'the electricity price'. Figures 6 and 7 show the resulting filled in load curve. After closing of the day-ahead market, the intraday market opens where participants can trade power continuously amongst each other (TenneT 2022). Lastly, real time imbalance as seen in Figure 8 is solved by ancillary services providers on the balancing market.

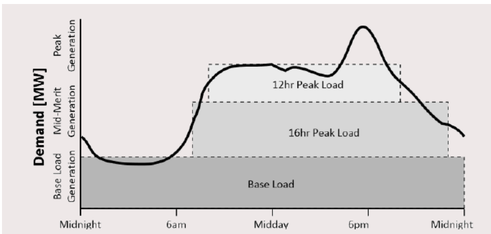

Figure 5: Futures market

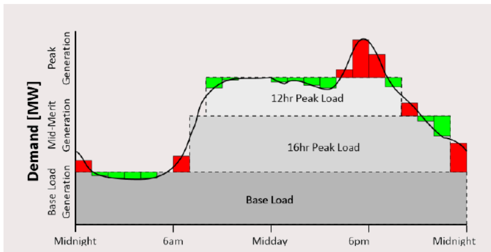

Figure 6: Day-ahead market

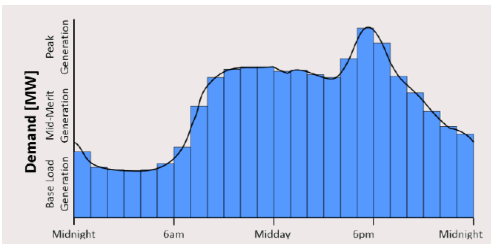

Figure 7: Demand after closing DA market

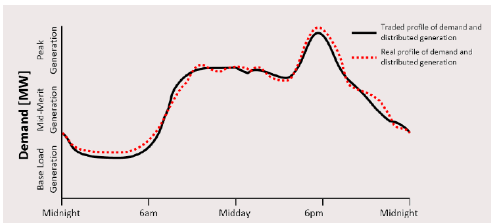

Figure 8: Remaining imbalance

Source: K. Kok (2021)

2.2 Demand response programs

A much used definition of demand response is given by the United States Department of Energy, stating demand response is "a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give

incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized" (Qdr 2006). This definition already classifies two types of demand response. The first type is price-based demand response. These DR programs rely on variation of electricity prices through time. During the day, prices for the same quantities of electricity vary driven by the actual demand and supply. When the demand is larger than the supply, prices are high, and when there is a surplus of generation, prices are low. The second type of demand response is incentive-based. In incentive-based DR, consumers are offered monetary incentives by a third party to curtail their load on demand. Penalties when the consumer does not cooperate may be included (Nwulu and Gbadamosi 2021).
There are three key price-based demand response programs, which will be briefly described below (idem):

- In **time-of-use pricing**, electricity prices vary during the day or seasonally. Prices are predetermined according to a fixed schedule and are static. In the Netherlands this is implemented as 'double tariff': from 7 am until 11 pm, consumers pay the high tariff, and during the night and in the weekend the low tariff (Essent n.d.).
- A more dynamic pricing strategy is **real-time pricing**, where consumers are communicated prices an hour up to a day ahead. Prices are based on forecasts of expected demand and supply.
- **Critical-peak pricing** is aimed at specific, shorter time intervals. CPP participants receive notice from the utility company announcing a peak price a few days per year. On these days the network experiences significant challenges in providing all consumers with electricity, and CPP participants are expected to curtail their load or else they pay a high price.

Likewise, there are three types of incentive-based pricing strategies:

- **Direct-load-control** gives utility companies direct control over certain energy-intensive appliances such as water boilers. Utility companies can remotely switch off these appliances to relieve the grid and give the participating consumer a discount on their electricity bill.
- A similar strategy is **Interruptible Programs**, however, it is aimed at large-scale energy consumers such as factories. Consumers are asked to discontinue their grid electricity consumption on request by switching on their own power generator or shift their operations to an off-peak moment. They are rewarded with reduced electricity prices. When complete shut-down of operations is not necessary, but consumers are asked only to curtail their load, this is called **Curtailable Load Program**. Penalties for non-compliance are less severe in CLP than in IP.

Usually, price-based demand response is more suited for residential consumers and incentive-based for industrial consumers.

2.3 Load flexibility

Demand response aims to flatten the load shape to reduce the costs and problems associated with high peaks. The monetary incentives to do so have been explained in the previous section. Consumers can change their load in response in a few ways, as seen in Figure 9.
In peak clipping, load is simply curtailed to reduce a peak. This is also often called peak shaving. Valley filling is the opposite: increasing the power consumption to fill troughs. These alterations usually go hand-in-hand, the load that was shaved during the peak is moved to a valley. This

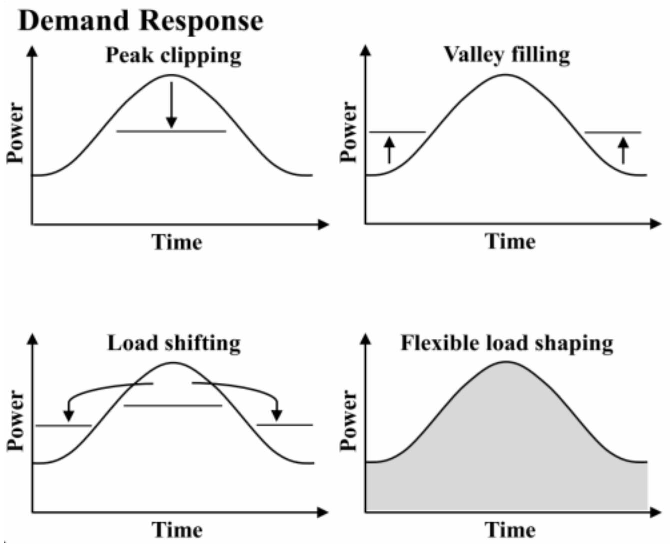

Figure 9: Types of load alterations (Lampropoulos et al. 2013)

is called load shifting. Flexible load shaping represents any controllable load systems during critical periods Zeiler 2020.

A load shifting action in response to a signal such as a changing electricity price typically looks as in Figure 10.

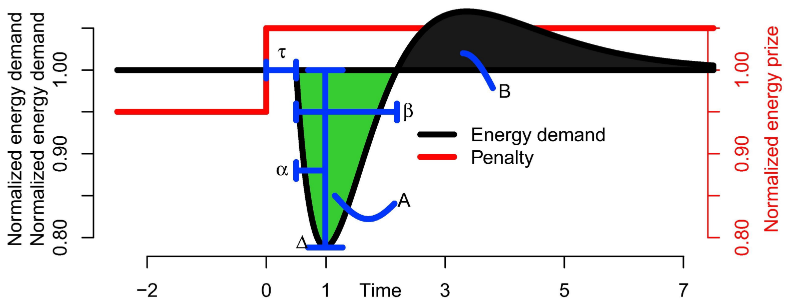

Figure 10: Visualisation of Flexibility Characteristics on a typical demand response curve. DR is initiated after the penalty signal (electricity price) jumps upward. Source: Junker et al. 2018

3 Methodology

This chapter starts with the general scope of the problem, after which the research approach is described.

3.1 General scope

This section itemizes a few assumptions to reduce the general scope.

- The study is limited to the Dutch market. While the European market is to an extent coupled, electricity prices and market structures still differ per country. Investigating the profitability of demand response for all different markets and price data, albeit interesting, requires too much time for the size of this project.
- In practice, individual buildings can not provide flexibility as the load of a single building is too small to make a noticeable difference. Therefore, aggregation of flexibility is required. This is reflected in market accessibility; there are power capacity thresholds to participate in electricity markets. The thresholds are typically in the MW range, while building electricity demand is in kW range. To limit the scope of the research and focus on the techno-economic side of demand response, the legal and organisational aspects of demand response and aggregation will not be considered a barrier to economic potential, meaning that in this study a single building can perform demand response.
- In the same vein, aggregation can increase flexibility performance by enabling synergy between different types of buildings, sharing their electricity or heat. For example, a restaurant with PV panels that opens in the evening could deliver its electricity during the day to a nearby office, or excess heat from a data centre can be used to warm a residential building. These interactions however are hard to generalize, and therefore more suitable to research in case studies than in this broader techno-economic study.
- The economic assessment will focus on the variable part of electricity prices. Offices also pay grid operators connection fees, in which flexibility can play a role; by reducing the monthly peak, the fees can be lowered and/or connection size enlargement deferred.

3.2 Research approach

To answer the research questions posed in Section 1.3, several research steps will need to be undertaken. The research set-up can summarily be described as collect data, create a computer model, run simulations and analyse results.

3.2.1 Literature research and data collection

The methodological steps relating to literature research/data collection are laid out below. It is expected from the existing literature that the HVAC is an interesting flexibility asset, therefore some steps relate to this. This study is done in cooperation with consultancy company Sweco, at the team Sustainable Buildings. This means that apart from gathering information through literature study, Sweco experts can be consulted on e.g. typical office building layouts, demand profiles etc.

1. **Inventorize the flexibility assets present in office buildings.**
   To know which assets are available for flexible operation of an office building, an inventory needs to be made of possible contributors to demand response. This includes all assets

that consume electricity, but also energy generation units (e.g. photovoltaic panels) and storage units. A decision should then be made which assets are the most interesting for demand response.
The flexibility asset information will be gathered by studying the available literature and consulting Sweco experts.

2. **Determine an office type**
The geometry, size and insulation levels of office buildings are of interest to determine how quickly an office cools down and heats up. A representative office building needs to be constructed.

3. **Research the various markets and DR programs a flexible office building could participate in.**
To study the potential profitability of DR, it is necessary to know in which markets flexibility can be sold. Various electricity markets exist with varying time-horizons. Additionally, more straightforward DR programs exist where flexibility providers are paid a fee to reduce their electricity consumption. This step should result in having electricity price data for various markets over the past years.

4. **Research control strategies for flexible operation.**
Demand response requires more complex control strategies than normally used in office buildings. A literature study will be carried out on the various control strategies that have been developed so far. Based on this research, a number of control strategies compatible with office buildings are selected to use in the simulation study.

5. **Evaluate user comfort**
User comfort norms need to be established wherein a building should operate. Several standards are available, as well as research into the topic. User comfort includes for example minimum and maximum indoor temperatures.

3.2.2 Model design

The profitability of demand response lies in adapting to electricity prices, in pursuance of saving money by using less energy when the price is high and consequently using more when the price is low. The resolution of these prices can be as small as 15 minutes. In order to calculate the monetary gains of a flexible office building, a model of an office building will be made and simulations run. Building simulation as a means to assess flexibility has been recognised by i.a. Junker et al. (2018). The model will include the geometry and flexibility assets identified in step 1 and 2, operated by control strategies identified in step 4, optimising energy savings under electricity prices determined in step 3, while maintaining user comfort as in step 5.

The developed model will be used to analyse the economic potential of demand response for office buildings. Results will show how much load can be shifted and money saved by a flexible office building. Different market data and control strategies can be applied to study the effect on profitability. The effects of differing flexibility assets and variations in office characteristics can also be studied. Especially the former is an interesting point of research. Office buildings could renovate or upgrade appliances to increase their capacity for flexibility, but this comes with a cost. The costs of upgrading can be contrasted with the higher profit from DR, to determine the pay-off from renovations.
The model design is visualized in Figure 11. The approach to implementing the model is discussed in the next sections.

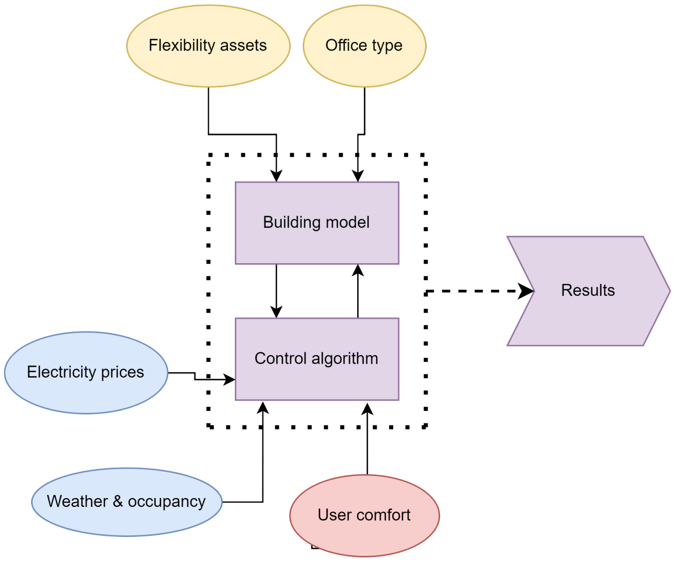

Figure 11: Diagram of the model design, with exogenous variables in blue, endogenous variables in yellow and constraints in red

3.3 Software

There are many software solutions for (thermal) building modelling, among them Modelica, Energyplus, SketchUp Sefaira, IES-VE, Vabi EPA & Elements, Designbuilder, ESP-r and TRNSYS. Creating a model in python or Matlab is also an option.

Modelling is always a trade-off between computation time and level of detail. For example, one could model the heating system of the building to the level of detail of the piping system: the distance hot water needs to travel from the heating unit to a room negatively influences the temperature of the water once it arrives in the room, resulting in less heating power the further away from the source. Moreover, the walls through which the pipes run would locally heat up, affecting the heat radiative power of the walls. Modelling these mechanisms results in higher accuracy, but a slower model. Considering the trade-off between detail and speed and some other factors, a list of requirements for the model can be made:

1. The simulation must be able to run at a temporal resolution of 15 minutes, which is the resolution of the aFRR market.
2. Simulation of the model must be fast for MPC. For MPC, the building will need to be simulated with various temperature setpoints each timestep, to determine the optimal control trajectory.
3. Simulation of the model must be fast for total simulation time. Especially combined with MPC, a slow model may result in simulation of one day taking several hours. However, weather and electricity prices vary greatly between days. To correctly assess the profits of DR, the possibility of running longer simulations over several days or weeks has priority over the accuracy of the thermal model. In other words, accuracy of the thermal model may be traded in for a shorter simulation time.
4. The model must be flexible enough to easily change parameters such as wall insulation or add assets such as a battery.

5. It must be possible to control the building dynamically, so changing control input during the simulation.

6. Preferably, the software is widespread and open-source, to make the study more reproducible.

Many of the modelling programs reported above (Sefaira, IES-VE, Vabi Elements, Designbuilder) give very detailed results on the temperature distribution over the building given a certain indoor temperature/setpoint, using e.g. finite element analysis. The result is meant to help designers identify problems in their building designs. These (graphical) simulations are quite computationally expensive and therefore not suitable for the intended purpose. A 1D model is preferred for computation time.

Energyplus, TRNSYS and Modelica are 1D building simulation tools. Energyplus is a popular open-course tool developed by the US Department of Energy with a good reputation. Its accuracy has been verified in studies that compare Energyplus results with actual measurements (e.g. Pombeiro, Machado, and Silva 2017).

However, these modelling programs do not allow for dynamic control of the building. The programs only allow for setting operational schedules beforehand, and then running the entire simulation. MPC requires the simulation of multiple control trajectories from the same initial state, which these programs are not designed to do. A solution is to couple a building modelling tool to Matlab or python to combine the flexibility of Matlab/python with the pre-made solver for building temperatures. However, the scope of these tools is often already beyond what is necessary for MPC, and the interface for communication with Matlab or python compounds the complexity (Sturzenegger 2014).

A more simple building modelling approach is thermal resistance-capacitance (RC) modelling. A resistance-capacitance model is a popular way of modelling heat dynamics of a building in a simplified way (Amara et al. 2015, Široký et al. 2011). Thermal RC models are analogous to electrical circuits, but instead of electric resistors and capacitors, walls and windows are modelled as having thermal capacity and resistance to heat fluxes. Voltage is replaced by temperature and current by heat flowing through a thermal circuit of walls, windows and air. An RC model can be made in any programming language and run step-by-step, allowing for changing the control input based on the current state. The model will be a white-box model. Modelling the building physics makes it easy to change building parameters or add assets. Fonseca, Chvatal, and Fernandes (2021) also recognizes white-box models as the preferred option for RC modelling.

3.3.1 BRCM toolbox

Matlab will be used to model the office building, because it is the most popular tool for developing intelligent building control (Shaikh et al. 2014) and provides many functions for modelling systems. A Matlab toolbox to create thermal RC models is the Building Resistance Capacitance Model toolbox by Sturzenegger (2014). The toolbox can generate matrices that describe the thermal behaviour of a building, and has been used to optimally control a Swiss office building. Figure 12 shows an example of a building RC model. The building envelop is of the 2R1C type: there is one capacitance which is the uniform temperature of the envelop, and the two resistances describe the heat transfer between the outdoor and the envelop, and the indoor and the envelop. The indoor contains a uniform temperature air mass, which interacts with the envelop and internal mass. There are also direct heat gains to the indoor: solar heat Q_{solar}, indoor heat production Q_{in} and cooling Q_C. The internal mass represents indoor walls and floors.

In the BRCM toolbox, a building geometry is defined through various Excel files that detail the building's walls, windows, materials, heat transfer coefficients etc. Materials have an

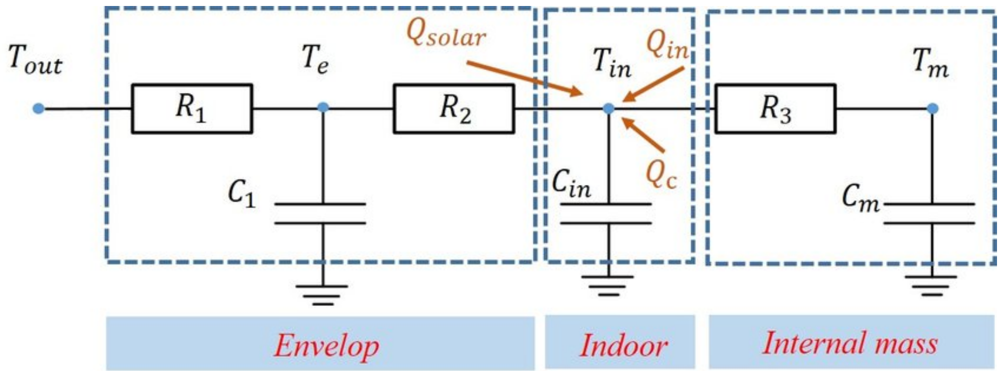

Figure 12: Example of a thermal resistance-capacitance model. Source: Wang and H. Chen (2018)

identifier, description and several parameters such as density and specific thermal resistance. Constructions consist of layers of materials and heat transfer coefficients for both sides of the construction. Lastly, a geometry can be defined by creating building elements with a specific area, vertices in a 3D space and a construction type. A building element is for example a wall, a floor or a roof. The toolbox then generates matrices that describe the heat flows between all building elements.

The BRCM toolbox makes a few assumptions that are listed below:

- The heat transfer coefficients are combined convective/radiative coefficients
- The model can have different zones, but the air temperature is uniform in each zone.
- The temperature within a layer of a building element is uniform.
- There is no conductive heat transfer between different building elements.
- All thermal model parameters (such as the heat transfer coefficients) are constant over time.

3.4 Modelling heating

This section provides some background for the thermal calculations done in Matlab by the BRCM toolbox The electricity consumption of a heating unit depends on the heat demand. The heat demand is given as

$$\dot{Q}_{dem} = \dot{Q}_{loss} - \dot{Q}_{sun} - \dot{Q}_{int} + \dot{Q}_{change}[W] \tag{1}$$

The heat loss $\dot{Q}_{loss}$ consists of conduction heat losses through the outer building shell and convection heat loss by infiltration. This is partly compensated by incoming radiation energy from the sun $\dot{Q}_{sun}$ and internal gains: the heat produced by people and appliances $\dot{Q}_{int}$. If $\dot{Q}_{change}$ equals zero, Equation 1 is a balance that keeps the temperature at a stable level. If $\dot{Q}_{change}$ is positive the heat demand will be higher and the temperature will rise.

The thermal capacity of a building element is calculated as follows (Amara et al. 2015):

$$C_r = \rho \cdot V \cdot c_p[J/K] \tag{2}$$

where

ρ_i = Density of the element
V = Volume of the element
$c_{p,i}$ = Specific heat capacity of the element

3.5 Planned analyses

The analysis to gain insight into the profitability of demand response for office buildings is twofold. Firstly, office buildings can shift their load to make a profit in demand response programs, the profitability depends on the type of DR program and the building's capacity for flexibility. Quantification of flexibility is necessary to analyse a building's flexibility performance. Secondly, office buildings may need to be fitted with new meters or smarter ICT components to be able to provide flexibility, which is an expense that should be subtracted from profits. Additionally, office owners may upgrade appliances, renovate their buildings or buy a battery to increase their capacity for flexibility and with that, their profits. The economic attractiveness of technological and structural changes will need to be calculated to see if total profitability can be improved.

3.5.1 Quantification of flexibility and profitability

A highly cited article on quantification of flexibility is Junker et al. 2018. Herein the Expected Flexibility Savings Index (EFSI) is presented as a Key Performance Indicator. the ESFI compares the total electricity costs of a flexible and a reference case. If FI<0, the flexible case is more expensive. If 0<FI=<1, the flexible scenario is profitable, with e.g. an ESFI of 0.10 meaning a reduction in costs of 10%. The equation is as follows:

$$ESFI = 1 - \frac{\sum_{t=0}^{n}(E_{el}^{t} \cdot p^{t})_{flex}}{\sum_{t=0}^{n}(E_{el}^{t} \cdot p^{t})_{ref}}[-] \tag{3}$$

For each time step i, electricity consumption E_{el} in kWh is multiplied with the electricity price p in euro/kWh to obtain the electricity costs for that time step. The sum over all time steps is taken to get the total costs.

Hall and Geissler (2021) compare seven popular flexibility factors and mark the ESFI and the Shifted Flexible Load factor as suitable for comparing a flexible case with a reference case.

The Shifted Flexible Load (S_{flex}) does not include costs but compares the amount of energy shifted at each time step to the base case. S_{flex} ranges between 0 and 1, with 0 meaning no electricity has been shifted and 1 meaning all electricity has been shifted.

$$S_{flex} = \frac{\sum_{t=0}^{n} max(E_{el,ref}^{t} - E_{el,flex}^{t}, 0)}{\sum_{t=0}^{n} E_{el,ref}^{t}}[-] \tag{4}$$

3.5.2 Effect of changes

The attractiveness of making changes to increase capacity for flexibility can be determined by calculating the payback time (PBT) of these investments. The investments should yield a higher profit from demand response but also cost money to acquire.
The payback time of an investment is

$$PBT = \frac{Initialinvestment}{Averageannualcashflow} \tag{5}$$

The cash flow is the annual income resulting from the investment. More complex cash flows can be calculated by adding cost components, such as maintenance Ebrahimi and Keshavarz 2015. If the PBT is longer than the lifetime of the investment, it is not an attractive investment. The shorter the PBT, the more attractive the investment.

4 Theoretical results

This section contains all the results from the literature survey and data collection research steps.

4.1 Energy asset inventory

Energy assets include i) electricity consuming appliances, ii) electricity generating units iii) storage units and iiii) building characteristics relevant for demand response. Building characteristics are relevant as the flexibility capacity of heating depends on the thermal inertia of the building. If a building quickly cools down after the heating is turned off, the heating can only be off for a short time. In a well-insulated building, heating could be turned off for a longer period and therefore provide more flexibility.

4.1.1 Electricity consumption

Common electricity consuming appliances in offices are those providing space heating, space cooling, (de)humidification and ventilation, (ICT) office devices, electric vehicles and lighting Aduda et al. 2016. The first four are provided by HVAC systems: Heating, Ventilation and Air-Conditioning. HVAC systems, office devices and EVs will be discussed below. Lighting will not be considered as it not very suitable to run flexibly, it is required for visibility. Assets that are suitable for flexible operation are typically assets that can store energy, be it electric or thermal.

Heating, Ventilation and Air-Conditioning

HVAC usually consists of an Air Handling Unit (AHU) installed on the roof that intakes air and prepares it for circulation inside the building, and one or more units for heating water. A schematic overview of an AHU is given in Figure 13. Air is extracted from both the building and

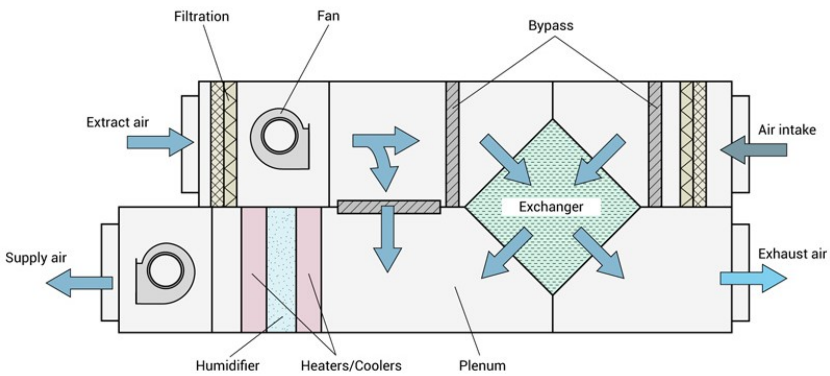

Figure 13: Diagram of Air Handling Unit. Source: Airtècnics (2021)

outside. Depending on the set-up, the flows are mixed or only one is used. Recirculation of air is becoming less popular in favor of using fresh air though, especially due to COVID-19. Still, in a heat exchanger, heat can be recovered from the indoor air flow to preheat the fresh, outdoor air flow. Hereafter, the filtered air flow is (de)humidified and heated or cooled as necessary. The air refresh rate will not be changed as fresh air is vital to employee productivity. A decrease in employee productivity is most probably much more costly than the potential profit from lowering the refresh rate. Sweco experts indicate that in the Netherlands (de)humidification devices are generally not installed. This leaves the heating/cooling as the only relevant HVAC component for demand response in this study.

Hot water is required in buildings for space heating and domestic hot water. Domestic hot water is used for washing dishes and clothes and for showering. This is a significant part of hot water demand in residential buildings, but in offices it will be considered negligible as there are very few of these assets per employee. Hot water for space heating is one of the largest, if not the largest, contributor to total energy demand. Water can be heated by a gas boiler, an electric boiler, a heat pump, district heating and more novel technologies. Only the technologies that convert power to heat can perform (electric) demand response: electric boilers and heat pumps. Electric boilers are typically used for domestic hot water, and heat pumps for space heating. Heat pumps are therefore the only space heating/cooling asset available for electric DR.

There are several HP types, which are distinguished by the heat source and heat sink. The heat sources and sinks are typically air or water. The HP types will henceforth be referred to as 'source/sink' HP. For example, an A/W HP has air as source and water as sink. Looking at the HP thermal power installed in the utility and agricultural sectors, 65% is from A/A HPs, 20% from open W/W HPs , 12% from A/W HPs and 3% from closed W/W HPs (CBS 2022c). A/A HPs are also known as 'reversible air-conditioners' and are primarily used for cooling. A/W heat pumps have water as the heat sink, which is used for radiators and underfloor heating. W/W HPs can be closed or open. In open systems, groundwater (or lake water) is pumped up, used as heat source in the HP, and then pumped down again. In closed systems, the HP transfer fluid is heated up/cooled down in a closed pipe going deep into the ground, so no fluid is pumped up from the ground.

A full model of a HP is not necessary for this study. Only the electricity consumption of the HP at variable heating power is of interest. This is expressed in the Coefficient of Performance (COP): the ratio between thermal power delivered and electric power supplied. A higher COP means a better efficiency. The COP depends on the temperature difference between the source and sink of the HP. Especially for A/X HPs, this difference can vary greatly during the day due to the changing outdoor air temperature. W/X HPs usually have a much more stable source temperature.

For a fully electric medium-sized building, an A/W HP will be assumed. A/A HPs can not provide enough heating and W/X HPs are usually large, costly installations that only large office buildings can afford. An A/W HP is a good solution for a medium-sized office building. The temperature dependent COP is experimentally found by Pospíšil et al. (2017) as:

$$COP = 0.0023 \cdot \Delta T_{aw}^2 - 0.2851 \cdot \Delta T_{aw} + 10.677 \tag{6}$$

where

ΔT_{aw} = The difference between outdoor air temperature and indoor water supply temperature

The hot water can be used to preheat the air in the AHU. If the conditioning of the air supply is not sufficient to maintain user comfort, the heating unit can also supply hot water to a radiant system for extra heat. Radiant systems typically involve pipes that run around the building and radiate heat to the interior. Free standing radiators can be used or floor surface heating. Additional cooling may also be installed to complement the forced air conditioning (Kubba 2017). Large buildings may be divided into zones that each have their individual heat demand. Figure 14 gives an example of a building heating system with a heat pump, additional electric boiler, thermal energy storage and the radiant space heating system.

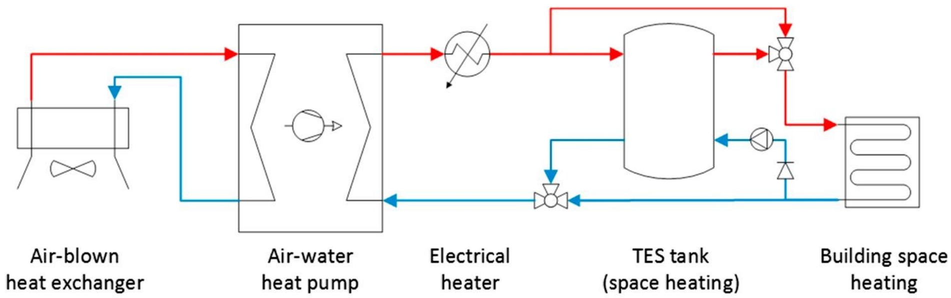

Figure 14: Simple process flow diagram of building heating system. Finck et al. 2018

ICT devices

Office devices are computers, servers, refrigerators, coffee machines etc. Most devices cannot be turned off/down easily (e.g. servers and coffee machines) and/or have a negligible energy consumption (coffee machines, refrigerators). An office device that could potentially perform demand response is the laptop. Laptops have internal batteries that can be charged in a smart way to provide demand response. The charging action could be shifted from on-peak to off-peak hours. It will be assumed that at any time, 90% of the building occupants have a laptop plugged in. Looking at Hewlett Packard's (HP) business laptop offerings[1], battery sizes range from 41 Wh for the more simple models to 56 Wh for the heavy-duty laptops. As more simple laptops suffice for most office employees, a battery size of 45 Wh will be assumed. HP laptops come with 45 Watt chargers.

The laptop capacity is aggregated into one 'large' laptop battery. The total laptop battery capacity is then:

$$C_{laptops} = N_{employees} * S_{pluggedin} * C_{1-laptop} \tag{7}$$

where

$N_{employees}$ = Number of employees
$S_{pluggedin}$ = Share of laptops that are plugged in
$C_{1-laptop}$ = Battery capacity of one laptop

100 employees would result in a laptop battery capacity of 4.05 kWh, which is approximately equal to one residential home battery. Laptop demand response may prove to have negligible impact, but since implementation into the model is simple, the potential will still be investigated.

EVs

Similar to laptop batteries, electric vehicles can be charged smartly to provide demand response. Vehicle-to-grid (V2G) technology in which EV batteries can be discharged to sell electricity to the grid is not considered, as almost no cars are suitable for bidirectional charging as of yet. Without V2G, the full capacity of the EV batteries cannot be used. It will be assumed that employees using an EV will charge their EV at work, drive home, drive back the following day and charge again. Therefore, the battery capacity that can be charged smartly during the day equals the drive from home to work times two plus some private use. Approximately half of employees travel to work by car, which is stable from 2018 to 2021 (CBS 2022a). They drive 26 kilometres to work pre-corona, and 23-24 during corona. Car owners drive an additional 10-15

[1] www.hp.com

kilometres per day for private motives, on average (CBS 2022b). It is likely a larger part of these additional kilometres are driven on trips in the weekend, and less during the week. It will be assumed car-driving employees travel 2x26+8= 60 kilometres on average between leaving work and coming back. Extra discharge due to the weekend or irregular office days are neglected. Employees will not come to the office every day, but this is accounted for in the occupancy of the building the amount of EVs will be based on. The last step is to translate the kilometers into the battery capacity that needs to be charged.

Business electric vehicles are on average more luxurious than private electric vehicles. Popular models are the Tesla Model 3, Kia Niro and Nissan LEAF (R. Kok et al. 2021). These cars have an expected fuel consumption rate of 20 kWh/100 km ANWB 2023. Driving 60 kilometres would therefore cost 12 kWh. In the Netherlands at the end of 2020, 15% of all business passenger cars were Battery Electric Vehicles (BEVs) and 4% were Plug-in Hybrid Electric Vehicle (PHEVs) R. Kok et al. 2021. BEVs always have a battery of at least 12 kWh. It will be assumed business PHEVs also have a battery of at least 12 kWh, making the split between BEVs and PHEVs redundant.

With this information, the total EV battery capacity available for smart charging (C_{EVs}) can be estimated based on the number of employees.

$$C_{EVs} = N_{employees} * S_{car-to-work} * S_{EVs} * C_{1-EV} \tag{8}$$

where

$N_{employees}$	= Number of employees
$S_{car-to-work}$	= Share of employees that travel to work by car
S_{EVs}	= Share of EVs (BEV+PHEV) in car fleet
C_{1-EV}	= Battery capacity of one EV available for smart charging

In an office with 100 employees present, this would result in a C_{EVs} of 114 kWh. Again, all EVs are aggregated into one large battery.

4.1.2 Electricity generation

The only electricity generation technology prevalent office buildings is solar photovoltaics. These may be installed on the roof, though solar car ports are also becoming popular. A solar carport is a parking place covered with a solar panel roof that can charge the parked EVs.

4.1.3 Energy storage

Thermal

As seen in Figure 14, HVAC systems can be augmented with additional thermal energy storage (TES). Finck et al. (2018) identifies thermal energy storage (TES) as an effective flexibility source. Many types of TES exist:

- Energy can be stored in the Building Thermal Mass (BTM) by raising its temperature which can be released later. The storage consists of the walls, roof, floors and encapsulated air in the building.
- Another type of sensible heat storage is a water tank, wherein water temperature can vary between 21 and 95 degrees celsius for space heating and domestic hot water.
- Latent heat storage is based on phase changes of materials. This can be done with water, which changes to ice or more advanced phase change materials such as molten salt and paraffin (Cabeza et al. 2011).

- Lastly, heat can be stored in reversible chemical reactions, which is called thermochemical heat storage.

To investigate the current profitability of DR (research question 3), only the first two types will be considered, as the last two are far from widely implemented. The water tank TES may also fall under RQ4, if the selected office type does not have a hot water tank. Aquifer thermal energy storage (ATES) should also be mentioned. Heat pumps (HPs) can use natural aquifers in the ground as hot and cold sinks. In summer, water is pumped up from the cold aquifer to cool the building and is then injected into the hot aquifer. In winter, vice versa. This type of TES mainly serves to increase the efficiency of the HP. Due to its seasonal cyclic nature, the storage is not very suitable for hourly HVAC demand response.

Electric

Using electric batteries for demand response is a well known application. The standard office type will be assumed not to have a battery, but it may be considered in future profitability.

4.2 Office types

In this section, a basic building type for analysis will be defined. The office will be medium-sized and relatively modern, as offices interested in and suited for demand response will likely be offices that have already taken various energy saving measures and are looking for what more they can do. Occupancy is also discussed in this section as it relates to building size.

4.2.1 Geometry

According to Economidou et al. (2011), approximately 20% of office buildings in the Netherlands are <500 m^2. A breakdown of the >500 m^2 building stock is given in Figure 15.

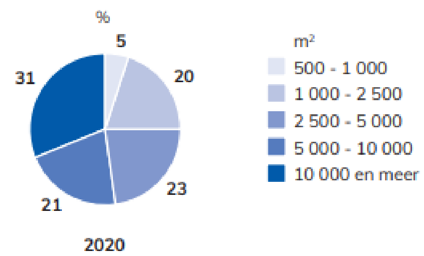

Figure 15: Dutch office stock by building size. Source: (Bak 2021)

A medium office size seems to be in the 2500-5000 m^2 range. A 4000 m^2 office will be used. The geometry is chosen to be 25 meters long, 16 meters wide and 35 meters high. The height of one floor is 3.5m. 60% of the external walls will consist of windows.

4.2.2 Insulation and thermal mass

Minimum insulation values of utility buildings are given in Table 1. R and U values determine the thermal resistance of building elements. The transmittance is the amount of solar radiation that is transmitted through a window.

	External wall R [m2 K/W]	Roof R [m2 K/W]	Floor R [m2 K/W]	Windows, insulation U [W/m2 K] (glazing)	Windows, transmittance [-]
<1965	0.19-0.85	0.22-0.85	0.15-0.83	5.1 (single)	0.85
1965-1974	0.43	0.86	0.17	2.9 (double)	0.75
1975-1987	1.30	1.30	0.52/1.30	2.9 (double)	0.75
1988-1991	2.00	2.00	1.30	2.3 (HR)	0.6
1992-2013	2.50	2.50	2.50	2.0 (HR+)	0.6
2014	3.50	3.50	3.50	1.6 (HR++(+))	0.6
2015-2020	4.50	6.00	3.50	1.6 (HR++(+))	0.6
>2021	4.70	6.30	3.70	1.4 (HR+++)	0.5

Table 1: Minimum wall, floor, roof and window insulation values for utility buildings through the years, decided on in the Dutch building directives. Source: ISSO (2020)

Since the Dutch Building Directive of 2012, the average U-value of all windows, frames and doors in new buildings must be below 1.65 W/m2K (Rijksoverheid 2011). Therefore, it will be assumed offices built in the 2014-2020 period will have HR++ or HR+++ glass in a wood/plastic frame with a U-value of 1.6. The most modern buildings (>2021) will have HR+++ glass. Before 2012, the maximum allowed U-value for windows, frames and doors was 4.2, allowing anything from double glazing to HR+++ (Rijksoverheid 2001). HR coating was commercialised in the early 1980s (Jones 2014), so HR glass will be assumed from 1988 onwards.

There are no standards for specific heat capacity of buildings, as it is not very relevant for energy saving standards. Specific heat capacity is expressed in Joule per kg per Kelvin. The heat capacity of the building therefore depends on the types of materials used and the mass of these materials. Sprecher et al. (2022) have studied the material intensity in the Dutch building sector. Based on demolition data of 25 office buildings, they find that the building construction (the walls and floor) contributes 90% of the total mass. The remaining contribution is spread over the roof construction, glass, gypsum internal walls, steel, insulation and wood. Considering the big difference in contribution to heat capacity between the construction and the other components, including only the heat capacity of the building envelop is likely sufficient for getting an estimate of the total heat capacity. Indoor gypsum walls will therefore not be modelled.

Sprecher et al. (ibid.) also find that the construction typically consists of concrete and/or clay brick. Specific heat values of concrete and brick vary across sources. For brick, the value ranges between 0.79 and 1 kJ/(kg K). For concrete, from 0.75 to 0.96 kJ/(kg K) (Engineering ToolBox 2013, Designing Buildings 2022, NREL 2023). As data on the breakdown of brick and concrete use in Dutch office buildings is not readily available and the specific heat capacities are in similar ranges, a uniform specific heat capacity of 0.85 kJ/(kg K) is assumed for the office construction. The envelop consist of 10 cm of brick/concrete, a layer of insulation and 10 cm of brick/concrete. The insulation thickness depends on the R-value from Table 1.

Since a modern office building will be modelled, the values from 2015-2020 will be used.

4.2.3 Occupancy

According to a Dutch survey by Haas, Hamersma, and Faber (2022), Dutch office employees worked from home on average 4 hours per week pre-corona, and 12 hours per week in May 2022. Assuming office employees are 25-65 years of age and have a higher level of education, their average work week is estimated to be 36 hours (CBS 2022d). This means that on average, office employees work on location 24 hours/3 days/60% of the work week post-corona. Pre-corona, this was 32 hours/4 days/80% of the work week. The occupancy rate is then defined as follows (partly adapted from Finck et al. (2018)): Occupancy rate (ϵ_t) post-corona.

$$\epsilon_t = \begin{cases} 0, & t = 19 - 7 \\ 0.1, & t = 7 - 8, 18 - 19 \\ 0.2, & t = 8 - 9, 17 - 18 \\ 0.5 & t = 9 - 10, 16 - 17 \\ 0.6, & t = 10 - 16 \end{cases} \tag{9}$$

Occupancy rate (ϵ_t) pre-corona.

$$\epsilon_t = \begin{cases} 0, & t = 19 - 7 \\ 0.05, & t = 7 - 8, 18 - 19 \\ 0.3, & t = 8 - 9, 17 - 18 \\ 0.7 & t = 9 - 10, 16 - 17 \\ 0.8, & t = 10 - 16 \end{cases} \tag{10}$$

With the occupancy rate and total amount of people employed, the current occupancy can be calculated at any moment in the day.

4.3 Electricity markets and DR programs

In the Netherlands, total electricity costs paid by consumers consists of various components:

- Variable electricity costs in euro per kWh (paid to supplier)
- Fixed delivery costs, a monthly fee paid to the supplier
- Fixed connection fees, paid to grid operator
- Variable connection fees, paid to grid operator
- Capacity tariff based on connection size, paid to grid operator
- A fee for administration, paid to grid operator
- Costs for use of measuring device
- Taxes

As mentioned in the scope, this study will focus on the variable electricity costs.

4.3.1 Dynamic pricing

As mentioned in Methodology section 2.2, incentive-based DR programs are more often targeted at industrial consumers and sometimes tailored to specific businesses. Reviewing the possibilities for demand response in the Netherlands, there seems to be no publicly available data on incentive-based programs. The Dutch TSO Tennet does have contracts with industrial parties such as a chlorine factory in Rotterdam to steer their production in case of congestion (NRC 2022). This DR program seems to be a direct-load-control program. The financial details are not publicly posted however, making it impossible to implement in this study. Moreover, the program seems to be targeted at industrial large-scale consumers.

Price-based demand response is a more suitable type of DR for office buildings. There do not seem to be any critical-peak-pricing schemes in the Netherlands, but there are opportunities of the real-time-pricing type.

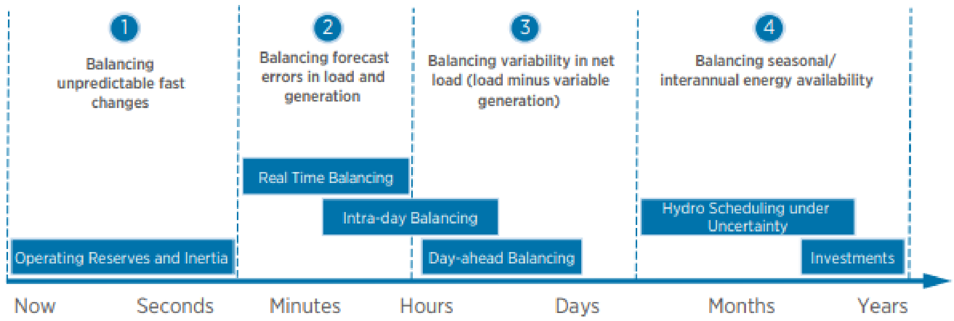

Figure 16: Different time scales in which flexibility has to be analysed. Source: (Taibi et al. 2018)

Figure 16 shows the time scales across which demand and supply need to be balanced. These time scales have been explained in the theoretical background. The relevant ones for demand response are 1-3. Day-ahead balancing is done on the spot market:

Day-ahead market. In this market, demand flexibility can help consume large influxes of electricity from renewable energy sources that may be generated at times demand is low. In the DA market, all participating parties define in blocks of one hour what amount of electricity they are willing to buy/sell at which price. The hourly electricity price is then set at the intersection of these bids. All buy bids lower than the price and sell bids higher than the price are not accepted. In order to make good bids, i.e. bids that are accepted but do not cause unwanted costs, bidders must predict the DA electricity prices. For example, if the prediction is that between 12:00 and 15:00 large amounts of cheap solar energy will be available due to sunny weather, buyers should try to place large bids in this time period. The order of actions in the DA market for a buying party would be: predict prices → schedule demand → receive DA prices.
Demand response is performed in the 'schedule demand' action, and would therefore be based on predicted prices. There is no general price prediction though and incorporating price prediction in the model is (far) beyond the scope as it is a complex topic. Consequently, it will be assumed the offices have perfect prediction and the action order is modified into: receive DA prices → schedule demand. There are energy suppliers in the Dutch market that offer dynamic prices to customers, for example Frank Energie, Tibber and Zonneplan[2]. These suppliers let customers buy electricity at DA prices, so using the DA prices as input is a valid method. Another assumption that is made, is that the DR does not influence the electricity price. For an individual building this is perfectly reasonable, but for large-scale demand response this might have to be taken into account. Day-ahead prices are obtained from the transparency platform of ENTSO-e. ENTSO-E is the European Network of Transmission System Operators (ENTSO-e n.d.).

Real Time Balancing is not done on the spot market, but is largely organised by TenneT, as they have the final responsibility for keeping the grid frequency at 50 Hertz. Parties providing balancing services to TenneT are called Balance Service Providers (BSPs). Imbalance is caused by electricity consumers and suppliers deviating from their planned consumption/production. Balance Responsible Parties (BRPs) maintain a portfolio of grid connections and are financially responsible for deviations. They pay an imbalance price for the deviations from the planned consumption/production in their portfolio. The balancing system consists of four balancing products (TenneT 2023):

Frequency Containment Reserves (FCR). Each European TSO is obligated to have a certain amount of FCR. FCR are automatically activated within seconds to maintain the correct grid frequency. This service is usually supplied by power plants. The contracted power must be available at all times during the contracted period. BSPs receive remuneration for their availability.

automatic Frequency Restoration Reserves (aFRR). aFFR bids are made to TenneT by BSPs for up regulating power (produce more or consume less) and down regulating power (produce less or consume more). The bids are placed in a merit order and TenneT then automatically accepts bids as necessary to correct imbalances in the grid. Bids can be made up to 60 minutes before the moment of delivery, and the market functions in blocks of 15 minutes.

manual Frequency Restoration Reserves, scheduled activated (mFRRsa). This reserve capacity is activated in case of incidents that cause substantial power deviations. It is sold through bids, but must be activated manually.

manual Frequency Restoration Reserves, directly activated (mFRRda). mFRRda are larger incident reserves, for long-lasting power deviations. For this ancillary service, parties with additional generation capacity are usually contracted. Similar to FCR, parties are obliged to be able to draw or supply the contracted power on call from TenneT over the entire contracted period. The contracted power may not be used for other purposes. BSPs are remunerated for the capacity they have available, and the delivered power. This service is usually supplied by parties owning an emergency generator. Additionally, BRPs can purposefully create imbalance

[2] `https://www.frankenergie.nl/`, `https://tibber.com/nl`, `https://www.zonneplan.nl/`

in their portfolio if it counteracts the system imbalance. They are remunerated for the imbalance price, which is based on the price in the aFRR market.

Evaluating the workings of the grid balancing system in the Netherlands, it seems aFRR is the most suitable product that could be delivered by a flexible building. FCR and mFRRda both require power capacity that is always available. This is not the case in office buildings, as power cannot be reduced if it results in user comfort violations or EV/Laptop boundary condition violations. Furthermore, FCR requires very high reaction times and mFRRda must be activated for multiple hours to compensate for a failing supplier. Both may not be possible for office buildings. The response time of HVAC systems is between 1 and 15 minutes (Aduda et al. 2016). FCR and mFRRda have strict contractual obligations that flexible buildings may not be able to fulfill.

The aFRR market is most suitable as demand response would be activated in blocks of 15 minutes and bids can be made freely. BSPs can also enter a contract with the TSO, committing to provide aFRR which they receive additional renumeration for, but freely bidding is also allowed. BSPs must still go through a verification procedure to gain access to the aFRR market though. aFRR price data can be found on the transparency platform of TenneT (TenneT n.d.).

4.3.2 Reference market

A flexible market needs to be compared with a reference market. The reference market will be a contract with a fixed electricity tariff over the whole year. For a fair comparison, the fixed tariff could be set to the yearly average of the day-ahead market. However, fixed tariffs are higher than the DA average due to consumers typically consuming electricity at a higher price point, i.e. their electricity consumption is not perfectly even over the day but spikes when prices spike. As a solution, the reference will also use the instantaneous DA price. Assuming the energy supplier makes no profit, this should on a yearly basis be similar to a contract with a fixed tariff.

4.4 Control strategies

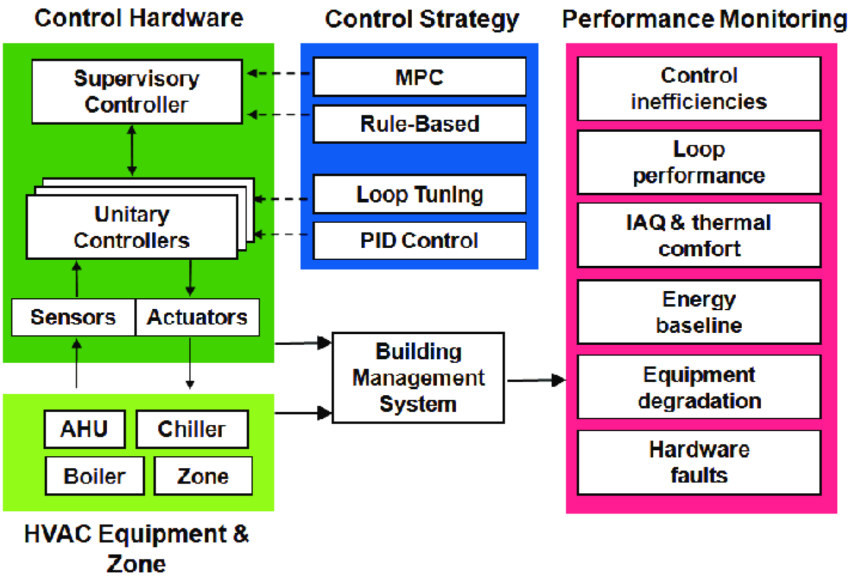

Figure 17: Key elements of HVAC control system Mařík et al. 2011

Key elements of the HVAC control system are shown in Figure 17. Each piece of equipment is controlled by its own unitary controller. Unitary controllers often use setpoints of a constant value and do not communicate with each other. Setpoints for temperature, relative humidity or hot water delivery temperature are determined for equipment per zone. Set-points are tracked by simple single-loop controllers such as thermostats (Morales-Valdés, Flores-Tlacuahuac, and Zavala 2014). For example, radiators are often controlled by thermostatic radiator valves. The mass flow rate of the hot water is adjusted based on the difference between the current room temperature and the setpoint. Floor heating systems have an on/off-control Reynders, Nuytten, and Saelens 2013. The system can be controlled more efficiently if a supervisory control system coordinates the unitary controllers Mařík et al. 2011.

The supervisory control system can be designed in many possible ways. Three control strategies will be applied in this research: a simple rule-based strategy, a smart rule-based strategy and a more advanced model-based strategy. These three control techniques are widely used in studies into demand response (Fonseca, Chvatal, and Fernandes 2021)

In rule-based control, setpoints are determined based on only the current circumstances and take few parameters into account. This is often already rudimentary implemented in office buildings with a day/night scheme. For example, if it is between 9:00 and 17:00, the temperature setpoint is 21 degrees and from 17:00 to 9:00, 18 degrees. In the smart rule-based strategy, the rules will be based on the electricity prices. As proposed by Finck et al. (2018), three price periods will be used. If the electricity prices are known well in advance (as in the day-ahead market), the mean price and standard deviation (sd) can easily be computed. If the electricity price is below 1 sd from the mean, it is considered low and if it is above 1 sd, it is considered high. During each pricing regime, different rules will be applied to the building. Rule-based control typically results in sub-optimal control (Mařík et al. 2011), but the computational complexity

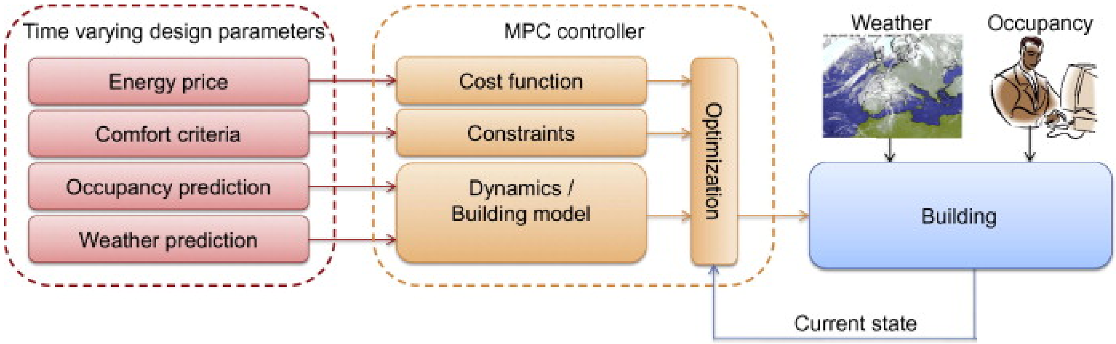

Figure 18: Basic principle of model predictive control for buildings Široký et al. 2011.

is minimal, investments do not need to be made and the algorithm is easy to understand and adapt by building managers. These advantages can induce conservative building managers to prefer this control strategy.

A more modern approach is model-based management. Model predictive control (MPC) systems use a building model to predict the interactions between the building installations and local conditions. Decisions on control variables are made based on the predicted consequences. This method also allows for cost-minimisation (or other types of objective functions) (Morales-Valdés, Flores-Tlacuahuac, and Zavala 2014). MPC has been studied extensively as a means to control HVAC installations (Široký et al. 2011, Sturzenegger et al. 2014). The basic working of MPC is shown in Figure 18. At each timestep, a finite-horizon optimal control problem is formulated and solved. The window can range from hours to days. A certain criterium is optimized (the cost function), subject to building constraints and dynamics. The output is a plan for the heating, cooling etc. The control problem is solved again for each timestep because the state of model changes (Široký et al. 2011). A strong advantage of MPC is the consideration of predicted future disturbances, such as occupancy and outside temperature. In this research, weather and occupancy predictions are assumed to be perfect. The control horizon of the MPC will be determined by the timescale at which the market information is available.

4.5 User comfort

User comfort is an important topic in DR for the built environment. In office buildings this is especially important, as employee productivity may not decrease as a consequence of performing demand response. The two main parameters of user comfort are thermal comfort and indoor air quality (Aduda et al. 2016). Thermal comfort is influenced by temperature and humidity, indoor air quality mainly consists of CO_2 level and humidity. As mentioned in energy assets, concessions on CO_2 level will not be made. The CO_2 level is a user comfort norm that is a large factor in productivity. High CO_2 levels can cause headaches and decrease productivity. Therefore, it is assumed that air circulation must be kept at the same level and cannot be scaled down to provide flexibility. This leaves temperature and humidity as the user comfort norms to use flexibly. However, Sweco experts indicate that humidity is rarely regulated in Dutch office buildings, but may be measured occasionally. Therefore, only temperature remains as a flexible user comfort norm.

4.5.1 Fanger's model

A common approach to evaluate thermal comfort is by using Fanger's model Fanger 1973. Fanger's model is used by the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) in their standard for thermal comfort. The international ISO norm also uses Fanger's method and the Dutch norm copies ISO (Nederlands Normalisatie Instituut 2005). It is also used in the sustainable building certification method BREEAM (DGBC 2021). Fanger defines an index named Predicted Mean Vote (PMV) to measure the thermal comfort of certain conditions. The PMV has seven values: +3 hot, +2 warm, +1 slightly warm, 0 neutral, -1 slightly cool, -2 cool, -3 cold. The PMV of a (conditioned) area is the prediction of the mean value if people were to vote on thermal comfort in this room. Acceptable conditions are assumed to be in the -0.5 to +0.5 PMV range. Calculation of the PMV takes into account metabolic heat gain, body external work, skin heat loss, sweat heat loss, respiration heat loss, radiative heat loss and convective heat loss. These calculations use the parameters water partial pressure in the air, clothing surface temperature, isolation level and area, convective heat transfer coefficient and air speed. A normal distribution can be applied to the PMV to get the Percentage People Dissatisfied (PPD) index. In the PMV range -0.5 to +0.5, 5-10% of people are dissatisfied. 5% is the lower bound of PPD, as due to natural diversity of people a thermal condition that satisfies everyone does not exist. Fanger's model is quite complex and involves non-linear equations. Solving the full model for hundreds, perhaps thousands of time steps in a simulation would require a lot of computation power.

Morales-Valdés, Flores-Tlacuahuac, and Zavala (2014) state that the PMV (or other thermal comfort calculations) can be used in two ways: as a penalty or as a constraint. In the former method, deviation from the thermal comfort norm (e.g. PMV=0) results in a penalty on the objective function of the model. Alternatively, hard limits on thermal comfort (e.g. PMV = [-0.5,+0.5]) can be set. These limits may either not be violated at any point in time, or the average over a time period must fall within the bounds, which is more relaxed. Similar approaches can be taken using the PPD metric. Lastly, instead of the PMV and PPD metrics, the deviation from a given temperature set-point can be penalised. In the end, the three approaches boil down to the same constraint on thermal comfort, as the temperature bounds can always mapped from the corresponding PMV and PPD. The choice between penalisation and constraining does influence the resulting user comfort. Morales-Valdés, Flores-Tlacuahuac, and Zavala (ibid.) perform a numerical study using the different approaches to user comfort to analyse the corresponding energy consumption. They find that penalisation gives more flexibility in the control system, but results in very volatile user comfort. At some points, the percentage of people dissatisfied is much higher under penalisation than constraining with the same energy demand. This counts for PMV and PPD both. As the volatile comfort resulting from penalisation is highly undesired, constraining PMV or PPD has preference. Constraining PMV or PPD gives very similar results, however using PMV is preferred over PPD as PPD is non-linear. PMV is also the most common indoor thermal comfort assessment indicator according to Sung, Hsiao, and Shih (2019).

4.5.2 Thermal comfort range

With Fanger's model, thermal comfort ranges for offices can be computed for summer and winter conditions. The required input is air speed, relative humidity, metabolic rate and clothing level.

Metabolic rate is measured in met, one met is equivalent to 58.5 W/m^2 (Morales-Valdés, Flores-Tlacuahuac, and Zavala 2014). Metabolic rates of different activities have been defined, a few are given in Table 2. It is assumed office employees have a metabolic rate of 1.1 met, which corresponds with the activity typing. Employees are not always typing, and may often be reading (1 met), but there will always be a part of the employees that are presenting (1.2 met) or walking about (1.7 met), so an average of 1.1 met can be assumed.

Activity	Metabolic rate [met]
Sleeping	0.7
Sitting (quiet/reading)	1.0
Sitting (typing)	1.1
Standing (relaxed)	1.2
Walking about	1.7

Table 2: Metabolic rates of different activities.

Clothing insulation is measured in clo, one clo equals 0.155 K·m2/W (ibid.). Values for many pieces of clothing have been determined. Office employees tend to dress similar due to corporate dress codes. Summer and winter clothing ensembles are determined in Table 3. The ensembles are constructed based on male employees. Female employees usually dress more varied, but it is assumed they dress for the same weather conditions, resulting in the same total insulation values.

Clothing piece	Insulation value (clo)	Summer	Winter
Underwear	0.04	X	X
Calf-length socks	0.02	X	X
Shoes	0.02	X	
Shoes or boots	0.06		X
T-shirt	0.08	X	X
Long-sleeve dress shirt	0.25	X	
Long-sleeve thick sweater	0.34		X
Straight trousers (thin)	0.15	X	
Straight trousers (thick)	0.24		X
Standard office chair	0.10	X	X
Total insulation (clo):		0.66	0.88

Table 3: Office employee clothing ensembles for summer and winter. Source: Sung, Hsiao, and Shih (2019).

A normal **airspeed** in office buildings is 0.1 m/s (Fanger 1973). **Relative humidity** should be between 40-60% indoors, 50% will be assumed.

With the above assumptions, a comfort range complying with ASHRAE standard 55-2020 can be constructed for cold and hot days (Figures 19 and 20). For a humidity of 50%, the cold temperature range is between 21.2 and 25.0 degrees celsius. The hot temperature range is from 22.7 to 26.1, which corresponds with a summer temperature range given by the Dutch occupational safety and health guideline (Arbo 2018).
Most of the days, the cold-normal temperature range shall be applied. If the average daily temperature is above 18 C, the hot temperature range is applied. This approximately 90 days per year. The indoor comfort temperature is not equal to the air temperature, but also depends

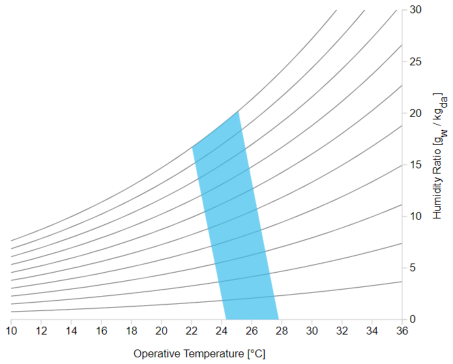

Figure 19: Summer comfort psychrometric chart. Made with tool by Tartarini et al. (2020).

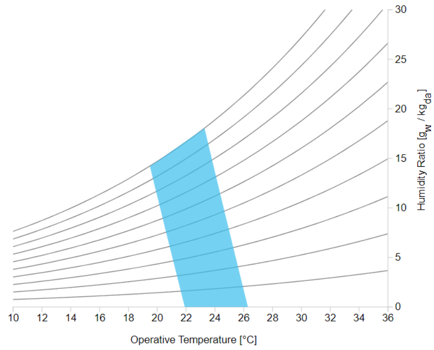

Figure 20: Winter comfort psychrometric chart. Made with tool by Tartarini et al. (2020).

on the temperatures of the walls, floors and ceilings, as they give of radiative heat. The comfort temperature is 50% air temperature and 50% surrounding walls and floor temperature. The contribution of the walls and floors is calculated in proportion with their surfaces.

5 Model implementation

5.1 Building model

The building model consists of the identified flexibility assets and a thermal model of the building geometry. The thermal model of the building is required to calculate the response of the building to changing the operation of the HVAC. This model is constructed with help from the BRCM toolbox.

5.1.1 Thermal model

The thermal model data can be found in Appendix A. Figure 21 shows the building geometry.

5.1.2 External Heat Flux Models

After the building construction has been set up, various BRCM modules are available to define External Heat Fluxes (EHFs). The **BuildingHull** model takes care of convective/conductive heat transfer through the external walls and windows as well as solar gains on the building. An **AHU** module is available to model the air handling unit, including options for an energy recovery wheel, evaporative cooling of return air and heating/cooling of supply air. For further heating/cooling needs, there are the **BEHeatfluxes** and **Radiators** models. BEHeatfluxes are building element heat fluxes, meaning a heat flux inside a building element such as a wall. With this model floor heating can be modelled. Lastly, there is an **InternalGains** model for gains due to occupants, lighting and appliances. In these modules, the data from the previous sections has been filled in, as well as the constraints discussed below.

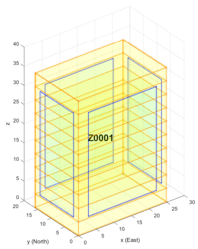

Figure 21: Modelled office building of 16x25x35 meters with 60% window surface.

5.2 Control and simulation

5.2.1 Variables and constraints

The building will be modelled as a discrete-time system:

$$x_{t+1} = A \cdot x_t + B_v \cdot v_t + B_u \cdot u_t + \sum_{i=1}^{n_u} (B_{vu,i} \cdot v_t + B_{xu,i} \cdot x_t) \cdot u_t \tag{11}$$

where

x_{t+1} = Temperatures of building elements at next time step
x_t = Temperatures of building elements at time t
v_t = Disturbances at time t
u_t = Control input at time t
n_u = Number of control inputs

Matrices $A, B_v, B_u, B_{vu,i}$ and $B_{xu,i}$ are generated by the BRCM toolbox. The first term describes the heat exchange between the building elements (the indoor air is also part of this vector), the second the heat gains/losses due to exogenous variables, the third the heat fluxes due to the control input. The fourth term describes the heat fluxes due to air moving in-/outside the building, due to natural infiltration or the AHU. This term introduces a mild non-linearity in the system. As this would cause a large increase in computation time for the MPC optimization, it can be circumvented by replacing the x_t component in that term with an estimation of x. The estimation of x will be based on the previous time step and is typically very close to the final x.

In the case of EVs and laptops, x is the state of charge of the battery and there are no disturbances.

$$x_{t+1} = A \cdot x_t + B \cdot u_t \tag{12}$$

For EVs, no discharge is assumed over the 8 hours period they are at the office, so $A = 0$. Laptops will discharge as they are actively used.

A breakdown of the variables is given in Table 4. Constraints are also given. The laptop and EV maximum capacities and charging power are calculated based on 400 employees. The state of charge of laptop batteries must always be above 20%. Laptops and phones often start giving warnings about the low battery state when the SoC falls beneath 20%. Office employees would likely be uncomfortable with their laptop charge going beneath 20% without the recharging starting. In the case of EVs, the available capacity is only a small part of the full battery capacity (see section 4.1.1), so the full range can be used. The HVAC constraints were taken from an example office provided by Sweco and scaled up. The heating capacities were set higher than the example because while testing the model, they were insufficient for maintaining the thermal comfort. The blinds setting ranges from a gain of 0.2 to 1.0, meaning 80% to 0% of the incoming irradiation is blocked.

Variable	Description	Constraint
x system state		
T_i	temperature of each building element i	comfort range
SoC_{Laptop}	state of charge of laptops [kWh]	$3.2 <$ & < 16.2
SoC_{EV}	state of charge of EVs [kWh]	< 456
u control input		
$P_{TABS,heat}$	Heating power of the floor heating system [W/m2]	< 43
$P_{TABS,cool}$	Cooling power of the floor heating system [W/m2]	< 31
$P_{AHU,heat}$	Heating power of the AHU [W]	< 62.866
$P_{AHU,cool}$	Cooling power of the AHU [W]	< 78.582
$\dot{m}_{AHU}$	Mass flow rate of air through AHU [kg/s]	$= 12.28$
$U_{blinds,i}$	Blinds setting on each building side N, E, S, W	$0.2 <$ & < 1
P_{Laptop}	rate of charging of laptops [kW]	< 13.0
P_{EV}	rate of charging of EVs [kW]	< 182.4
v disturbances		
T_{amb}	ambient temperature [C]	–
T_{soil}	soil temperature [C]	–
P_{IG}	Internal gains [W/m2]	–
$P_{sol,i}$	Solar irradiation on each building surface i [W/m2]	–

Table 4: List of all variables in the building model.

Additionally, non-negativity constraints are active for all variables. Weather data were taken from the KNMI. The internal heat production is 180 W for each employee; 100 W for ICT such as laptops, beamers, servers and coffee machines and lighting, 80 W of metabolic heat production (VABI 2023). At night, there is 5 W per person active still.

5.3 Basic rule-based

The basic rule-based algorithm tries to keep the indoor comfort temperature at 22 ℃, or 23 ℃on hot days. In the weekends and at night, the HVAC is mostly off but keeps the temperature within 22 ℃± 5 ℃. The algorithm starts preheating/cooling the building from 6:00 am, and on especially cold days at 4:00 am. EVs and laptops start charging from 9:00 am until full. The fixed temperature setpoints are chosen because this is the reference scenario, and most office buildings operate on set points instead of Fanger's ranges.

5.4 Smart rule-based

The smart rule-based algorithm keeps the temperature in the comfort range. Within the range, the heating/cooling is maximized in a low pricing regime, turned off in a high pricing regime, and set to 40% power in a medium pricing regime. The EVs and laptops are similarly maximally charged, not charged and charged at approximately 15%.

5.5 MPC

The MPC optimizes the control input through solving a linear program. Constraints are set to ensure the system state gets updated correctly, the temperatures stay within the comfort lower and upper bound, and the input stays within the constraints. The objective is to minimise the costs, which is the product of the energy consumption and the electricity price. Initially, the DA market is used, so one day is optimized each time. Withing that day, a rolling window is used of 12 hours. At 12 am, the control input is optimized until 12 pm, and so forth. This speeds up the computation time considerably. It takes approximately 3 seconds to run one day, and 15-20 minutes to run one year. The resolution of the model is 15 minutes. The EV and laptop charging are also optimized by using simple battery models.

For weather and electricity prices, 2019 was used for the standard office model. This is regarded as a normal year, before COVID-19 and before the current energy crisis, and will therefore serve as the baseline.

6 Results

In this section, results of the base case as described in the previous sections are presented and verified against TNO data. After the initial results, various scenarios will be tested and their effect on the economic potential is investigated.

6.1 Base case results

Firstly, the initial results will be discussed and the three algorithms compared. To study the behaviour of the three algorithms, the control of the three assets is plotted in the figures below for 1 day (3rd of January 2019).

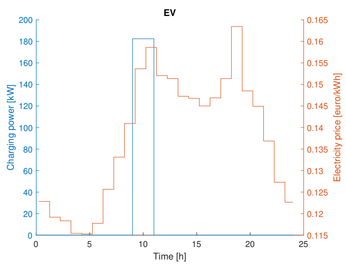

Figure 22: Basic RB

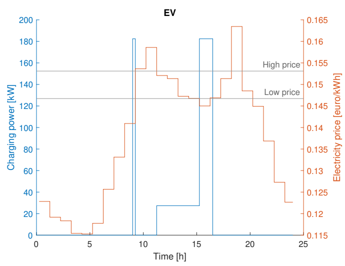

Figure 23: Smart RB

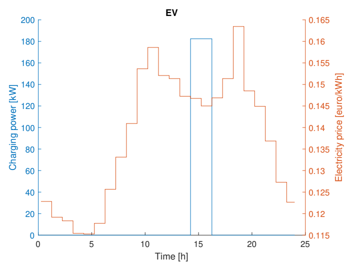

Figure 24: MPC

The basic rule-based control strategy charges the EVs right away, between 9 and 11 at a fairly high price. The smart rule-based strategy charges maximally when the price is below the low price line, at 15% when the price is medium and zero when the price is at its highest. The MPC charges only at the lowest price points.

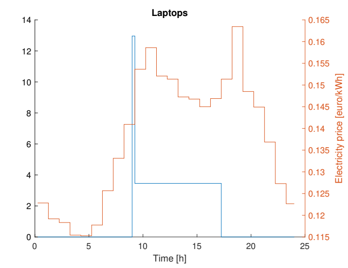

Figure 25: Basic RB

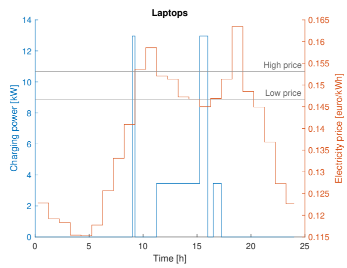

Figure 26: Smart RB

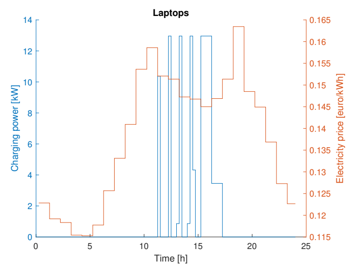

Figure 27: MPC

The basic RB strategy again charges right away, and then continues charging at the laptop discharge rate. The smart RB strategy is also similar to the EV result. The MPC shows more on/off charging behaviour. It lets the laptops drain to a lower battery level and then charges maximally.

hTABS is the underfloor heating, hAHU the air handling unit heating

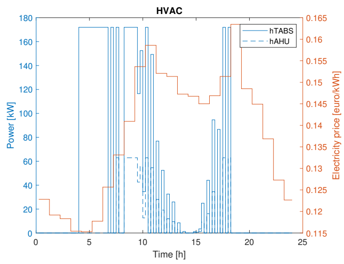

Figure 28: Basic RB

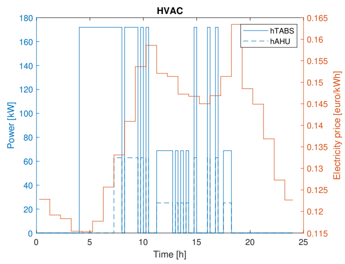

Figure 29: Smart RB

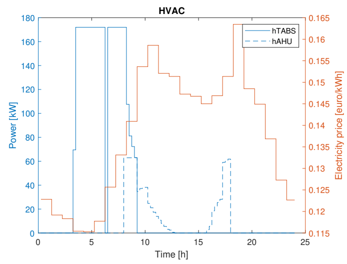

Figure 30: MPC

The basic RB pre-warms during the early morning and then turns the heating on/off as necessary. It results in quite some heating power being supplied in higher price periods, i.e. between 9:30 and 11:00 and 17:00 to 19:00. The smart RB has a peak in the lowest price point, but also needs to heat in the morning during the high price to get the building to the comfort level. The MPC is clearly the winner by using the underfloor heating maximally at the start of the day to pre-heat the building, and then only heats up the incoming air the rest of the day. On this day, the basic RB HVAC uses 1,210 kWh, the smart RB HVAC 1,424 kWh and the MPC 990 kWh.

In Tables 5, 6 and 7, the results are seen for running the simulation for an entire year.

EV	Basic RB	Smart RB	MPC
Consumption [kWh]	94850	94850	94850
Bill [euros]	11270	10480	10390
Mean price [euro/kWh]	0.119	0.111	0.110
DR savings [euro]	-	790	880
ESFI	-	7.0%	7.8%
Sflex	-	0.91	0.96

Table 5: Comparison of annual electricity consumption between the three control algorithms for EV control

The smart RB and MPC are both able to reduce the charging costs for EVs. They perform quite equally, meaning planning the charging based on low and high price regimes is almost as good as optimization. With S_{flex} being close to 1, almost all energy is shifted. Despite almost all charging power being shifted to the lowest price points, the reduction in costs is quite minimal. It is likely the 2019 DA prices are not variable enough to profit much from. This is partly due to the electricity price consisting for ~50% of the DA price and ~50% of fixed taxes. The variable cost component is then only 0.05 euro/kWh.

Laptops	Basic RB	Smart RB	MPC
Consumption [kWh]	7860	7860	7860
Bill [euros]	900	880	880
Mean price [euro/kWh]	0.115	0.112	0.111
DR savings [euro]	-	20	20
ESFI	-	2.2%	2.2%
Sflex	-	0.26	0.54

Table 6: Comparison of annual electricity consumption between the three control algorithms for laptop control

The cost reduction for laptops is minimal.

HVAC	Basic RB	Smart RB	MPC
Consumption [kWh]	59720	47600	43250
Bill [euros]	7120	5700	5040
Mean price [euro/kWh]	0.119	0.120	0.117
corrected DR savings [euro]	-	-28	114
corrected ESFI	-	-0.4%	1.6%
Sflex	-	0.46	0.69

Table 7: Comparison of annual electricity consumption between the three control algorithms for HVAC control

The HVAC consists of the AHU heating and cooling, and the underfloor heating and cooling. The MPC is much more efficient than the rule-based strategy in terms of electricity consumption. This energy saving effect, although nice, is not the primary interest. To calculate the DR savings and ESFI of DR, the electricity bills are corrected to eliminate the energy saving effect. The MPC bill without DR but with energy savings would be the MPC consumption times the basic RB mean price. Comparing this with the actual bill gives the corrected DR savings. The example is worked out below.

$$correctedDRsavings = (43250 \cdot 0.119) - 5040 = 5154 - 5040 = 114[euro] \tag{13}$$

The smart RB performs worse than the basic RB, though the difference is small. It could be that there are not enough low price periods to take advantage of. The MPC shows some savings, but the amount is almost negligible. The reason is probably the same as with the EVs. Additionally, the HVAC has strict comfort constraints which the EV does not suffer from, reducing the profits even more.

6.2 Verification

Dutch research organisation TNO studied the gas and electricity usage of office buildings in the Netherlands using 2019 data (Sipma 2022). The average gas consumption split over energy labels is given in 31. These numbers can be compared with the thermal energy supplied to the modelled office to verify the energy consumption of the heating installations.
The modelled office building is well-insulated, fairly new and all-electric, placing it probably in one of the best energy label categories. Reading Figure 31, the average expected gas consumption should be 60 kWh/m^2/year. With a boiler efficiency of 90%, this gives 54 kWh/m^2/year thermal

energy supplied to the building. The thermal energy supplied to/extracted from the building in the model is presented in Table 8.

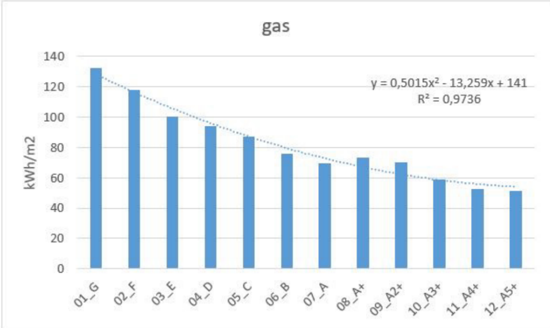

Figure 31: Average annual gas consumption of Dutch office buildings, split over energy labels. Source: Sipma 2022

	Basic rule-based fixed setpoint	Smart rule-based	MPC	Basic rule-based temperature range
	Thermal E[kWh/m2]	Thermal E [kWh/m2]	Thermal E [kWh/m2]	Thermal E [kWh/m2]
Total	60.7	44.0	38.1	41.4
Heating	35.2	35.0	35.9	34.6
Cooling	25.4	9.1	2.2	6.8

Table 8: Annual thermal energy supplied to modelled building in all algorithms, normalized by building area.

Ideally, the thermal heating energy required in the basic rule-based scenario should be similar to the TNO data. Since the former is 35.2 kWh/m^2 and the latter 54 kWh/m^2, they are not very close but also not wildly different. The difference can be explained by multiple factors:

- TNO works with the so-called 'usable surface' in its analysis. This is the total surface minus the surface occupied by walls, stairwells, elevators and vides. Many offices also have a large entrance hall or canteen where floor space is missing.
- The TNO database is dominated by small offices. Only 30% of the analysed offices are >1000m^2. The report does provide a further breakdown of gas intensity between office sizes, with the >1000m^2 category having an average gas intensity closer to 50 kWh/m^2/year, so 45 kWh/m^2/year thermal power supplied. According to the analysis in subsection 4.2, this is a very large category, so the actual number may still vary considerably within this size category.
- Offices are all different and for example employee behaviour and control strategy can have a large impact on the energy consumption. The TNO study also reports a factor 4 difference in total energy consumption between the 10% lowest and 10% highest energy consuming offices.

If the 'usable surface' is actually 80% of the total surface, the modelled building consumes 44.0 kWh/m^2 of heating energy. Comparing that with the 45 kWh/m^2/year for larger buildings, the modelled result is very close to the observed data. The smart rule-based and MPC algorithms use a similar amount of heating energy over the year. The small differences can be explained by two mechanisms. The smart RB and the MPC should use *less* energy than the basic RB because they use a different comfort setting. The smart RB and MPC have a lower comfort bound of 21.2 ℃on cold-normal days while the basic RB tries to keep the temperature at 22 ℃±0.4. On the other hand, the smart RB and MPC can overheat the building at times, which consumes *more* energy but could result in lower costs if it is done in low-price periods. In the smart RB algorithm, the first mechanism seems to dominate while in the MPC, the second likely causes the extra energy consumption.

The cooling is harder to verify as it is lumped into a number for total electricity use in the TNO data study. Looking at Table 8, the differences in cooling energy are striking (the physically correct term is extracted heat instead of cooling energy, but for readability 'cooling energy' will be used). The basic RB uses 2.8 and 11.4 times more cooling energy than smart RB and MPC respectively. The difference is largely explained by the different comfort setting. This is seen in the last column, which are the results from running the basic rule-based control with the temperature range from the flexible control strategies instead of the fixed setpoint. Here, the maximum indoor temperature can be as high as 26.1 ℃instead of 23 ℃±0.4, which lowers the cooling energy required from 25.4 kWh/m^2 to 6.8 kWh/m^2. The smart RB uses more cooling energy, likely due to overcooling in low-price periods. The MPC uses very little cooling energy. This is likely due to two advantages the MPC has: its 12-hour ahead optimisation means the algorithm knows far ahead when it's going to be a warm and sunny day and can cool the building cheaply at night by letting outside air in. The rule-based algorithms also use this pre-cooling strategy, but only up until their setpoint/comfort bound. The MPC can intelligently cool down the building below the lower comfort bound and let the early morning sunshine heat up the building again up to the lower comfort bound, so the resulting temperature at e.g 9.00 am is lower than in the rule-based strategies. Furthermore, in the rule-based strategies the blinds are closed if the solar irradiation is higher than 200 W/m^2 and open otherwise. In the MPC strategy, the blinds are also closed if the solar irradiation is higher than 200 W/m^2, but otherwise the MPC can decided whether the blinds should be open or closed. On hot, sunny days, the MPC can therefore keep the blinds down the whole day to reduce the solar heat coming in.

The HVAC electricity consumption in Table 7 stems from dividing the thermal energy consumption in Table 8 by the COP of the heat pump, which is different at every time step dependant on the outdoor temperature and heating/cooling mode. Over an entire year, the seasonal COP (SCOP) and seasonal energy efficiency ratio (SEER) can be calculated, which are the average COPs for respectively heating and cooling mode. The SCOPs and SEERs of the three control strategies are as follows:

Control strategy	SCOP [-]	SEER [-]
Basic rule-based	3.5	5.3
Smart rule-based	3.5	4.7
MPC	3.5	4.7

Table 9: SCOP and SEER of each control strategy

The SCOP should be approximately 3.1 (Nederlands Normalisatie Instituut 2022) and the SEER typically ranges between 4 and 6 (Energy Star 2023). The model's COP and SEER appear to be within the right range. Although the COP is slightly higher than the standard value suggested by the Nederlands Normalisatie Instituut, it should be noted that there is variability in heat pumps.

6.3 Scenarios

To study the future profitability of the modelled office building, various scenarios will be simulated in which variations in parameters will be made and their impact on the economic potential of demand response investigated. The first scenarios will deal with the endogenous variables, followed by the exogenous variables.

6.3.1 Higher capacity - Endogenous

The poor profitability of HVAC DR could be due to the HVAC installed capacity being too low. If the capacity is low there is less room for flexibility, as the assests will often need to operate at maximum capacity to retain indoor comfort, irregardless of the current electricity price. Changing the floor heating capacity from 43 W/m^2 to 50 W/m^2 and the AHU heating capacity from 62,866 W to 72,296 W, the results are as in Table 10. The cooling capacity is not changed as the MPC uses little of it. The smart RB is left out as the DR savings were negative in the base case. The DR savings are slightly increased and the total consumption

HVAC	Basic RB (std W)	MPC (std W)	MPC (high W)
Consumption [kWh]	59720	43250	42660
Bill [euros]	7120	5040	4960
Mean price [euro/kWh]	0.119	0.117	0.116
corrected DR savings	-	113.7	123.4
corrected ESFI	-	1.6%	1.7%
Sflex	-	0.69	0.70

Table 10: Comparison of annual electricity consumption between standard capacity basic RB and MPC, and increased capacity MPC.

slightly decreased, but the change in capacity does not seem to have a large effect. The current dimensioning ensures thermal comfort can be maintained on each day in the year, but the capacity is quite tight. Dimensioning for the worst day of the year, however, means that on most other days the system is already overdimensioned. A further increase in capacity does not appear to enhance the results.

6.3.2 Insulation - Endogenous

The modelled office is a modern office complying with years 2015-2020 insulation standard. Changing that to the 1992-2013 standard, the results are as in Table 11. The heating power of the underfloor heating was slightly increased, to 45 W/m^2 to be able to maintain thermal comfort. The electricity consumption is considerably higher in all control strategies. The ESFI has not changed much from Table 7.

6.3.3 The future EV fleet - Endogenous

In the current model, EV capacity was based on 2019 data. However, by 2030 all newly sold cars in the Netherlands must be electric. By 2040 or 2050, perhaps all cars are electric. Changing share of EVs in the employee car fleet from 19% to 80%, the results are as follows:

HVAC (R=2.5)	Basic RB	Smart RB	MPC
Consumption [kWh]	72810	60130	57380
Bill [euros]	8700	7240	6700
Mean price [euro/kWh]	0.119	0.120	0.117
corrected DR savings	-	-57.5	154
corrected ESFI	-	-0.7%	1.8%

Table 11: Comparison of annual electricity consumption between the three algorithms with low insulation.

EV	Basic RB	Smart RB	MPC
Consumption [kWh]	399360	94850	94850
Bill [euros]	47470	44140	43796
Mean price [euro/kWh]	0.119	0.111	0.110
DR savings [euro]	-	3330	3674
ESFI	-	7.0%	7.8%

Table 12: Comparison of annual electricity consumption between the three control algorithms for EVs, with higher EV penetration.

6.3.4 Simulation year - Exogenous

The 2019 electricity prices are relatively low and consistent. In a more volatile market, the profits from demand response may be higher. The results for HVAC and EV are seen in the tables below. Laptops have been left out due to the small capacity. The weather in 2022 was hotter in summer and colder in winter compared to 2019, leading to an increase in electricity consumption. The results have improved significantly with the 2022 electricity prices. The

HVAC (2022)	Basic RB	Smart RB	MPC
Consumption [kWh]	63320	47530	45510
Bill [euros]	23070	16600	14550
Mean price [euro/kWh]	0.364	0.349	0.320
corrected DR savings	-	715	2029
corrected ESFI	-	3.1%	8.8%

Table 13: Comparison of annual electricity consumption of the HVAC between the three algorithms with 2022 electricity prices

DR savings are higher due to a 3x higher electricity price, but the ESFI is also higher, showing flexible operation has saved costs.

6.3.5 aFRR market - Exogenous

As described in 4.3, an office could also participate in the aFRR market. Participating in the aFRR market would be rather complicated to do rule-based, so only the MPC is considered here. To optimize on the aFRR market, blocks of 1 hour are considered. The aFRR optimization is done after the DA planning has been determined. Within a 1 hour block, the total electricity consumption must be the same as to not deviate from the DA planning. For the HVAC, the AHU heating and cooling may not deviate more than 20 kW to prevent large swings in thermal

EV (2022)	Basic RB	Smart RB	MPC
Consumption [kWh]	94850	94850	94850
Bill [euros]	33380	26790	25890
Mean price [euro/kWh]	0.352	0.282	0.273
DR savings	-	6590	7490
ESFI	-	19.7%	22.4%

Table 14: Comparison of annual electricity consumption of the EVs between the three algorithms with 2022 electricity prices

comfort. The results are seen below, for 2019 and 2022. The first thing that is noticed is

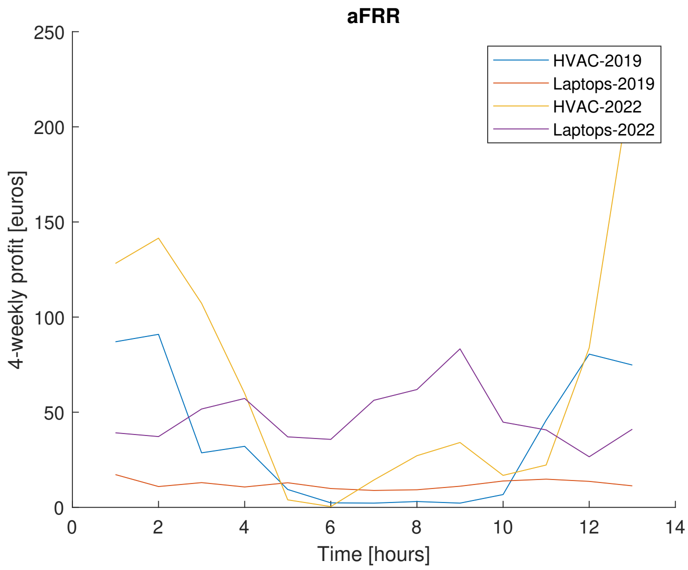

Figure 32: 4-weekly profits from the aFRR market for HVAC and laptops in 2019 and 2022.

	HVAC	Laptops
2019	466	158
2022	867	613

Table 15: Annual aFRR profits

that the EV is missing. Coincidentally, the charging power of the EVs and the EV capacity have a ratio where the EVs are charged in exactly two hours at maximum power. In the case of MPC, the EV charging power is therefore always 0 or maximum in a 1 hour block. Due to the energy conservation constraints, there is no room to react to the aFRR market. The HVAC and laptops have a more spread consumption profile, allowing for aFRR services. The results are quite positive. The 2019 aFRR profits are much higher than the 2019 DA profits but although the 2022 aFRR profits are higher still, they are much lower than the 2022 profits on the DA market.

Figure 32 shows the profits through the year. Evidently, the HVAC cannot provide much balancing service during the summer months when the electricity consumption is lower. The laptops have the advantage of being able to operate on the aFRR market all year long, resulting in high profits relative to the laptop aggregated battery size.

6.4 Costs

The costs adapting a building to be able to provide DR can vary greatly depending on the metering that is already present. As mentioned in the introduction, Dutch offices are required to measure their HVAC consumption and perform other energy-saving measures by 2023. This might mean the investment costs for DR-readiness are low for Dutch office buildings, but it depends on the building. RVO (2023) provide a database of costs of taking energy-saving measures. For example, it costs 6,000 euros to install an automatic pump control for a heat pump. To install a weather-dependant temperature control, 1,200 euro need to be paid, based on a 2,500 m^2 building. Besides hardware costs, software developers and/or building maintenance engineers would need to be paid for an improved rule-based control system or a model of the office to perform MPC. The costs for HVAC DR may be quite high, but with an annual profit of 2000 euros (in 2022), it could be earned back. EV and laptop DR have much lower investment costs. There is no hardware change required, only a software change needs to be made. With the high profits from EV in the DA market and laptops in the aFRR market, the payback times should be fairly short.

7 Conclusion

The first research question has been answered in the section 4.1 and the results. HVAC, EVs and laptops were initially identified as possible providers of demand response. From the results, it can be concluded that the laptop capacity is too small to make a meaningful difference on the DA market, but on the aFRR market performs quite well. The EV on the other hand is the most profitable asset in the DA market, but does not perform well in the aFRR market due to the DA optimization resulting in strong on/off behaviour. The HVAC MPC control saves 114 euros in year 2019 and 2029 euros in year 2022, which is a decent result but the investment costs could be high.

The second research questions concerns the control strategies. From the results, it can be seen that the HVAC is hard to optimize with a rule-based strategy. To perform HVAC DR, MPC is required. For laptops and EVs, the rule-based strategy is almost as good as the model optimization. Either could be implemented, the MPC is not much more complex than the rule-based algorithm. To participate in the aFRR market, it is recommended to use an optimization algorithm. Another thing that should be mentioned is the energy-saving capability of the MPC. For the HVAC, the profits due to saving energy far outweigh the profits from demand response.

Research question three asks what the current profitability is. The base case DR profitability is quite poor. The annual profit is around 1000 euros. The size of the building should be taken into account here; the office is 40,000 m^2 with 400 employees. The turnover of the business(es) housed in this office building is much higher. It is questionable if 1000 euros is worth the hassle of implementing DR.

The next research question is about whether changes made to the base case can improve the economic potential. From the results, it appears that a higher HVAC capacity or a lower insulation level do not affect the results much. This is positive, as it means older buildings or those with lower capacities can also provide DR. Changing the amount of EVs present at the office has a large impact on EV DR savings.

The fifth and last research question deals with future profitability. No future electricity prices have been tested, as constructing these prices would require considerable literature reviewing. Very recent prices (2022) have been tested though. 2022 was a year with high prices due to an energy crisis, no one knows the future but future electricity prices could very well be akin to 2022 prices. With the energy transition in sight, it is at least unlikely 2019 prices will become the norm again. The changes in electricity prices have a high impact on economic potential. The HVAC DR savings increase almost twentifold, and the EVs nearly tenfold. The total is around 10,000 euros per year. The aFRR market returns a 600 euro profit in 2019 and 1500 in 2022. This shows that DR profits are highly dependent on the electricity market, and that the profits going forward will likely be quite positive. However, it should still be placed into perspective with the size of the building. If each employee earns 40,000 euros per year, 10,000 euros is not much compared to the labour costs alone: 16 million.

To conclude, economic potential highly depends on the electricity market and while the payback time of investments seems positive, especially for EVs and laptops, the profits may not be very significant compared to an office turnover. Moreover, the EVs seem the best candidate for DR. The profits are the highest and the investment relatively low. Especially with the rising EV penetration, this will likely become even more profitable in the future. HVAC DR is also promising, but the building control is quite complex. It is recommended to focus on energy-saving measures to reduce HVAC consumption, as this has a larger impact than DR. Laptops unsurprisingly do not turn high profits in the DA market. They do, surprisingly, perform well in the aFRR market. It remains the question whether office employees find it worth it to give the charging of their belongings out of hand though.

8 Discussion

"All models are wrong, but some are useful". Any model that tries to approximate such a large system as an office building can be improved. For example, user behaviour can have a large impact on building operation. If employees open windows, carefully constructed heat exchange equations can be blown away. The BRCM toolbox is also not perfect. As mentioned before, for example conductive heat transfers between floor and walls are not considered. Furthermore, perfect prediction of the weather and occupancy is assumed, which is a large advantage for the MPC, as seen in the results of the cooling. Fanger's method is, while still in use, quite old. Vellei and Le Dréau (2019) for example propose an extended Fanger's model taking the rate of change of comfort into account.

There are some factors the model is sensitive to, the first one being the COP. The COP determines the electricity consumption from the thermal input. If the SCOP is 3 instead of 3.5, the entire HVAC consumes 15% more energy. Furthermore, the percentage of window surface in the walls influences the HVAC behaviour considerably. Larger windows mean more heat loss in winter, but also more solar heat gain. In summer the HVAC will need to work harder, in winter it depends on the daily solar power. The EV results highly depend on the assumed EV capacity. The EV capacity calculation rests on many factors: the average distance driven per day, the share of employees coming to work by car, the share of cars that are electric and the amount of office days of employees. Changes in these parameters can quickly double or triple the EV DR savings.

One limitation was seen in the results: the EVs could not perform balancing services. To enable this opportunity, the DA optimization may have to be adjusted to prevent maximum charging, or there needs to be one optimization algorithm that optimizes profits on both markets at the same time. A number of other changes are also of interest to future research: thermal storage was not implemented due to modelling complexity, but may improve the MPC business case. Furthermore, it would be interesting to investigate the potential of varying the refresh rate. Being able to flexibly refresh the air could also help maintain indoor comfort as efficiently as possible.

More scenarios could be investigated, but one should be careful with making the distinction between energy-saving and DR. For example, the user comfort bounds could be lowered, but this would likely mainly lead to an energy use reduction instead of more flexibility, as the MPC already does not use the temperature range too much. Another interesting option would be installing solar panels. It is also the question however whether this would increase the demand response or simply lower the energy consumption.

Further research could also focus on other control strategies. Besides MPC, machine learning and multi-agent systems are gaining in popularity.

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A Thermal model data

THERMAL MODEL DATA of Building 'SmallOffice'

ZONE DATA (1 zone/s)

identifier	description	area	volume	group
Z0001	Thermal Zone 1	4000	13600	

BUILDING ELEMENT DATA (15 building element/s)

identifier	description	construction_identifier	adjacent_A	adjacent_B	window_identifier	area
B0001	North wall	C0002	AMB	Z0001	W0001	560
B0002	Ground floor	C0005	GND	Z0001		400
B0003	East wall	C0002	AMB	Z0001	W0002	875
B0004	South wall	C0002	AMB	Z0001	W0003	560
B0005	West wall	C0002	AMB	Z0001	W0004	875
B0006	Roof	C0001	AMB	Z0001		400
B0008	Interior floor	C0003	Z0001	Z0001		400
B0009	Interior floor	C0003	Z0001	Z0001		400
B0010	Interior floor	C0003	Z0001	Z0001		400
B0011	Interior floor	C0003	Z0001	Z0001		400
B0012	Interior floor	C0003	Z0001	Z0001		400
B0013	Interior floor	C0003	Z0001	Z0001		400
B0014	Interior floor	C0003	Z0001	Z0001		400
B0015	Interior floor	C0003	Z0001	Z0001		400
B0016	Interior floor	C0003	Z0001	Z0001		400

CONSTRUCTION DATA (4 construction/s)

identifier	description	material_identifiers	thickness	conv_coeff_adjacent_A	conv_coeff_adjacent_B
C0001	Roof	M1111,M2222,M1111	0.05,0.067,0.05	convCoeff_RoofExt	convCoeff_CeilingInt
C0002	Exterior Wall	M1111,M2222,M1111	0.1,0.05,0.1	convCoeff_WallExt	convCoeff_WallInt
C0003	Interior Floor	M1111,M1111	0.1,0.04	convCoeff_FloorInt	convCoeff_FloorInt
C0005	Slab	M1111,M2222,M1111	0.1,0.039,0.04	convCoeff_CeilingGND	convCoeff_FloorInt

MATERIAL DATA (2 material/s)

identifier	description	specific_heat_capacity	specific_thermal_resistance	density	R_value
M1111	100mm brick/concrete wall	850	1	2000	
M2222	insulation	800	90	50	

WINDOW DATA (4 window/s)

identifier	description	glass_area	frame_area	U_value	SHGC
W0001	North window	336	0	UValue_Window	GValue_Window
W0002	East window	525	0	UValue_Window	GValue_Window
W0003	South window	336	0	UValue_Window	GValue_Window
W0004	West window	525	0	UValue_Window	GValue_Window

PARAMETER DATA (7 parameter/s)

identifier	description	value
convCoeff_CeilingInt	Convective coefficient of ceiling to zone (default, considering thermal radiation)	8
convCoeff_FloorInt	Convective coefficient of floor to zone (default, considering thermal radiation)	5
convCoeff_RoofExt	Convective coefficient of a surface to ambient air (default)	30
convCoeff_WallExt	Convective coefficient of a surface to ambient air (default)	30
convCoeff_WallInt	Convective coefficient of wall to zone (default, considering thermal radiation)	7
GValue_Window	GValue of Window with EP ConstructionExteriorWindow (default value)	0.6
UValue_Window	UValue of Window with EP ConstructionExteriorWindow (default value)	1.6