Comparison of smart control strategies for heat pumps

Quantification of the potential of various smart control strategies for heat pumps to mitigate grid congestion, and comparison of the barriers to their implementation

Author: Ilian de Redelijkheid

Supervisors: Prof. Dr. Wilfried van Sark and Nico Brinkel, Copernicus Institute

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Abstract

As a side effect of the energy transition, the Netherlands experiences severe grid congestion. This can be mitigated by distributing the load on the grid more evenly over time. Heat pumps are a major contributor to the grid load. Different smart control strategies have been developed for load shifting of heat pumps. The aim of this project was to quantify the grid congestion mitigation potential of heat pumps in the Netherlands for different smart control strategies, and to identify the barriers to the implementation of each smart control strategy. This was achieved by comparing a set of promising smart control strategies in a simulation of a typical Dutch neighborhood. Different scenarios were used to determine the effectiveness of each strategy in situations with more or less heat pumps, varying insulation levels for the houses, and a range of smart control adoption rates. Seven control strategies were compared, with varying complexity. The results of the simulations show that the constant heating strategy and model predictive strategy with day-ahead pricing have the best grid congestion mitigation potential in scenarios with a high heat pump adoption rate. The constant heating strategy however results in an increase in electricity usage and costs for the heat pump of up to 13%. The model predictive strategy with day-ahead pricing resulted in a decrease instead for the electricity and costs of 15-20%, but is much more complex to implement in practice. In the scenarios with lower heat pump adoption rates the model predictive strategy with "optimal" pricing performed the best, with a reduction in peak loads and costs of up to 30%.

Contents

Nomenclature

Indices:

- b: building.
- $cooling$: the threshold at which cooling is assumed for the inside environment.
- f: floor.
- $glass$: the glass components, mainly windows.
- hg: the internal heat gains from occupants and devices.
- i: "inside", the space to be heated.
- o: "outside", e.g. the outside air temperature.
- r: roof.
- s: solar.
- $water$: concerning the water used in the heating system.
- we: external walls.
- wi: internal walls.

Symbols:

- A_x is the area of building element x, in m^2.
- ACR is the air change rate due to infiltration and ventilation, in h^{-1}.
- cc is the cloud cover ratio (no unit).
- COP is the coefficient of performance of the heat pump (no unit).
- COP_x is the coefficient of performance of the heat pump of type x (no unit).
- C_{hs} is the charge of the heating system (radiator or floor heating) in kJ.
- $\Delta T_{calibrated}$ is the effect on the inside temperature of adding 1 kW of heat to the space heating system.
- ϵ is the absorptivity of the surfaces of the building elements (no unit).
- GSF is the glazing solar factor (no unit).
- HP_{power} is the electrical capacity of the heat pump, in kW.
- HP_{state} is the on/off state of the heat pump, ranging from 0-1 or 0%-100%.
- $HP_{state,new}$ is the new HP state required to reach the new set-point in one time step.
- $HP_{state,old}$ is the HP activation level in the previous time step (ranging from 0 or off, to 1 or on full power).
- I_{hs} is the inertia of the heating system, or the time it takes to fully heat up or cool down, in minutes.
- $M_{th,x}$ is the thermal mass of building element x, in kJ/°K.
- $Q_{c,x}$ is the total conductive heat flow towards building element x, in kW..
- $Q_{c,x,y}$ is the total conductive heat flow from building element x towards building element y, in kW.
- Q_{hg} is the internal heat gains from devices and people, in kW.
- Q_{HP} is the thermal power provided by the heat pump, in kW.
- Q_{hs} is the heat flow to the inside air provided by the heating system, in kW.
- $Q_{i,x}$ is the total infiltration and ventilation heat flow towards building element x, in kW.
- $Q_{r_{diff},x}$ is the diffuse solar radiation absorbed by building element x, in kW.
- $Q_{r_{dir},x}$ is the direct solar radiation absorbed by building element x, in kW.
- $Q_{tot,x}$ is the total heat flow towards building element x, in kW.

- r_{bb} is the black body radiation, in kW.
- r_{diff} is the diffuse solar radiation, in kW.
- r_{dir} is the direct solar radiation, in kW.
- $Rc_{x,y}$ is the thermal resistance between building elements x and y, in K/W.
- $\Delta T_{expected}$ is the expected increase of the inside temperature due to the heating system only, in $°K$.
- ΔT_{real} is the real change in inside temperature.
- $T_{cooling}$ is the inside temperature at which cooling is assumed. This is set as the limit for the inside air temperature (in°K).
- $T_{correction}$ is the difference between the expected temperature change and the actual temperature change (in°K).
- $T_{set-point}$ is the new set-point (in°K).
- T_x is the temperature of building element x, in°K.
- $T_{x,new}$ is the new temperature of building element x, in°K.
- $T_{x,new}$ is the temperature of building element x in the previous time step, in°K.
- γ is the azimuth angle, in degrees.
- θ is the zenith angle, in degrees.

1 Introduction

In 2015, the Netherlands signed the Paris agreement, together with 195 other countries [1]. Since then, these countries set new national climate goals to reduce the emission of anthropogenic greenhouse gases. In order to reach these goals, the adoption of renewable energy technologies was stimulated. A shift took place away from fossil fuels, towards renewable electricity. In the Netherlands, the renewable electricity production mainly consists of photovoltaics (PV) and wind farms. The capacity of PV was already significant when the Paris agreement was signed, and it is still increasing. The country installed 4.1 GW in 2022, accelerating its upward trajectory from the 3.6 GW installed in 2021 and 3.5 GW in 2020 [2]. The growth in the residential sector played a significant role, contributing 1.8 GW or 46% of capacity additions, thanks to the net-metering policy that has been consistently in place [2]. Wind energy has also grown significantly as a source of renewable electricity [3]. Capacity of onshore wind parks has been steadily increasing since the early 2000s. Since 2015, significant offshore wind capacity was added, and the growth of onshore capacity increased [3]. In 2022 renewable electricity generation amounted to 36.6% of the total generation in the Netherlands [4].

Additionally, a shift is happening on the demand side as well, aided by substantial subsidies from the Dutch government [5], [6]. In the transport sector, the share of electric vehicles has been increasing steadily in recent years (see figure 1.a). At the same time, the heating sector is transitioning from the use of gas in boilers to the use of (renewable) electricity for heat pumps. Figure 1.b depicts this trend for households, services, and agriculture.

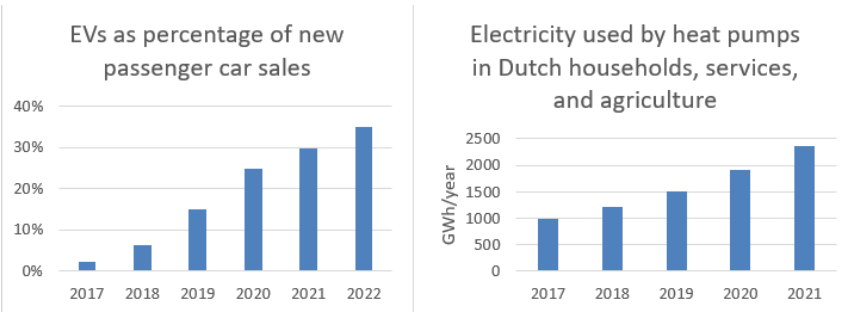

Figure 1: Development of the use of EVs and heat pumps in the Netherlands. The left figure(a) shows the percentage of new passenger car sales that are EVs [7]. The right figure(b) portrays the electricity used by heat pumps in Dutch households, services and agriculture between 2017 and 2021 [8].

The electrification of the transport and heat sectors leads to a large increase in electricity use, which causes an increased load on the electricity grid. Both electric vehicles and heat pumps are often using electricity during specific times of the day. For example, heat pumps are often used to heat the house in the morning, when people get ready for work. Later during the day heat pumps are used to heat the house when people come home after work, and during the evening [9]. This usage pattern leads to a specific power profile, as depicted in figure 2.a [10]. EVs are used to drive to work, and to go back home in the evening. When people arrive back home, they plug in their EVs to recharge for the next day. The grid load of these devices also tends to coincide with the electricity use of other electric appliances such as cooking appliances and lights, with a peak in the morning and a peak in the evening (see figure 2.b) [11].

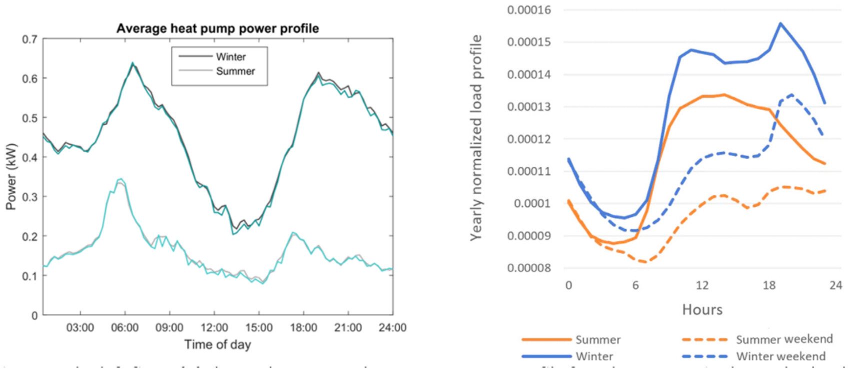

Figure 2: The left figure(a) shows the average heat pump power profile for a heat pump in the Netherlands, for a typical winter day and a typical summer day [9]. The right figure(b) shows the electricity load of a typical Dutch household, for a weekday and a weekend day both in summer and winter [11].

During peak hours, a lot of electricity is used simultaneously, which requires a large grid capacity. The large grid capacity is needed to transport the required amount of power from the source (e.g. power plants) to the destination (e.g. households). At these peak hours the required capacity could become larger than the existing grid capacity, leading to grid congestion. Grid congestion occurs when there is a need to transport more power than the power lines in the grid are capable of. A large part of the Netherlands is frequently confronted with grid congestion [12] (see figure 3).

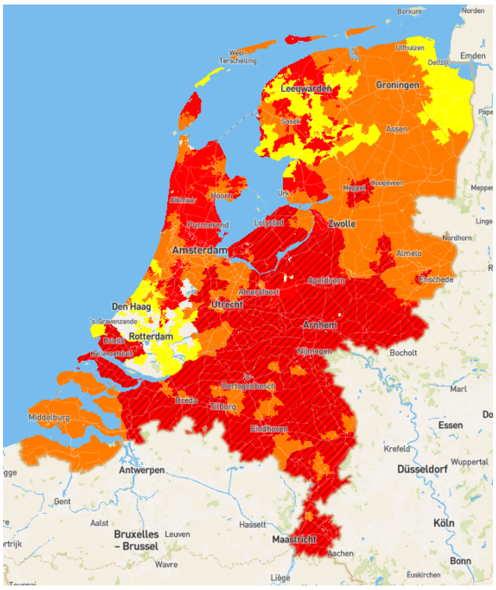

Figure 3: Map of the grid congestion due to electricity consumption in the Netherlands. The red areas suffer from severe grid congestion [12].

If no measures are taken to mitigate grid congestion, 1.5 million grid users will experience problems before 2030 [13]. Over 350,000 users will regularly experience undervoltage, causing lamps to flicker and equipment to falter. Roughly 400,000 users will have an increased risk of power outages, and approximately 750,000 users will be hindered by overvoltage. This causes PV inverters to shut down and their electricity generation to be curtailed.

Additionally, the waiting list for new connections will increase significantly, causing delays for many projects [13].

There are multiple ways to limit grid congestion, and the problems it causes. One way is to increase the energy efficiency of appliances, reducing the electricity they require from the grid. Another way is to build more grid capacity. The Dutch network operators are planning to double the capacity of the grid over the coming decades, but this process has not yet alleviated the lack of grid capacity in many regions [14]. For example, grid congestion impacts nearly 90% of the new build projects in the Municipality of Utrecht, many of which cannot get a grid connection at all [14]. Increasing the energy efficiency of appliances and the grid capacity are long-term solutions. A solution that can be implemented quicker is to manage the usage of the grid on the demand side. This Demand Side Management (DSM) often entails spreading the electric load over time, in order to reduce the peak loads on the grid [15].

One of the devices that shows great potential for DSM is the heat pump. The timing of the electricity consumption of heat pumps can be flexible, due to the heat inertia of buildings. A heat pump can heat the building at an earlier time, and the building will still be close to the right temperature when required [15]. Some heat pumps also include a heat storage system, to increase their flexibility. This flexibility can be exploited to move their grid load from peak hours to off-peak hours [16]. In order to do this on a large scale, heat pumps could be integrated into the smart grid. Smart control strategies can be employed to make optimal use of the flexibility of heat pumps, contributing to the mitigation of grid congestion [16].
The next section discusses the existing research into the impact of smart control of heat pumps on grid congestion.

1.1 Scientific background

A substantial amount of research already exists on smart control of heat pumps. Models have been developed for various countries, climates and systems, and with various objectives. Different smart control strategies are applied in simulations to quantify heat pump flexibility and the potential to mitigate grid congestion. For instance, Schachter et al. modeled an aggregation of fifty well insulated flats [17]. Each flat had a heat pump and a large Thermal Energy Storage (TES). The TES was set to stay in a temperature range between 40-55°C. Two scenarios were analyzed: heating when residents got home from work, and price optimization. The price optimization saved roughly 60-70 pounds per year per dwelling, and the more variable the prices, the higher the savings.

Schibuola et al. [18] used a cost minimization function to control a system with a heat pump and local PV. The method achieved a cost reduction up to 30%. Additionally, the amount of electricity exchanged with the grid was reduced by 12% and 8% for import and export respectively. The analysis also considered comfort issues. Arteconi et al. [16] built a model of a typical dwelling in Northern Ireland. The model included a heat pump with a thermal energy storage. They found that the heat pump can be forcibly shut down for a three-hour period, without significant loss of comfort. Barrett et al. [19] improved the flexibility in their model by using two heat pumps with a combined TES unit. The first heat pump uses the water from the TES as a source to cover the residential heating load. The second heat pump uses the outside air, to heat the water tank during favourable weather. Preheating the water this way increases the efficiency of the first heat pump. Felten et al. [20] constructed a model with an air-to-water heat pump, for a typical household in Germany. Their implementation of a cost minimization strategy showed that the total electricity costs can be significantly reduced. However, as the investment costs of heat pumps are still high, this setup was still deemed generally economically nonviable.

The effectiveness of smart control of heat pumps has been tested in practice as well. Vanhoudt et al. [21] performed lab tests on a residential heat pump with wind and/or solar power. Using an active control strategy lowered peak loads, increased self-consumption, and decreased exchange with the electricity grid was achieved, compared to a regular heat-driven control. The active control strategy did however result in an increase in electricity consumption of 8-12%. A larger pilot project has been analysed by Sun et al. [22]. The project concerned is the FREEDOM pilot in England, with a focus on smart hybrid heat pumps. Smart control increased the average efficiency of the heat pumps. The system value (i.e. the total decrease in costs in the energy system) of smart control of heat pumps was estimated to be between 2.1 and 5.3 bn£/year, if implemented in the entire country.

Müller et al. [23] combined a model with a pilot. They proposed a demand response method that does not require data. The main idea is to request heat pumps to turn off when there is too much demand, and release this restriction later. The method relied on the willingness of users to offer extra flexibility (discomfort) in exchange for compensation. Real experiments were conducted where the electric load caused by heat pumps was reduced for one hour. A load reduction of 40-65% was achieved in most cases. A large rebound effect was present, but it could be decreased in several ways. Mor et al. [24] used a simulation to assess the value of the flexibility of heat pumps under different circumstances, and market schemes. They modeled and tested scenarios ranging from the Spanish day-ahead market to the Swiss and German ancillary service markets. Their results show significant potential of flexibility in the countries they analysed.

Additionally, there are papers that compared multiple pilot projects from the recent past. Péan et al. [25] reviewed numerous pilot projects, in which smart control of heat pumps was used. Their paper provides an extensive overview of the different smart control strategies. The strategies are classified based on the aspects considered in the minimization function. Gercek et al. inspected energy data of 217 households from three smart grid pilot projects in the Netherlands [26]. They concluded that the electrification of heating systems in buildings by using heat pumps leads to an increase of annual electricity consumption and peak loads of approximately 30% compared to the average Dutch households without heat pumps, if a basic heat-driven control is used.

In conclusion, a substantial body of literature already exists on smart control of heat pumps. Multiple methods have been used to quantify the flexibility of heat pumps. Models have been created to optimize the scheduling of heat pumps for different climates and different settings, each of which shows that smart control of heat pumps would significantly reduce the peak loads on the grid. There have been pilot projects implementing various smart controls. However, it is hard to compare the different studies, as multiple factors are different each time (climate, control strategy, heat pump adoption rate, type of housing, amount of insulation, size of thermal energy storage, presence of PV, etc.). To determine which smart control strategy is optimal, all other factors should be identical. No studies have performed such an analysis yet. This thesis attempts to fill that gap. The focus is on the Dutch climate.

1.2 Research objective and process overview

The research objective of this thesis is "to quantify the grid congestion mitigation potential of heat pumps in the Netherlands for different smart control strategies, and to identify the barriers and challenges of each smart control strategy".

The process to meet the research objective consists of three parts. The first part is to identify suitable scenarios of heat pump adoption and building insulation levels in the Netherlands. Next, promising smart control strategies are identified, together with potential barriers to their implementation. For the third part, a model is developed, to quantify the performance of each smart control strategy in an equal setting. The model is applied to the most probable scenarios from step one, with each of the control strategies from step 2.

1.3 Scientific relevance

This thesis contributes to filling the research gap that was introduced in the introduction. This provides insight into the trade-off between complexity and effectiveness of smart control strategies. Additionally, the model that was developed could be used in future research to analyze other scenarios, and the grid congestion mitigation potential in other locations. Additional variation in control strategies could also be compared using this model (e.g. different types of cost optimization strategies).

1.4 Societal relevance

The results of this thesis give an overview of promising smart control strategies for heat pumps, the barriers to their implementation, and a quantification of their effectiveness in mitigating grid congestion. Policy makers can use this to make an informed choice on how to implement smart control of heat pumps. The sooner this is implemented, the sooner the grid congestion can be decreased, mitigating the problems it would cause otherwise. This would in turn contribute to speeding up the energy transition.

1.5 Reader guide

The next chapter gives an introduction to the technical aspects of heat pumps. Chapter 3 explains the methods, starting with the main simulation model, followed by the scenarios that it simulates and the control strategies that are compared. Chapter 4 contains the results of the simulations. Chapter 5 is the discussion, including recommendations that follow from the results, limitations of the project, directions for future work and a comparison of the results to the literature. Chapter 6 is the conclusion.

2 Theory

2.1 Introduction to heat pumps

There are three main types of heat pump (HP) in use: air sourced HPs, water sourced HPs and ground sourced HPs [15]. The general working principle is the same for all types. The process is illustrated in figure 4 [27]. Heat pumps are used to move heat from a colder environment (e.g. the outside environment during winter, or the inside of a building in summer) to a hotter environment (e.g. the interior of a building in winter, or the outside during summer). First, a very cold (liquid) heat transfer medium (in figure 4, on the bottom left) is brought in contact with the cold environment, which increases its temperature to reach the temperature of the colder environment and causes it to transition into a gaseous state. Then the heat transfer medium is compressed, which increases its temperature, to a temperature above that of the hotter environment. The heat transfer medium is then brought in contact with the hotter environment and gives off its excess heat. The heat transfer medium is then expanded to its original volume, which causes it to cool down to its original temperature and become a liquid again. The cycle then repeats. This way, heat is transferred from the cold environment to the hotter environment. The efficiency, or Coefficient of Performance (COP), is lower if the temperature difference between the hotter medium and the colder medium is larger [28]. The theoretical maximum efficiency of a heat pump is calculated as:

$$COP_{heating} = \frac{T_H}{T_H - T_C} \tag{1}$$

where $COP_{heating}$ is the efficiency, T_H is the temperature of the hot environment, and T_C is the temperature of the cold environment. For heat pumps, the COP is generally larger than one, as the heat comes from the cold environment, and it is transferred to the hot environment. This costs relatively little energy, resulting in a COP of 3-4.5 for most heat pump types.

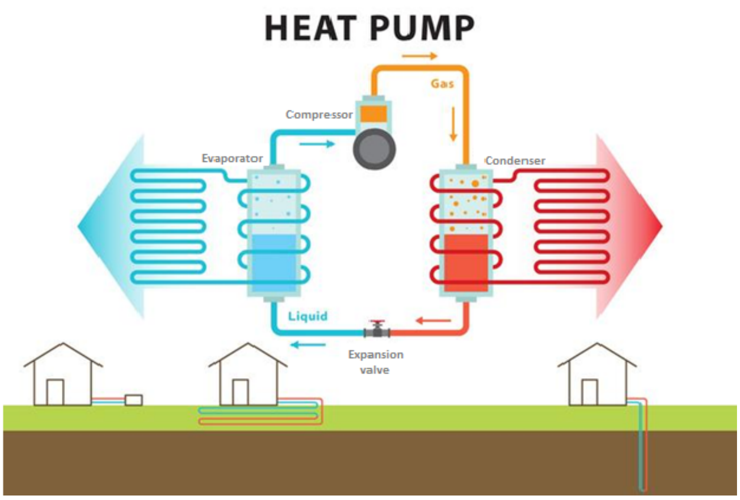

Figure 4: Schematic of the working principle of a heat pump (original image altered, source: [27]).

Table 1: Summary of the main types of heat pump, adapted from [29]. The installation costs are indicative, as they differ per region.

Technology	Installation cost	Average COP	Environmental Impacts	Pros	Cons
Air Source Heat Pump	Low	3	- Highest environmental impact in cold regions - Leakage of refrigerant can cause pollution - Causes noise pollution	- Less or no pollution concerns - Simple operation - Low Maintenance Cost - High COP - Low primary energy consumption	- Frost formation on outer units - COP varies with ambient temperature - May need supplemental heat system for better performance
Water Source Heat Pump	Medium	4.5	- Can cause water pollution, stratum settlement and trigger geological disasters	- Highly efficient - Not affected by ambient conditions - Can utilise heat from rivers and lakes	- Requires water bodies or storage tanks in vicinity - Needs regulatory permission for installation
Ground Source Heat Pump	High	3.5–4	- Unchecked heat transfer fluids are hazardous - Surface water can enter borehole - Can perturb groundwater temperature - Reduces emissions with low payback period	- Highly efficient and shows great energy saving potential - High COP - Utilises vast source of heat - Very reliable source of heat - Can operate in regions with extreme winters	

The types of heat pump mainly differ concerning the heat source. Air sourced heat pumps (ASHPs) use the air outside as the heat source. ASHPs are either air-to-water or air-to-air heat pumps. Air-to-water heat pumps use set central heating systems to distribute the heated water. Air-to-air heat pumps produce warm air that is circulated by fans. ASHPs are often combined with floor heating. The efficiency of ASHPs depends strongly on the outside air temperature, which varies a lot during the year.

Water source heat pumps (WSHPs) use ground water, rivers or lakes as a source of heat. It thus depends on the location if a WSHP can be installed. They are cheaper than ASHPs and require less electricity, as the water generally has a higher temperature than the air during winter. Another benefit is that the temperature of the water varies a lot less during a year, and the efficiency of the WSHP is thus more constant.

Ground source heat pumps (GSHPs) use the energy naturally stored in the ground, with similar benefits to those of the WSHPs. A subclass of GSHPs is the geothermal heat pump, which uses the heat from the ground on a deeper level. The temperature is higher there, which results in higher efficiency and lower operational costs. However, the initial investment is a lot more expensive. Geothermal heat pumps have the most constant efficiency. Table 1 provides an overview of the three types of heat pump, with additional details on their characteristics.

In practice, hybrid heat pump systems are often used. They consist of conventional heating systems like electric heaters or gas boilers in combination with heat pumps. This has the advantage that the heat pumps require less capacity, as the electric heater or gas boiler can cover the peak loads. These peak loads only happen rarely (during very cold days, or when the demand for domestic hot water is high), so the heat pump covers most of the heat demand.

3 Methods

In order to reach the research objective, three steps were taken. The first step was to create a model that can simulate a neighborhood with houses with heat pumps. The second step was to create a set of scenarios to analyze. Finally, promising smart control strategies were identified, together with their drawbacks and potential barriers to their implementation. The model was applied to each of the scenarios with each of the smart control strategies. The results from the model were then compared for each control strategy, using a set of key performance indicators. Section 3.1 describes the model that was used for the simulations. Section 3.2 contains the methodology that was used to construct the scenarios. Section 3.3 describes the control strategies that were used and the key performance indicators.

3.1 Model simulations

In order to quantify the impact of heat pumps on the electricity grid, a model was created that can simulate the scenarios constructed in section 3.2. A schematic of the model is shown in figure 5. The model simulates a collection of 200 households with heat pumps for one year. The model consists of four parts: the inputs for the simulation, a set of databases that is used for each household simulation, a loop over each time step for the simulation period (here the actual calculations are performed), and an output section. The four parts are discussed in the next sections. Section 3.1.5 describes the software and hardware that was used to create and run the model.

3.1.1 Inputs for the simulation

The model requires a set of data inputs (boxes 1 and 6) and a set of settings (boxes 2-5). The first data input is the hourly weather data for one year. In this project, the weather data for 2023 from [30] was used, as this is the most recent completed year. The next data needed for the input are the inside temperature set-points. These were obtained with a tool from the University of Twente [31] that is capable of generating artificial load profiles for households for electricity use, domestic hot water use, and inside temperature set-points, among others. The ALPG assumes a set-point of 0°C for non-occupancy periods. This minimum was changed to 14°C as this was deemed more realistic. The inside starting temperature was taken to be the temperature set-point in the first time step. Another input was the acceptable temperature variation to ensure comfort, which was set to be at most 2 degrees above the set-point. The next input required was the existing electricity usage of the simulated households, from lighting and electrical appliances, and the production by PV panels. For this, the same tool was used. The final input data were the day-ahead electricity prices, which were obtained from the ENTSO-E Transparency Platform [32].

The other inputs that the model used are a set of settings (boxes 2-5). The first setting is the type of inhabitants, as classified in [31] and described in section 3.2.4 (example types are: SingleWorker, DualWorker and FamilyDualWorker). The second setting is the distribution of house types, from section 3.2.3. The third setting is the distribution of heat pump types for the simulation. The final setting was the control strategy to be used for the simulation.

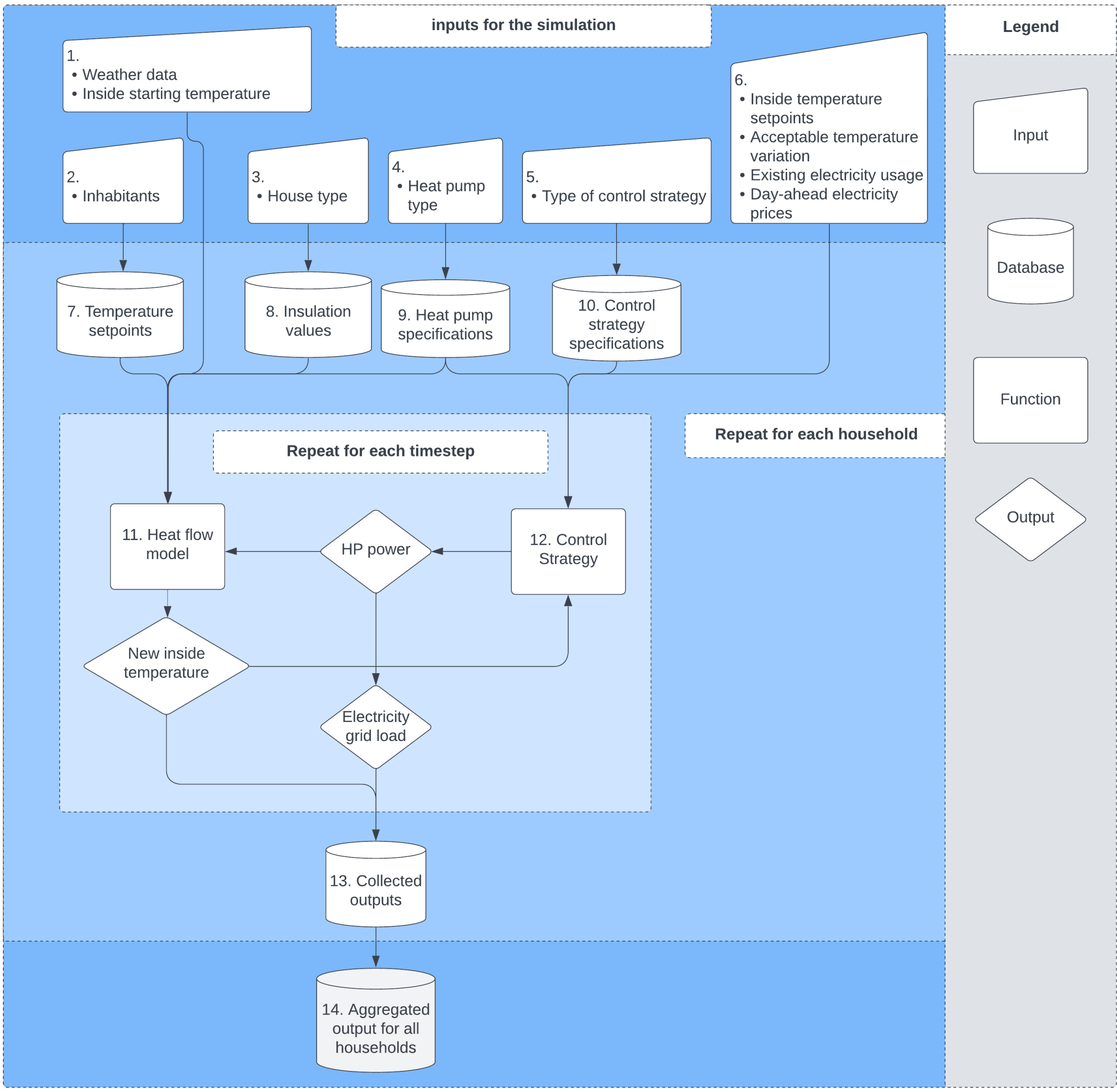

Figure 5: Schematic of the model. Boxes 1 and 6 are data inputs. 2-5 are setting inputs. 7-10 are databases with information corresponding to the different options for the setting inputs. Boxes 11 and 12 represent the functions that calculate the heat balance and the decision from the control strategy. Box 13 is the output of the simulation for one household. Box 14 represents the aggregated output of the entire model.

Furthermore, the model makes use of several databases. The type of inhabitants for each house is linked to a database with temperature set-points (box 7). The house type is linked to insulation values and other (thermal) properties of the house, like surface areas of the building elements (box 8). The heat pump type determines the capacity and efficiency of the heat pump (box 9). The last database contains the functions and starting data for each control strategy (box 10).

3.1.2 Calculation loop

The households are then consecutively simulated. Each house is simulated for 1 year, in time steps of 15 minutes. Each time step, the current temperature is sent to the control strategy, which then makes a decision on the required heating (box 12). This decision is sent to a heat flow model (box 11), which calculates the resulting heat flows between all building elements, resulting in a new inside temperature. The new inside temperature and the grid load caused by the heat pump are then recorded and the calculation moves on to the next time step (box 13). The control strategies are described in detail in section 3.3. The heat flow model contains the main calculations for the model and is described in sections 3.1.3 and 3.1.4.

3.1.3 Heat flow model setup

For the heat flow model the shape of the building is assumed to be a box, with equal amounts of windows in each wall, excluding two walls for a terraced house. The walls are modeled as an inner wall and an outer wall, each with thermal mass, with insulation in between. The roof and floor are not divided into inner and outer sections, but do include insulation. Figure 6 shows the connection between each building component. Each component is modeled as a resistor (insulation), a capacitor (thermal mass) and a second resistor (insulation on the other half of the element), similar to the approach in [33].

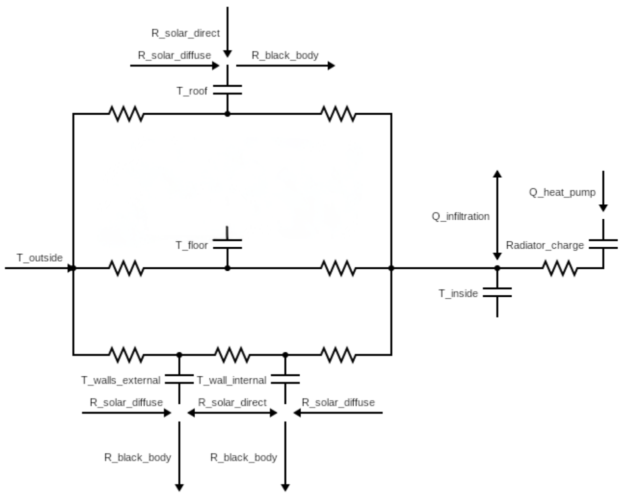

Figure 6: Schematic of the heat flow model.

The following section shows the equations used to calculate the heat balance for each building element, starting with the inside, and working outwards to the external walls, roof and floor.

3.1.4 Heat flow model equations

The heat flow model considers all main heat flows in the simulation: conduction, infiltration, convection and radiation. All symbols are explained in the nomenclature. Some symbols are also explained here in the text for easier reading. All equations are based on concepts from [34], unless a different source is stated. Each time step, the heat flows are calculated in the following order.

The inside air

First, the heat flow from the heat pump (HP) to the space heating system is calculated as:

$$Q_{HP} = HP_{state} * HPpower * COP \tag{2}$$

Here, the COP is calculated according to the following trend as found for ASHPs in a paper by Akmal et al. [35]:

$$COP_{ASHP} = 0.0008 * (T_{water} - T_i)^2 - 0.138 * (T_{water} - T_i) + 7.4545 \tag{3}$$

The new charge of the heating system due to the effect of the HP is then calculated as:

$$C_{hs,new} = C_{hs,old} + Q_{HP} \tag{4}$$

This charge leads to a heat flow from the heating system to the inside air, equal to:

$$Q_{hs} = C_{hs}/I_{hs} \tag{5}$$

where I_{hs} is the inertia of the heating system, set as the time it takes to fully charge or discharge. Additionally the inside air exchanges heat (through conduction) with the inside walls, roof and floor respectively, following these equations:

$$Q_{c,wi,i} = (T_{wi} - T_i)/Rc_{wi,i} * A_w/1000 \tag{6}$$

$$Q_{c,r,i} = (T_r - T_i)/Rc_{r,i} * A_r/1000 \tag{7}$$

$$Q_{c,f,i} = (T_f - T_i)/Rc_{f,i} * A_f/1000 \tag{8}$$

Where T_x is the temperature of element x, $Rc_{x,y}$ is the thermal resistance between elements x and y and A_x is the area of building element x. Then there is the heat flow between the inside air and the outside air due to infiltration:

$$Q_{i,i} = ACR * M_{th,i} * (T_o - T_i) \tag{9}$$

where ACR is the air change rate and $M_{th,x}$ is the thermal mass of element x. The internal heat gain from households appliances and people is Q_{hg}, which is obtained using the artificial load profile generator of the University of Twente [31]. All these heat flows are added to get the total heat flow to/from the inside air:

$$Q_{tot,i} = Q_{c,i} + Q_{hs} + Q_{i,i} + Q_{hg} \tag{10}$$

The new inside air temperature is then:

$$T_{i,new} = min(T_i + Q_{tot,i}/M_{th,i}, T_{cooling}) \tag{11}$$

A cooling mechanism is assumed that limits the temperature to a maximum of 30°K. The new inside air temperature is stored in a list and returned at the end of the calculation. This way, all temperatures can be updated simultaneously. Next, the charge of the space heating system is updated as:

$$C_{hs} = C_{hs} - Q_{hs} \tag{12}$$

The internal walls

Then, the heat flows concerning the inside walls are calculated (where the old inside air temperatures are still used). The conduction is given by:

$$Q_{c,wi} = (T_i - T_w i) * A_w / Rc_{wi,i} + (T_{we} - T_{wi}) * A_w / Rc_{we,wi} \tag{13}$$

The inside walls do not have a direct interaction with the HP, nor is there enough air in the wall for infiltration. The wall does have an interaction with light. The radiation heat exchange is modeled in three parts. The diffuse solar radiation is calculated as the energy of the diffuse light that hits the windows times the fraction of light that passes through the glass (the glazing solar factor, or GSF):

$$Q_{r_{diff},wi} = r_{diff} * A_{glass} * GSF * 0.5 \tag{14}$$

The factor 0.5 accounts for the fact that only light from one half of the sky can reach each window, as the other half is blocked by the house. The direct solar radiation involves the relative position of the sun compared to the windows. Here, the astral module is used to find the solar zenith at the time and location of the simulated neighborhood. This gives the formula:

$$Q_{r_{dir},wi} = r_{dir} * A_{walls} * GSF * tan(\theta_s) * \sum_{i=0}^{4} max(0, (cos(|\gamma_s - \gamma_b - 90 * i|)) \tag{15}$$

Here $tan(\theta_s)$ accounts for the vertical angle between the window and the sun. The part involving γ accounts for the horizontal angle, for each of the walls. Finally, the inside walls emit black body radiation. For this step, the total visible fraction of space is used, like in [33]. The black body radiation is calculated as:

$$Q_{r_{bb},wi} = -5.67 * 10^{-8} * (T_{wi} + 273.15)^4 * A_{glass} * \epsilon/2 * (1 - 0.55 * cc) \tag{16}$$

Here ϵ is the absorptivity (the fraction of incoming radiation that is absorbed). cc is the cloud cover ratio, or the part of the sky that is obscured by clouds). This gives a total heat flow of:

$$Q_{tot,wi} = Q_{c,wi} + Q_{r_{diff},wi} + Q_{r_{dir},wi} + Q_{r_{bb},wi} \tag{17}$$

and a new inside wall temperature of:

$$T_{wi,new} = T_{wi} + Q_{tot,wi} / M_{th,wi} \tag{18}$$

, which is again saved in a list to return at the end of the calculation.

The external walls

Next, the heat flows of the external walls are calculated. The conduction part is:

$$Q_{c,we} = (T_w i - T_w e) * A_w / Rc_{wi,we} + (T_o - T_{we}) * A_w / Rc_{o,we} \tag{19}$$

The radiation is calculated similarly to that of the the internal walls, but now with the outside wall area instead of the window area:

$$Q_{r_{diff},we} = r_{diff} * A_{walls} * \epsilon * 0.5 \tag{20}$$

$$Q_{r_{dir},we} = r_{dir} * A_{walls} * \epsilon * tan(\theta_s) * \sum_{i=0}^{4} max(0, (cos(|\gamma_s - \gamma_b - 90 * i|)) \tag{21}$$

$$Q_{r_{bb},we} = -5.67 * 10^{(} - 8) * (t_w e + 273.15)^4 * A_{walls} * \epsilon / 2 * (1 - 0.55 * cc) \tag{22}$$

This gives a total heat flow equal to:

$$Q_{tot,we} = Q_{c,we} + Q_{r_{diff},we} + Q_{r_{dir},we} + Q_{r_{bb},we} \tag{23}$$

and a new temperature:

$$T_{we,new} = T_{we} + Q_{tot,we} / M_{th,we} \tag{24}$$

The roof

The calculations for the roof are very similar: The conduction:

$$Q_{c,r} = (T_i - T_r) * A_r / Rc_{i,r} + (T_o - T_r) * A_r / Rc_{o,r} \tag{25}$$

The radiation:

$$Q_{r_{diff},r} = r_{diff} * A_r * \epsilon \tag{26}$$

$$Q_{r_{dir},r} = r_{dir} * A_r * \epsilon \tag{27}$$

$$Q_{r_{bb},r} = -5.67 * 10^{(} - 8) * (t_r + 273.15)^4 * A_r * \epsilon * (1 - 0.55 * cc) \tag{28}$$

and as total:

$$Q_{r_{tot},r} = Q_{r_{dir},r} + Q_{r_{diff},r} + Q_{r_{bb},r} \tag{29}$$

This gives a total heat flow equal to:

$$Q_{tot,r} = Q_{c,r} + Q_{r_{tot},r} \tag{30}$$

and a new temperature:

$$T_{r,new} = T_r + Q_{tot,r} / M_{th,r} \tag{31}$$

The floor

The heat flows for the floor are simpler, because all the radiation is assumed to hit the walls and roof (this could be modeled more accurately in future work, but adds additional complexity to the model, resulting in longer calculation times). Then the only heat flow is the conduction:

$$Q_{c,f} = (T_f - T_i) * A_f / Rc_{f,i} + (T_f - T_o) * A_f / Rc_{f,o} \tag{32}$$

and the new floor temperature is:

$$T_{f,new} = T_f + Q_{tot,f} / M_{th,f} \tag{33}$$

In practice, the ground temperature is often different from the air temperature, leading to lower heat losses. In this model, this is replaced by a higher thermal resistance of the floor, as data on ground temperature were not available. **Update of the temperatures**

At the end, the temperatures for all of the building elements are updated and used as input for the next time step.

3.1.5 Modeling approach

The modeling was done entirely in python 3.10, using jupyter notebooks. The following packages were used:

- astral, version 3.0
- matplotlib, version 3.9.2
- numpy
- pandas, version 2.2.2
- scipy, version 1.14.1
- tqdm, version 4.66.5
- os (included in python 3.10)
- datetime (included in python 3.10)
- csv (included in python 3.10)
- random (included in python 3.10)

The simulations with the MPC control strategy were run on an HPC from the Earth Sciences and Physical Geography departments of Utrecht University. The other simulations which required significantly less computing power were run on a personal device.

Additionally, input data for the model were generated using the Artificial Load Profile Generator from the University of Twente [31] (internal heat gains, PV electricty profiles, temperature set-points and electricity consumption from lighting and electrical appliances). Running the ALPG requires a different environment. For this study, the anaconda distribution of Spyder was used, with python 3.10. Additionally, the required version of astral is 1.10.1 for the ALPG. The code was modified with regards to the amount of solar panels for each house. This was set to an amount that covers the net consumption of the household, if possible, or else to the maximum amount of solar panels that can fit on the roof. The rest of the code was unmodified since it was obtained from [31] on 3-9-2024, except for the input file.

3.2 Identification of scenarios

The next objective was to create suitable scenarios for the simulation, to compare the impact of different smart control strategies for heat pumps on the grid congestion in the Netherlands. The general setup for the simulation was as follows. The simulation consists of a set of 200 terraced houses representing the average Dutch urban neighborhood in 2023. A varying amount of the households has air sourced heat pumps combined with floor heating. The rest has other heating systems that do not use electricity. The amount of heat pumps (HP adoption rate) varies between 0% and 100% between the scenarios. The next sections describe the settings that are identical for all scenarios in more detail. Section 3.2.5 describes the differences and provides a table with an overview of all settings.

3.2.1 General inputs

In general, data for 2023 was used, as this was the most recent complete year. The weather data was from De Bilt, because this is often done to represent the average weather in the Netherlands [30]. Day-ahead electricity prices were used for some of the control strategies [32]. These were taken for the year 2023, to match the weather data. The model has a resolution of 15 minutes, which is standard for this type of simulation. A neighborhood of two hundred households was simulated, which is in the range of grid connections given in [36]. The areas for the different building elements were taken to be the average for terraced houses in the Netherlands [37, 38, 39]. 32% of the houses is randomly selected to have solar panels, according to [40]. The amount of solar panels is chosen to match the yearly electricity consumption of the household (excluding the HP) if possible. If the roof area of the house is too small to fit this amount of solar panels, the PV area is set equal to the area of the roof.

3.2.2 Heat pump adoption

For the heating system, air sourced heat pumps were used for every building. This is the most common type of heat pump in the Netherlands. Additionally, the houses that have a heat pump are assumed to have floor heating, as this is commonly the case. The temperature of the floor heating is set to 35°C [41]. This floor heating system typically heats up or cools down in around 3.5 hours [42, 43]. The heat pump adoption rate was varied between 0-100% in increments of 10%.

3.2.3 Insulation levels

Two insulation levels were used for the buildings. The first insulation level is that of renovated buildings, according to the building regulations from Bouwbesluit 2012 [44]. The second insulation level corresponds to the insulation level of new buildings, according to the same regulations. The simulation uses a range of insulation values between 80% and 100% of the regulation values, as not all measures are implemented equally in practice.

The infiltration and ventilation heat flows are simplified into one constant air change rate (number of refreshes of the air per hour). For the renovated houses the air change rate was set to 0.3/h and for the new houses it was 0.2. These values are respectively average and good, compared to the range given in [45]. The thermal mass of the air inside the buildings is the volume of the building times the heat capacity of air [46]. The wall areas are calculated from the floor area and the volume, assuming a square floor and a flat roof.

3.2.4 Demographics

In order to determine the behavior of the inhabitants of the houses, a load profile generator was used [31]. This is a program that simulates the behavior of the members of a household, and generates the temperature set-point for the thermostat and the electricity usage for electric appliances.
The load profile generator recognizes seven types of household: SingleWorker, SingleRetired, DualWorker, DualRetired, FamilyDualWorker, and FamilySingleWorker. No direct data was available for the Netherlands about the distribution among these types. Therefore the percentages for each type were constructed from multiple sources. Of all households, 53% are single people, 21% are couples without children, 20% are couples with children, and 6% are families with a single parent [47]. Additionally, of the entire population, 8.2% is either jobless or unable to work, 12.9% is retired, 64.6% works, and the remainder are children [48]. Additionally, the assumption was made that 80% of retired people are couples.
The calculation to convert these percentages into the final percentages is included in appendix A. The final percentages are shown in table 2

Table 2: This table shows the results from the demographics calculation that were used as an input for the load profile generator.

Dual retired	5%
Single Retired	10%
Dual worker (parttime)	3%
Family single worker	11%
Family dual worker	15%
Single Worker	43%
Dual Worker	13%

3.2.5 Variations between scenarios

The different scenarios vary in three aspects: the insulation level, the heat pump adoption level, and the control strategy. Three types of insulation level are used. In one type, all houses are renovated houses and have corresponding insulation levels. In the second type, all houses are new built and have higher insulation values. For the third type, half of the houses are new and the other half are renovated. In order to function properly, the heat pumps need to have the right capacity. If the capacity is too low, the inside temperature can not reach the set-point during the winter. If the capacity is too high, the heat pump is more expensive than required. The optimal capacity is dependent on the heat loss of the house. This is calibrated for the different types of household in this project, by running a test simulation and recording the highest activation requested by the reference control strategy (normally between 0 and 1) and the capacity was then scaled accordingly.

The heat pump adoption rates vary between 0% and 100% with increments of 10%. Finally, each scenario has one of the 7 strategies, for a total of $3x10x7 = 210$ scenarios. Table 3 summarizes the data inputs and settings for the simulation.

Table 3: Summary of the data inputs and settings for the simulation.

Data inputs and settings	
Weather data (year)	De Bilt, 2023
Day-ahead prices (year)	2023
Demographics	Utrecht average
Timestep	15 minutes
Number of households	200
Areas (walls, roof, floor)	(100, 119, 119)
Radiator inertia	210 minutes
Insulation values (Rc-values for walls, roof and floor*)	(4.7, 6.3, 3.7) as according to "bouwbesluit 2012" for new residential buildings
Thermal capacity for the inside air, inside walls, outside walls, roof and floor	(567, 27200, 32368, 32368, 32368) kJ/K
Building orientations	0 degrees rotation for every building
HP types	Air sourced heat pumps (ASHPs) for every building
Water temperature	55C
Air change rate	0.3/h
*These values are processed to obtain Rc values that the model can handle. The final Rc-values are [1, 4.7, 0.5, 6.3/2+0.5, 6.3/2+1, 3.7/2+1, 3.7/2], for the components: Rc_walls_internal_to_inside, Rc_walls_external_to_walls_internal, Rc_walls_external_to_outside, Rc_roof, Rc_roof_to_inside, Rc_inside_to_floor and Rc_floor_to_outside.	

3.3 Identification of smart control strategies

3.3.1 Overview

The final step was to determine a set of promising smart control strategies, how they could be implemented and their potential drawbacks. A lot of options are presented in the literature.

A distinction is made between Rule-Based Control (RBC) strategies and Model Predictive Control (MPC) strategies [49]. Rule-based controls are controls which have the form "if a condition is satisfied, then an action is triggered". RBCs rely on the monitoring of a specific trigger parameter (e.g. room temperature or electricity price) with a fixed threshold value. When the threshold is reached, the state of the heat pump is changed, according to the predefined strategy [49]. On the other hand, MPC is a more complex strategy, which uses a simulation of a building to predict the effect of control actions. MPC is an optimization problem, which attempts to find the best solution for the operation of the heat pump, over a certain time horizon while satisfying a set of constraints [49]. In this thesis, a further distinction is made between rule-based control strategies and fixed control strategies. Fixed control strategies only have a time-based rule, that is fixed in advance (e.g. preheating between 16:00 and 18:00), and are therefore less complex than other rule-based control strategies.

For this project, seven control strategies were selected, including a reference control, two fixed control strategies, two rule-based control strategies and two model predictive control strategies. Table 4 shows a summary of the strategies and their main characteristics. The strategies are discussed in detail in the next sections.

Table 4: Summary of the control strategies, their main concept, drawbacks, requirements and complexity.

Control strategies summary			
Control strategy	**Main concept**	**Main drawbacks and requirements**	**Complexity**
Reference control (RC)	Has as only goal to maintain the desired inside temperature.	Does not shift loads.	Low
Constant heating (CH)	Similar to the reference control, but the temperature is always kept above a minimum of 18°C (instead of 14 for the reference).	Requires more energy.	Low
Fixed control (FC)	Preheats during set hours of the day, in order to lower heat demand during predefined peak hours.	Requires data on past grid usage to determine peak hours. Needs significant finetuning to determine optimal preheating periods.	Low
Rule based control v1 (RBC1)	Uses day-ahead electricity prices to deduce the timing of the peak hours for the coming 24 hours and preheats the house in the hours before.	Requires price data, and thus an internet connection.	Medium
Rule based control v2 (RBC2)	Similar to v1, but with the actual grid load from the reference case as price data. This is expected to yield better results, because the day-ahead prices are less suitable to predict the actual grid load.	Requires an internet connection, accurate grid load predictions, and implementation of a more regional pricing scheme.	Medium
Model predictive control v1 (MPC1)	Each house uses a simulation of itself and its surroundings, in order to predict the effects of using the heat pump at each given moment in the coming 24 hours. The accurate price data from RBC2 is used, together with the simulation and a solver to calculate the optimal scheduling, resulting in the lowest costs, and hopefully, the lowest grid congestion.	Requires price data, and thus an internet connection. Also requires an accurate model of each house that uses this strategy, which is expensive and difficult to obtain.	High
Model predictive control v2 (MPC2)	Similar to v1, but with the actual grid load from the reference case as price data. This is expected to yield better results, because the day-ahead prices are less suitable to predict the actual grid load.	Drawbacks and requirements of RBC2 and MPC1 combined.	High

3.3.2 The reference control

The reference control represents the default control that most existing households have. It consists of a single controller which can be programmed with desired temperatures for each hour of the day, with different settings for each day of the week. Its main drawback is that most people use similar settings resulting in high simultaneity of heat demand, resulting in grid congestion. Below is the description of the implementation.

The reference control is designed to match the inside temperature to the set-point temperature as closely as possible. In order to do this, it calculates the required power from the heat pump in every time step. For this calculation it needs to know the power capacity of the heat pump, the outside temperature, and the current temperature of the heating system. Additionally, the thermal mass of the air inside the house has to be estimated, as well as the inertia of the heating system. This information is used to calculate the heating load for the heat pump to reach the desired temperature. On top of this, the strategy uses a correction for the unknown heat losses in the system, e.g. due to changing weather. This correction is determined by calculating the expected change in temperature given the power of the heat pump from the previous time step, and comparing it to the actual change in temperature. The heat pump (HP) activation required to reach the desired temperature in the coming time step is the combination of the calculated power and the correction. The exact behavior is described in the following formulas. First, the the expected temperature increase due to the previous heating period is calculated:

$$\Delta T_{expected} = \frac{C_{hs} + HP_{state,old} * HP_{power} * COP}{I_{hs} * M_{th,inside}} \tag{34}$$

where C_{hs} is the charge of the heating system, $HP_{state,old}$ is the old activation state of the HP, HP_{power} is the capacity of the HP, COP is the coefficient of performance, I_{hs} is the inertia of the heating system and $M_{th,inside}$ is the thermal mass of the air in the heating zone. Next, the real change in temperature is calculated as:

$$\Delta T_{real} = T_{inside,new} - T_{inside,old} \tag{35}$$

The difference between the real change and the expected change is the "temperature correction" and approximates all unknown heat flows:

$$T_{correction} = \Delta T_{real} - \Delta T_{expected} \tag{36}$$

Next, the HP activation required for the heat pump to reach the required inside temperature is calculated as:

$$HP_{state,new} = \frac{(T_{setpoint} - T_{inside,new} - T_{correction}) * M_{th,inside} * I_{hs} - C_{hs}}{HP_{power} * COP} \tag{37}$$

Finally, this activation level is limited to be between 0 and 1 (representing 0% and 100% of the heat pump capacity).

3.3.3 The constant heating strategy

The first "smart" control strategy tests the effect of more continuous heating. To test this, the minimum set-points are increased to 18°C, instead of the standard 14°C. This is expected to lead to higher overall heating load and electricity consumption, but might lower the simultaneity of heating periods. This is the only change made here, with respect to the reference control strategy.

3.3.4 The fixed control strategy

The second smart control strategy is the Fixed control strategy. The main idea is to preheat during set hours of the day, in order to lower heat demand during the peak hours. This requires data on past grid usage to determine peak hours for the neighborhood. The effectiveness of the strategy depends a lot on the actual preheating schedule that is chosen. Finding a good schedule requires significant testing and fine-tuning, which might be very time consuming.

For this strategy, specific hours are determined to be peak hours, for each scenario. These are determined by simulating the scenario with the reference control strategy and making a graph of the resulting average grid load over the winter months. An example graph is shown in 7. These graphs were used to select the start of the peaks manually, as it is difficult to determine a rule that works well in all scenarios. This is further complicated by the fact that the evening peaks are often higher, but less caused by the heat pump. This is also clearly visible in this example figure. Next, 3 hour long preheating periods are constructed, in which the set-point is slowly increased from the normal set-point to two degrees above the normal set-point. After the preheating period, so during the peak periods, the set-point is set to normal again. This way, the built-up heat can dissipate, lowering the demand for new heat during the peak period. Apart from the time-based change in set-point, the strategy is identical to the reference control.

3.3.5 Rule-based control v1

The third strategy is the Rule-based control strategy. This strategy attempts to find the peak periods for each individual day (instead of for an average day like in the fixed strategy), and preheat accordingly. This is done using price data (e.g. day-ahead electricity prices) to determine the most expensive hours, which are assumed to coincide with high grid loads. This price data is provided to the control unit via an internet connection, which

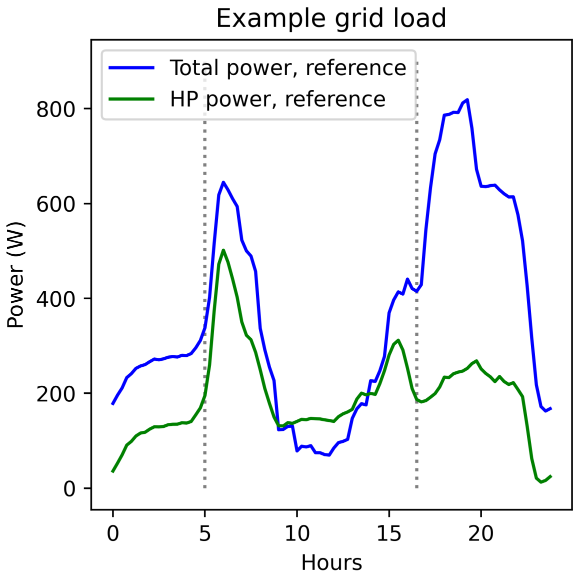

Figure 7: Example graph to illustrate the fixed control strategy. The graph shows the average day of electricity use over the year for the average house, for the heat pump and for the total of heat pump, solar panels, and all other electrical appliances. The data is from a scenario with the reference control strategy, 32% of the houses with PV, and all houses as renovated houses. The gray dotted lines are the starts for the peak hours for this scenario, as manually determined from the graph.

potentally makes it vulnerable to cyber attacks. This strategy also requires significant finetuning, just like the fixed control. The implementation is described below.

For this strategy a threshold percentage is defined, and price data are used. Day-ahead electricity prices were used, as these are readily available in reality, and have a high correlation with energy demand and grid load. These inputs are used as follows: each time step, the current price is compared with the prices for the coming 24 hours. if the price is in the lowest x% (this is the threshold percentage), and the price after y hours (dependent on the inertia of the heating system) is in the highest x%, the set-point is increased by 2 degrees. An illustration is shown in figure 8. Apart from the dynamic change in set-point, the same calculations are performed as in the reference control.

3.3.6 Rule-based control v2

This strategy is the same as RBC1, but with different price data. To test the limits of this strategy, the grid load of the reference case is used as the second type of price data, which has a correlation of 1 with itself. This is expected to yield better results.

In practice this could be hard to implement. It would require very accurate grid load predictions for each neighborhood which are then used to construct a local (day-ahead) pricing scheme. On top of the technical difficulties, such local pricing can be seen as discriminatory, and might even be prohibited by law in some countries. Again, this price data needs to reach the control unit, resulting in the same drawbacks as before.

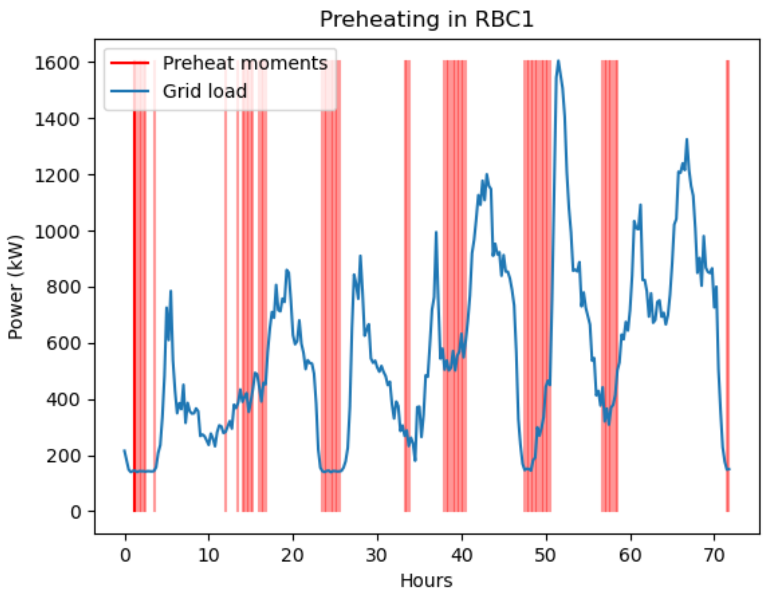

Figure 8: Example graph to illustrate the automatic preheat period detection. The graph shows the grid load for the entire neighborhood for the first three days in January. In the red areas, the price (grid load) is low, and after 3.5 hours (the reaction time of the heating system) the price is high.

3.3.7 Model predictive control v1

The model predictive control is the most complex to implement. The main idea is to use a simplified model of the house to predict the effect of activating the heat pump at any moment in the coming 24 hours. Together with a pricing scheme, and a solver, the optimal scheduling of the heat pump can be calculated, resulting in the lowest costs (and hopefully the lowest congestion). This is the most complex type of strategy. The hardest part in practice is to obtain accurate models of the houses involved. It is expensive and time consuming, but might be worth it in the long run.

Figure 9 contains an overview of the steps for the implementation. The top half contains the calculations and the bottom half contains a decision tree based on the results of the optimization (linear solver).

It all starts with a simplified model of the house. The model is similar to the heat flow model described in sections 3.1.3 and 3.1.4, but simplified to make it linear. This is done, because linear optimization is a lot quicker than non-linear optimization. The method to make it linear was to decouple the effects of the heat pump from the rest of the heat flows. Then linear combinations of the effect of the heat pump at different times can be added to the temperature in the house in the case of no heating, to find the temperature with heating. Appendix B shows the effect this has on the accuracy of the model.

The MPC1 strategy starts with a calibration step to find the effect on the inside temperature over time of adding heat to the space heating system. For this, the heat flow model from section 3.1.4 was used, but with starting temperatures of 0°C for all building elements and a constant outside temperature of 0°C. This way, there are no heat flows. Then, 1kW of heat was added to the heating system, and the evolution of the inside temperature was

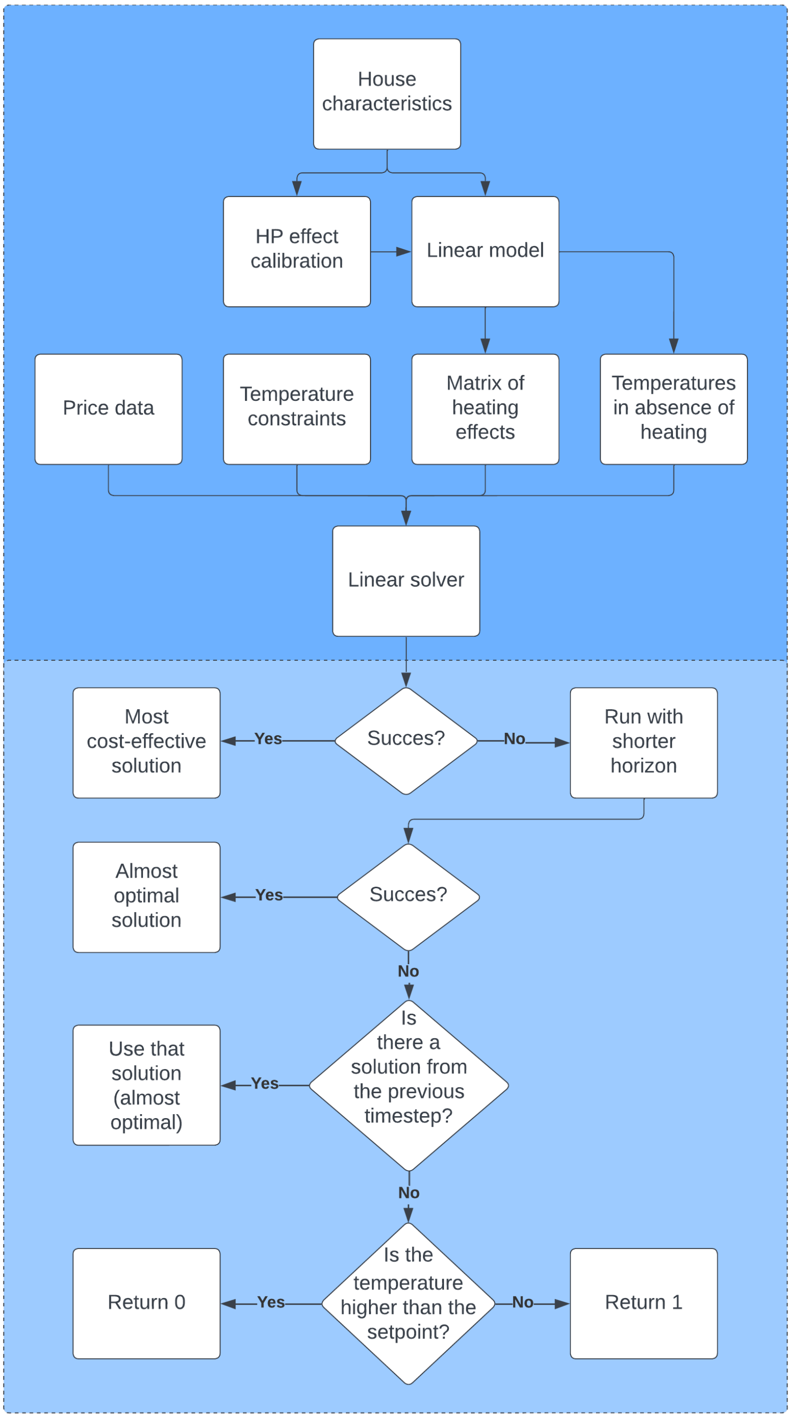

Figure 9: Flowchart for the model predictive control strategy. The top half is the technical implementation. The bottom half contains a decision tree based on the results of the solver.

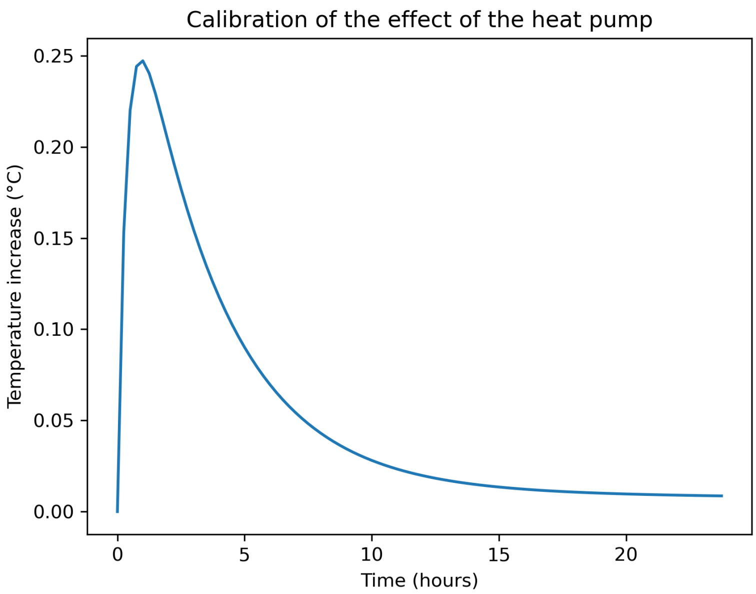

Figure 10: This is the output of the calibration of the heat pump effect for one of the households. It shows the inside temperature increase over time due to 1 kW of heat added to the space heating system.

tracked. This gave the isolated effect of adding 1kWh of heat to the heating system. Figure 10 shows that this leads to a slightly delayed increase of the temperature, which peaks at around 0.25°C, and then slowly decreases again.

Next, the heat pump effect is placed in a matrix, where each row contains the total effect of heating in the corresponding time step. This is the calibrated heating effect multiplied by the COP for each time step, with added zeros at the start, and the end clipped off, to maintain the same time span. Table 5 shows a simplified example.

Table 5: Example of the matrix containing the effects of adding heat to the heating system.

	Calibrated heating effect:	**0,1**	**0,25**	**0,15**	**0,1**	**0,05**	**0,04**
Timestep:	COP:						
1	**3**	0,3	0,75	0,45	0,3	0,15	0,12
2	**3,5**	0	0,35	0,875	0,525	0,35	0,175
3	**4**	0	0	0,4	1	0,6	0,4
4	**4**	0	0	0	0,4	1	0,6
5	**4,5**	0	0	0	0	0,45	1,125
6	**5**	0	0	0	0	0	0,5

The linear model also simulates the temperature in the house for the case that no heating is applied at all. For this, the linear model keeps track of its own estimation of the temperature of each building element and receives the actual inside temperature every 24 hours.

The next step is the actual solver. For this, the mixed integer linear programming (milp) function from the scipy.optimize package for python was used [50]. This solver finds the optimal values for a set of decision variables (in this case a list of activations for the heat pump), so that the total costs (using the day-ahead electricity

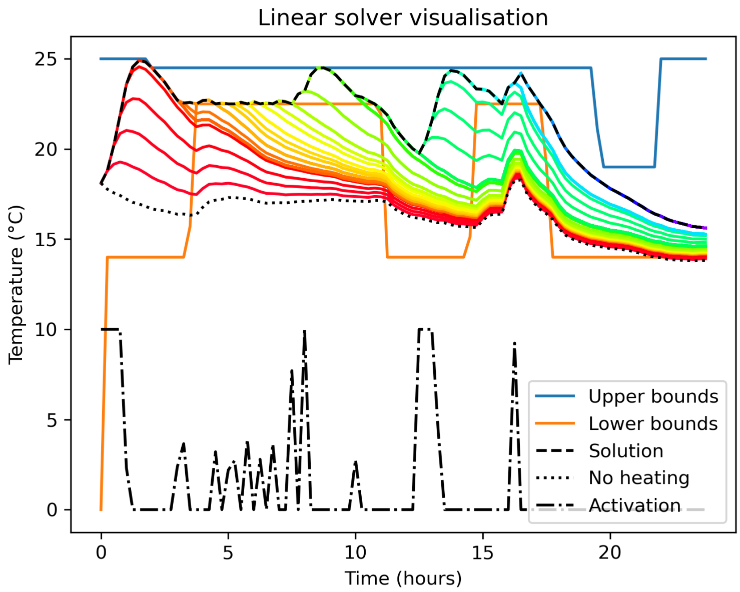

Figure 11: Visualization of the workings of the linear solver.

prices in this version) are minimized, where the decision variables are bound (activations are limited to 0%-100% of the heat pump power), and a set of constraints is satisfied (the temperature should stay in a certain range). Figure 11 shows an example.

The top line represents the upper constraints for the inside temperature. These were constructed in a specific way to allow enough freedom for the model to work properly, and still maintain a reasonable level of comfort for the inhabitants: The start (first 8 time steps) of it is set to 25°K, to avoid errors. Next, a maximum deviation above the set-point is set (2 degrees in this project). Then, it takes for each time step the maximum of the set-points for the coming 8 time steps, and adds the maximum deviation. finally, the values below 19 are set to 19. The lower bounds are just the temperature set-points, with an exception for the current time step, which is lowered to avoid errors when the current temperature is below the current set-point. The bottom line shows the optimal HP activations found by the solver. These bring the temperature from the case with no heating (dotted line) to a temperature between the bounds (the dashed line). Each activation adds an amount of temperature according to:

$$\Delta T = HP_{state} * \Delta T_{calibrated} * HP_{power} * COP \tag{38}$$

The added effects (the colored lines in figure 11) compound to reach the solution with the lowest costs that satisfies all given constraints. The exact representation for the solver consisted of the cost function to be minimized:

$$\sum_{i=1}^{t_{horizon}} c_i * x_i \tag{39}$$

where $t_{horizon}$ is the time horizon in number of time steps, c_i is the electricity price at time step i, and x_i is the activation of the heat pump.

The solution had to satisfy the constraints that the activations were bound to be between 0 and 1:

$$0 \leq x \leq 1 \tag{40}$$

where x is the vector of activations. The solutions had to satisfy the constraints:

$$b_l - T_{noheating} \leq Ax \leq b_u - T_{noheating} \tag{41}$$

where b_l is the vector of lower bounds as described above, b_u is the vector of upper bounds s described above, $,A$ is the matrix of heating effects as described above, and $T_{noheating}$ is a vector of the inside temperature that would be present in the house over time if the heat pump would not be activated. This way, $b_l - T_{noheating}$ effectively forms the lower bound on the desired temperature effect of purely the heat pump, and $b_u - T_{noheating}$ the upper bound on the temperature effect of the heat pump.

The bottom half of figure 9 shows the next steps in the process. As the linear model is slightly different from the actual simulation, there might be slight differences that can cause the solver to be unable to find a solution. This is often the case if it waits a bit too long before heating and can not reach the set-point anymore. To counter this, if there is a solution, the maximum of the future two time steps is taken. This means the heating starts a bit sooner than optimal, but less crashes of the solver.

If no solution is found, the solver is rerun with a shorter horizon (looking 6 hours ahead instead of 24), as the model sometimes underestimates the long term heating potential, and does not find a solution for a later part of the day. If there is again no solution, it checks if there was a solution from the previous time step and takes that as a result. If the solver has longer term problems (e.g. during the days in summer where it is too hot for a long time) the strategy returns a set value of 0% if it is hotter than the set-point, and 100% if it is colder than the set-point (e.g. due to a heat pump with an insufficient capacity to heat the house during a very cold day).

3.3.8 Model predictive control v2

Similar to the second rule-based control version, the second MPC version uses the "optimal" price data. This is better aligned with the grid load and could lead to more effective load shifting. This is again the only difference between the two versions. This is the hardest strategy to implement, as it has the same requirements and drawbacks as the RBC2 and MPC1 combined.

3.3.9 Key performance indicators

These control strategies are compared based on a number of Key Performance Indicators (KPIs). The first indicator is the grid load over the year. This is analyzed with load duration curves, to show both the duration and amplitude of the grid load during the year. The second indicator is the total electricity consumption, as this is expected to increase for some strategies and might negatively impact the energy transition, trading one problem for another. The third indicator is the total electricity costs. The final indicator looks at the comfort level of the inhabitants, as load shifting means shifting of heating periods, which might lead to too cold and too hot periods.

4 Results

For the results section, the scenarios are grouped according to the insulation levels used for the households (renovated houses, new houses, or a 50/50 mix between the two types). The scenarios with the renovated houses will be discussed, as well as interesting differences between the groups. The main results for each control strategy are discussed here and are shown in table 6. The next sections cover the results in more detail.

As shown in table 6, the constant heating strategy is the best at mitigating grid congestion in scenarios with high heat pump adoption rates and a large set of the households equipped with smart control. It performs well on comfort. On the downside, the total electricity consumption is increased by 13% and the costs are increased by 12% with day-ahead pricing. With the "perfect" pricing, it is again one of the cheaper strategies. The fixed control and rule-based controls do not achieve significant peak load reductions. They result in a slight increase in total electricity consumption and the electricity costs are similar to those for the reference. The model predictive control v1 performs well in mitigating grid congestion in all cases. it also achieved a reduction in total electricity consumption and heating costs of 17%. The model predictive control v2 has a large potential to reduce peak loads in cases with lower household adoption rates (20-40%) or lower smart control fractions. With day-ahead pricing it results in a cost reduction of 5% compared to the reference. With "perfect" pricing this reaches a reduction of 30%.

Table 6: Summary of the most important results for each control strategy.

Summary of the results for the control strategies				
Control strategy	Grid congestion mitigation potential	Total electricity consumption	Heating costs compared to reference	Comfort
Constant heating (CH)	Highest with high HP adoption and smart control rates (up to 13% lower grid peaks)	+13% compared to reference	Highest with DA prices (+12%). Low with perfect pricing (-4%)	Optimal (equal to reference)
Fixed control (FC)	Low with current settings (up to 10% lower grid peaks in some cases)	+4% compared to reference	<5% deviation from the reference	Sometimes too hot
Rule based control v1 (RBC1)	Low with current settings (up to 1% lower grid peaks in some cases)	+3% compared to reference	<5% deviation from the reference	Sometimes too hot
Rule based control v2 (RBC2)	Lowest with current settings (no lower grid peaks in any scenario)	+6% compared to reference	~5% more expensive than reference	Sometimes too hot
Model predictive control v1 (MPC 1)	High in all cases (up to 10% lower grid peaks)	-17% compared to reference	Low: -17% with both pricing schemes	Sometimes too cold
Model predictive control v2 (MPC 2)	Highest with low HP adoption and smart control rates (up to 10% lower grid peaks)	-4% compared to reference	Low: -5% with DA, -30% with perfect pricing	Sometimes too hot

In the sections below the different control strategies are compared in detail considering the key performance indicators. The differences for varying heat pump and smart control adoption levels are discussed. The analysis starts with the grid load over time, followed by the total electricity consumption, the heating costs and finally the comfort analysis.

4.1 Grid load

The main objective of the smart control strategies in this project was to mitigate grid congestion. Figure 12 shows the total grid load over the year, sorted from high to low (a load duration curve). This graph shows the results for the cases with 100% renovated houses, 100% HP adoption, and all of the HPs having smart control. The standard grid capacity for a neighborhood of this size is shown as a dotted line [36]. Each strategy has one line, and there is another line for an equal mix of all the control strategies.

On the left axis, starting from the top, there are the two rule-based strategies. These strategies create the largest peaks. This is caused by the fact that each household has the same price data, and starts preheating at the same time, causing new peak loads for the grid. The next in line is the model predictive control v2, which has a similar issue, because all households receive the same price data. The model predictive control v1 scores a lot better. A deeper look into the results shows that for this version, the price data are not variable enough to actually loadshift, and the strategy just minimizes the consumption (which leads to the lowest costs with the DA-pricing scheme).

The fixed control strategy is closer to the reference, as the preheating is done slowly. The fixed control increases the temperature set-point in a timespan of 2 hours, instead of in 15 minutes (one time step), like the rule-based controls. The line below the reference represents a mix of all the control strategies, which performs well. This is because it lowers the simultaneity caused by the control strategies, avoiding the creation of new grid load peaks. Finally, there is the constant heating strategy, which performs the best in this scenario, as it keeps the temperature inside the most stable, leading to lower variations in the heating load, and lower peak loads.

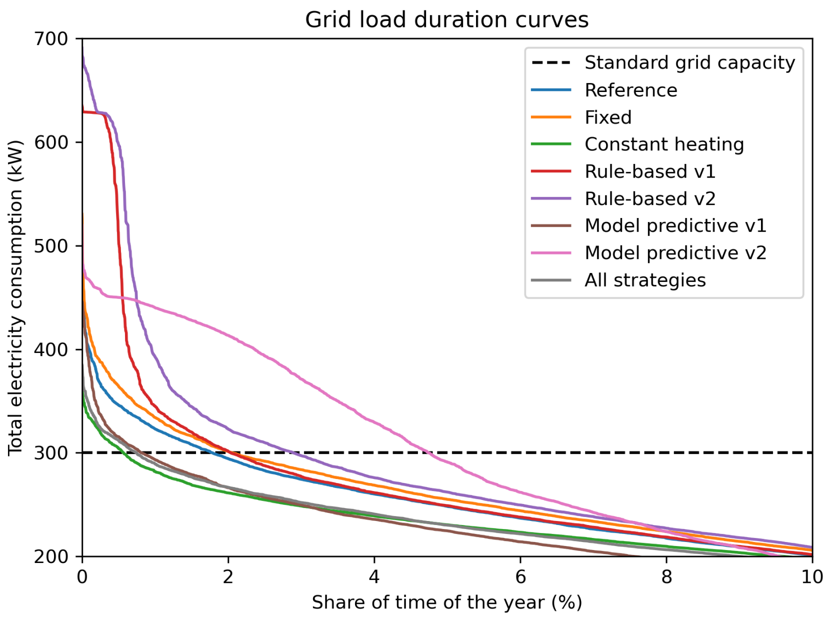

Figure 12: Load duration curves for the different control strategies in the case with renovated houses and 100% heat pumps and 100% of those having smart control.

However, this does not necessarily mean that the constant heating control strategy is the best in general. Figure 13 shows the value of the 99% grid load peak, for each strategy for different percentages of smart control. This value is a strong indicator for the severity of the grid congestion. The figure shows that the constant heating control and MPC1 are more effective the higher the smart control fraction, whereas the other strategies are more effective with lower smart control fractions. The model predictive control clearly shows an optimum around 30% to 40%. For the remaining control strategies there is a less clear optimum, somewhere between 0-20%.

Similarly, some strategies perform better in neighborhoods with a lower HP adoption rate, as there are less heat pumps that can create new peaks, and these heat pumps can shift away from existing peaks (form other appliances). Figure 14 shows the value of the 99% grid load peak, for the cases with 100% smart control, but with varying HP adoption levels. Here again the constant heating strategy performs well with the high adoption cases, and the model predictive is optimal with an adoption level around 20%. This time, the fixed control strategy also shows a clear optimum around 20%.

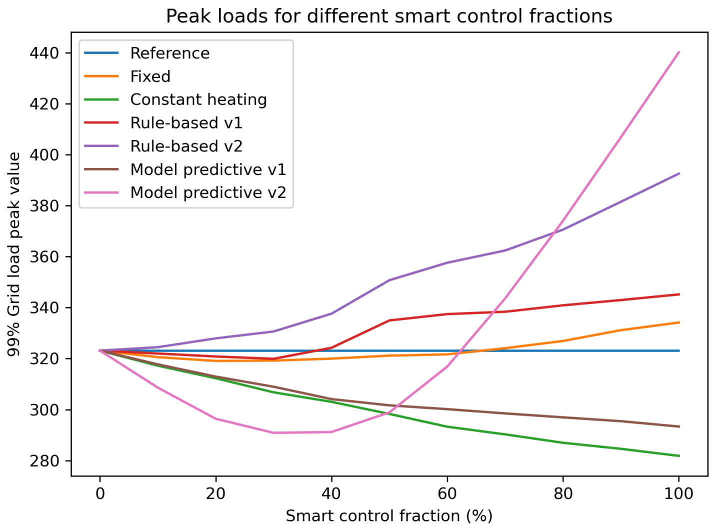

Figure 13: Plot of the 99% peak grid load as a function of the smart control fraction, for each control strategy. Some strategies have a clear minimum. For others the peak load keeps decreasing or increasing with higher smart control fractions.

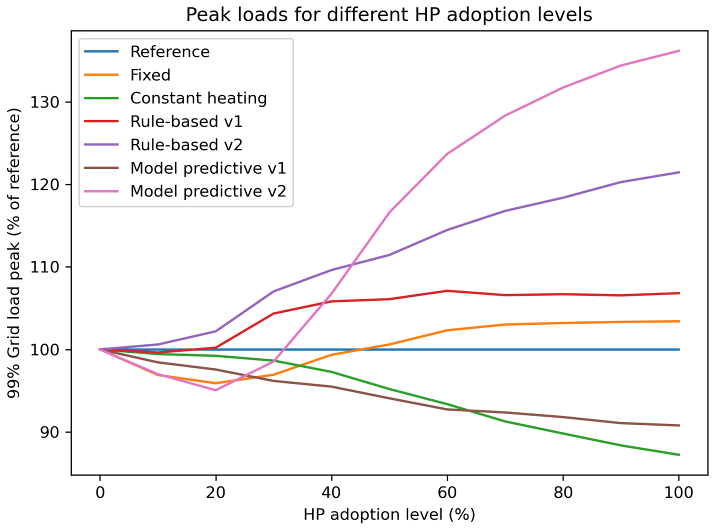

Figure 14: Plot of the 99% peak grid load as a function of HP adoption rate, for each control strategy, compared to the reference. Some strategies have a clear minimum. For others the peak load keeps decreasing or increasing with higher HP adoption rates.

4.2 Total electricity consumption

The next key performance indicator is the total electricity consumption. Figure 15 shows the total electricity consumption for the cases with all renovated houses. Here, the constant heating strategy performs the worst, as it keeps the house at a higher temperature than required, resulting in a higher heat loss, heat load and total consumption. Most other strategies use slightly more than the reference, because the added heat from the pre-heating is dissipated to the outside over time. The only strategies that use less than the reference are the model predictive controls. This is likely because the MPC strategies minimize the costs, which entails a low amount of heating. The MPC strategies also have more information about the dynamics of the house than the reference, which means they can waste less energy and more exactly match the set-point. The MPC v1 uses the least, because it focuses more on load reduction than on load shifting, because of its less variable pricing scheme.

Figure 16 shows the consumption of the heat pump relative to the reference case. The main outliers here are the constant heating control strategy, which uses 13% more than the reference, and the MPC v1, which uses 16% less than the reference.

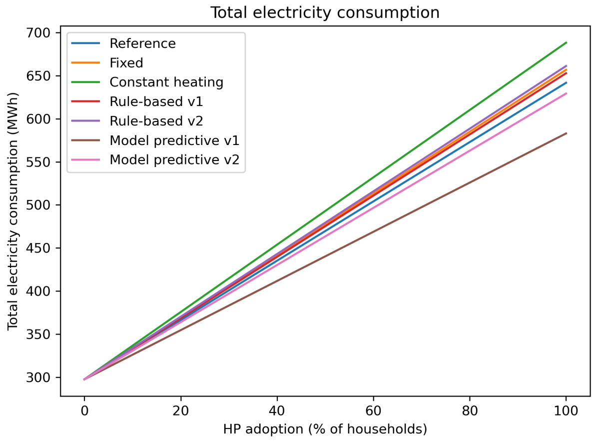

Figure 15: Total electricity consumption as a function of the HP adoption rate for each of the control strategies. This is for the cases with the renovated houses and 100% smart control.

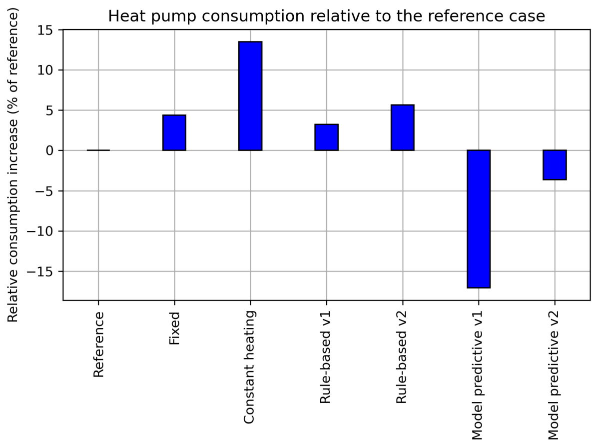

Figure 16: Consumption of the heat pump compared to the reference strategy.

4.3 Costs

The strategies are also compared by their total costs. The comparison is split into two parts: The costs with the day-ahead pricing scheme and with the "perfect" pricing scheme which is identical to the reference grid load.

Figure 17 provides the costs for just the heat pump operation, relative to the reference, if DA-pricing is used. Here the constant heating strategy is the most expensive, which is to be expected, as it uses the most heat. The fixed and rule-based strategies are also slightly more expensive than the reference, as preheating also means a higher heat loss and higher costs. The MPC v1 is the cheapest here, with a reduction of 16% in costs compared to the reference. The MPC v2 is also cheaper than the reference, because of the correlation between the DA-prices and the grid load.

Figure 18 shows the costs for just the heat pump operation, relative to the reference, if the "optimal" pricing is used. Here the constant heating strategy performs better, as it heats all day instead of mainly during peak moments, which reduces the amount it has to heat during the peak hours, thus trading a few expensive hours for a lot of cheap hours. The fixed and rule-based strategies are also slightly cheaper now, as the preheating hours are a lot cheaper now compared to the peak hours. The MPC v1, which optimizes using the DA-prices still performs great, with a reduction of 16% in costs compared to the reference, as it effectively minimizes the heat load in general. The MPC v2 is optimal here, as this is the price scheme it is using to minimize the costs. A decrease of over 30% compared to the reference is reached with this "perfect" pricing scheme.

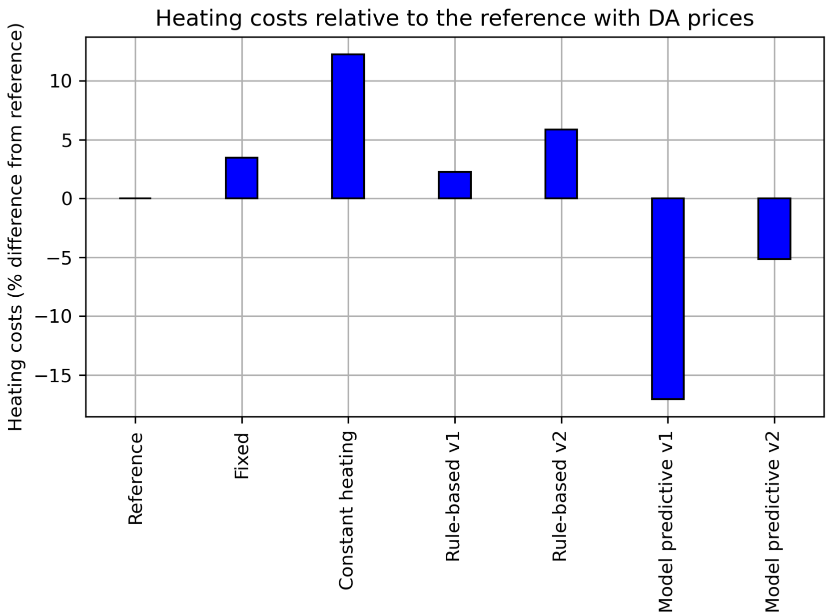

Figure 17: Heat pump electricity costs, compared to the reference. This is the case with Day-ahead pricing.

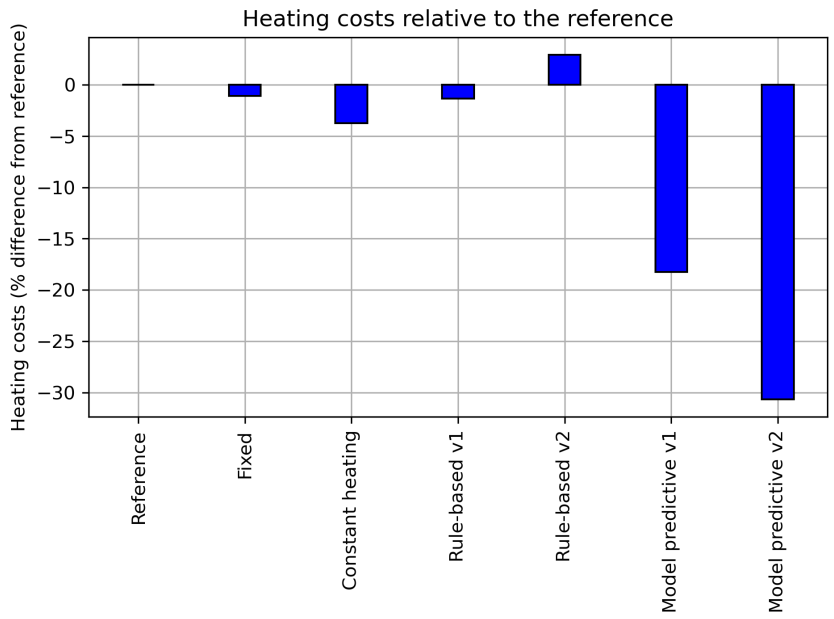

Figure 18: Heat pump electricity costs, compared to the reference. This is for the cases with "optimal" pricing.

4.4 Comfort

The final KPI is the comfort of the inhabitants. This is quantified by calculating the difference between the actual temperature inside and the set-point, during periods that at least one person is awake in the house. This analysis looks at the winter period, as this is the time that the heat pumps are mostly used. (Also, if the entire year was analyzed, the results would be dominated by the heat in the summer.)

Figure 19 shows the average temperature difference with the set-point during the winter. These average values are very small and are normally not noticeable. However, if combined with figure 20, some more insights can be obtained. Figure 20 shows temperature duration curves. In general, there are very few days where the heat pump does not have the capacity to heat the house. There are also some days that are very sunny, and the house heats up too much. During the rest of the days, some strategies preheat more than others, which might lead to discomfort. A line is drawn for an increase of 2 degrees, which is the preheating restriction given to the strategies in the model. The rule-based v2 and model predictive v2 preheat the most, leading to a higher chance of discomfort. the constant heating is almost identical to the reference here, as it only preheats in the periods that no-one is home. The MPC v1 minimizes the heating to save on costs, but sometimes underestimates the heating load, leading to a slight increase in cold days.

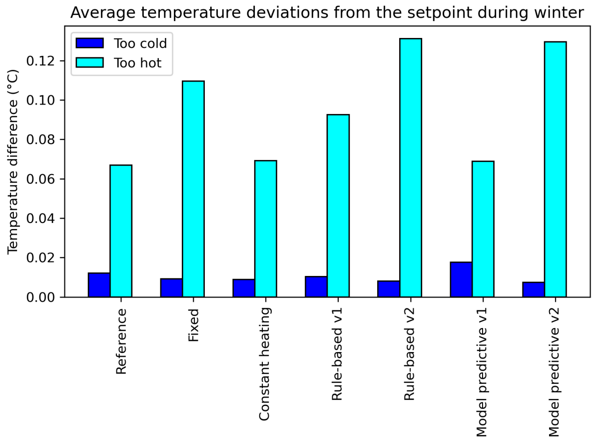

Figure 19: The difference between the inside temperature and the temperature set-point during occupation periods (when at least one person is home and awake). The data is split into moments when the inside temperature is higher than the set-point (too hot) and moments when it is lower (too cold).

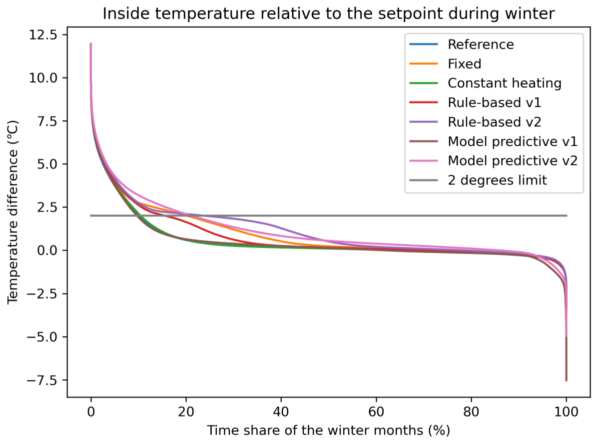

Figure 20: Duration curves for the temperature difference between the inside temperature and the temperature set-point.

4.5 Differences between insulation scenarios

The cases with new houses and those with a mix between new houses and renovated houses yield similar results to the cases with all renovated houses, except for the model predictive control strategies. This is likely due to some mistake in the input or code for these exceptions. The MPC strategies result in the highest costs in these scenarios, even though they attempt to minimize the costs. They also result in the highest grid congestion and total consumption. Due to time constraints, the bug that caused this was not found before the end of the project.

5 Discussion

This section contains the recommendations that follow from this research. Then, the limitations of the study are discussed, and directions for future research are given.

5.1 Recommendations

Given the difference in complexity and performance between control strategies, and differences in the amount of heat pumps in neighborhoods in the Netherlands, there are multiple recommendations.
It is advisable to use a constant heating strategy for all houses with floor heating and heat pumps, as soon as possible. This is one of the most effective strategies at mitigating grid congestion and very easy to implement. However, this does increase the total electricity consumption significantly. To counter this, the next step could be to start creating simulation models of real houses and switching to model predictive control for part of the houses. This could be matched with day-ahead pricing, or an area specific hourly electricity price that matches the local grid load more closely. The day-ahead pricing is already widely used by electricity companies for other uses and is easily accessible. More local pricing would work better for load shifting, but is not yet available and might be perceived as unfair by residents or even be prohibited by the government in some countries. Another recommendation for the short term is to add heat storage to houses with a heat pump, to further increase the potential for load shifting.

For the long term, most of the houses could have their own simulation models, and could have more smart functions and appliances. In such cases, a switch could be made towards aggregated (model predictive) smart control to minimize the total costs (and energy usage) for everyone, without creating new peak loads on the grid. This might be difficult to implement, because it would mean that an aggregator gains control over the heating systems for the users directly, which the users might not be comfortable with. Users might be more willing to participate if there is adequate (financial) compensation.

5.2 Limitations

This section describes the limitations of this study.

5.2.1 Limitations of the scenarios

The scenarios covered variations in HP adoption level, smart control percentage, the type of control strategy used and the insulation values of the houses. There are other factors that might be influential to the results, but were not included in the study. No variation was made in the PV adoption level, as it does not directly interact with the control for the heat pump (except for the pricing for RBC2 and MPC2, which is based on the total grid load). It does however impact the grid congestion directly, and should be considered in cases where the grid capacity is known. This study only uses an indication for the grid capacity and the focus is on the grid loads caused by the heat pumps.

The building layout and shape are also simplified as the goal was to test the effects for the average neighborhood in the Netherlands. These simplifications might lead to a higher heating load, as the entire house is assumed to be heated. Also, the orientation of the buildings and surroundings (e.g. trees) are the same for all houses, impacting the amount of solar radiation that reaches the house. The type of heat pumps is also identical for all houses, where this would be a mix in reality. These effects are expected to impact all control strategies equally, giving similar relative results. Adding variations in all these aspects would likely result in a larger spread of heat demand in time, resulting in lower but wider grid load peaks, decreasing the grid congestion for the reference strategy.

The fixed and rule-based strategies are expected to perform slightly worse if the grid peak hours are longer, as the heat from the preheating lasts for a limited time. The longer the peaks. the smaller the fraction of the peaks can be mitigated by these strategies. The constant heating and MPC1 strategies are expected to perform the same as with the simplified scenarios, as they do not use any aggregated data and the houses are still similar on average. The MPC2 strategy gets different price data with broader peaks, which might slightly decrease its effectiveness.

The types of inhabitants were also the same in each scenario, where in reality this differs significantly between neighborhoods. Old (retired) residents tend to be home more and prefer higher temperatures, whereas younger people are home less and prefer lower temperatures. Most people go on holidays as well, which is not included in the current model for occupancy of the houses. These factors mainly influence the results for the constant heating strategy. In neighborhoods where people are home a lot and prefer high temperatures, the constant heating strategy requires less additional heat, while still reducing the demand during peak hours. If people are home less, the constant heating strategy uses more additional heat compared to the reference strategy, resulting in relatively higher total consumption and heating costs. The other strategies focus more closely on the time frame around the peak hours, which is less dependent on the demographics of the neighborhood.

5.2.2 Limitations of the control strategies

In general, there was limited fine-tuning performed for the control strategies, which likely gives suboptimal results for some. For example, the fixed control strategy has a set time when the peak period starts, and a set duration of preheating before the start. Also the amount of preheating (e.g. to 2 degrees above the set-point) is a parameter for this strategy. each of these parameters was fine-tuned by testing and evaluating the results. This has been done manually, which made the options that were tested limited.

Mainly the fixed and rule-based control strategies relied on manual fine-tuning and might benefit from more fine-tuning. However this was limited in this project by the time it takes to run the model (each run took 20 minutes). In a real-world scenario more time and computing power could be available to tune these parameters, but the effectiveness might be limited by higher variability in the data used for the fine-tuning and changes in the neighborhoods over time.

Furthermore the set of control strategies that were compared was limited to a small set, covering enough different strategies to evaluate the trade-off between complexity and effect. Many more examples of both fixed control strategies and rule-based control strategies can be found in the literature. Model predictive control strategies can also vary a lot, including multiple aspects in their respective cost functions, like comfort, GHG emissions and self-consumption. MPC can also be used more directly to minimize the grid congestion, by including the total grid load of the neighborhood in the cost function and setting a limit for the grid. But that would require a larger optimization model which includes the entire neighborhood, requiring a different model structure than used in this project.

The MPC strategies used a linear model for the optimization. This linear model simplifies some of the heat flows, and separates the effect of the heat pump from the rest of the heat flows. A test was performed to identify the effect of this simplification (see appendix B). On average, the temperature deviation for the inside air was around $0.25°C$, which was deemed acceptable.

5.2.3 Limitations of the heat flow model

Ventilation and infiltration is significantly simplified, to keep the calculation time and data requirements lower. The surroundings of the buildings were not taken into account either. The equations for the floor were modified as well, as hourly data about the ground temperature were not readily available. The floor heating system was added later in the process, and implemented as a heat storage that directly heats the inside air, instead of heating the floor first and then the air. The convective heat flows are simplified and included in the heat conduction equations in the form of a higher Rc-value. Again, most of these simplifications have an almost equal effect on all control strategies, resulting in similar relative results. The quantitative results can be improved by making the model more detailed, but this will also result in longer running times.

The modeling of the heat pump is also simplified, to allow for a linear optimization and less calculations in general. The heat pump is modeled to provide any amount of heat between 0-100% of the HP capacity each time step (15 minutes). In reality, heat pumps can only perform a limited number of cycles per hour and each cycle takes a set amount of time. Most heat pumps also have a minimum load (e.g. 30%) or even have only an on/off state. These matters would complicate the model, and differ for each model of heat pump. This is expected to have only a small impact on the results, as the length of the time step is long enough that these dynamics could be included.

5.3 Future work

Future research could include new scenarios with varying amounts of heat storage, and control strategies that are designed with heat storage in mind. With added heat storage (e.g. hot water tanks) the quantity of loads shifted can be increased. The moments of heating the water and heating the living space can be further apart due to the typical low heat loss of a designated heat storage compared to the thermal mass that stored the heat in this study.

Following this, it could be valuable to make an economic analysis of the added value of heat storage and its load shifting potential, compared to the costs of the heat storage. Additionally, aggregated control strategies could be implemented (e.g. combined load optimization for the entire neighborhood). This way, new peaks due to synchronized control strategies can be avoided, leading to even less grid congestion. Quantifying the potential of such control strategies would be a valuable addition to the results from this study.

More future research could focus on the development of better bottom-up simulation models that can handle calculations for large amounts of houses. The behavior and consumption patterns of people also change continuously, and new models need to adapt to these changes, requiring continuous research in this direction. More research in the direction of demand side management is also possible. Other loads could be considered for load shifting, like electric vehicles, washing machines and cooking appliances. Load shifting could also increase self consumption of PV electricity and improve self sufficiency.

5.4 Comparison to the literature

A paper by Masy et al. included a similar setup for a house in Belgium and contained some strategies corresponding to strategies from this project [51]. The "K45" house had similar insulation values to the renovated house from this study. Their constant heating strategy ("RBC2-constant temperature") resulted in a cost increase of 5% compared to the reference, and a significant amount of heating volume shifted. This increase in costs is similar to the increase found in this study. The grid mitigation potential is defined in a completely different manner, which makes it hard to compare the results. The "optimal control-intermittent heating with PP pricing" strategy from the paper is similar to the MPC1 strategy from this project and resulted in significant volumes shifted, a small reduction in costs (3%), and an increase in electricity usage of 12-18% compared to the reference. These results are different from the ones from this study, as the pricing scheme was variable enough to result in load shifting, but not variable enough to result in the cost savings achieved with MPC2. The reference strategy was likely more optimized in that paper as well, resulting in a necessary increase of the consumption for load shifting, while in this study the MPC was more efficient in heating the building than the reference strategy.

Paper [52] included a strategy similar to the fixed control strategy from this project. They achieved a cost reduction of up to 34% and turned off the heat pump almost completely during peak hours. The difference in cost reduction with the reduction found is this study can be explained by the difference in pricing schedule. Where this study used an hourly cost schedule that differs each day, instead of one with predefined price blocks which are the same everyday (which was used in the other paper). The higher load shifting potential that was found is explained by the different climate (Portugal instead of the Netherlands) with warmer winter days and lower heat losses. Also, no new peak loads were observed, because the case study was on only a single building.

Other papers achieved better results for the simpler strategies, by including hot water tanks as additional heat storage. This way enough heat could be stored to completely avoid heat pump operation during almost all peak hours. For example, Coninck et al. managed to reduce the amount of peak loads by almost 50% where the remainder was not caused by the heat pump [53], and Lee et al. used heat storage in an net zero energy building to maintain a heat pump grid load near zero during predefined peak hours [54]. These results far exceed the potential for houses without additional heat storage as found in this study.

6 Conclusion

The aim of this project was to quantify the grid congestion mitigation potential of heat pumps in the Netherlands for different smart control strategies, and to identify the barriers and challenges of each smart control strategy. This was achieved by comparing a set of promising smart control strategies in a simulation of a typical dutch neighborhood. Different scenarios were used to determine the effectiveness of each strategy in situations with more heat pumps or less heat pumps, varying insulation levels for the houses, and a varying amount of the houses with smart control.

Seven control strategies were compared, with varying complexity. A reference strategy that aims solely for optimal comfort was used as a baseline. A strategy was included that has the same goal, but keeps the temperature on a higher minimum (constant heating). The third (Fixed), fourth (RBC1) and fifth (RBC2) strategies used previous grid load data or price data to determine peak grid load hours. They then preheat the house in the hours before the peak loads, reducing the required heat during the peak hours. The sixth (MPC1) and seventh (MPC2) used models of the houses to predict the future effect of activating the heat pump, combined with electricity price data, to find the scheduling of the heat pump with the lowest costs. Two price schemes were used (v1 and v2), the day-ahead pricing (which correlates with the grid load) and the "optimal" pricing which is based on the actual grid load of the neighborhood.

The strategies were compared on their grid congestion mitigation potential, the heat pump electricity consumption, the heating costs and the comfort for the inhabitants. The results of the simulations show that the constant heating and MPC1 strategies have the best grid congestion mitigation potential in scenarios with a high heat pump adoption rate. The constant heating strategy however results in an increase in electricity usage for the heat pump and in heating costs of up to 13%. The MPC1 strategy results in a decrease instead for the electricity use and heating costs of 15-20%, but is much more complex to implement in practice.

In the scenarios with lower HP adoption rates the MPC2 performed the best, with a reduction in peak loads and costs of up to 30%. The MPC1 and constant heating strategies achieved less results in these scenarios, as there were less heat pumps to start with. The other strategies performed worse than the reference, likely due to insufficient fine-tuning.

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Appendices

A Demographics calculation

For the calculation of the inhabitant types, we start with 100 adult people, which are divided into households. First, the amount of retired households was determined. 12.9% of all people are retired. Part of the population consists of children, who can not own a household. This results in 15.1% of the people that can own a household being retired. Additionally, a household with a couple has two people, whereas the other households have one person. These 15.1% can be divided into 7 households with two people, and 1 household with 1 person.

Next, the amount of part-time working couples and families with one worker is determined. For this, the fact is used that 8.2% of people are jobless, which is then normalized to get 9.6% if children are excluded. Both a part-time couple and a family with two parents and one worker consist of two adults, one of which is assumed to be "jobless", and one that works full-time. Additionally, it is assumed that 90% of the part-time households are covered by families with a stay-at-home parent, and only 10% are couples without children. This results in 1 household with a part-time couple, and 9 households with families with a single worker.

Next, the full-time workers are sorted into households. This step starts with the ratios between household types: 20% are families with two parents, 53% are single person households, 21% are couples, and 6% are families with a single parent. However, if these households are assigned the proper amount of people, 141 people are needed. Hence, each of these numbers is divided by 1,41. Then the households that are already counted in the other classes are subtracted, to avoid double counting. Finally, the full-time working families with single parents and two parents are combined, as they belong to the same class. The calculation and results are shown in table 7.

Table 7: This table shows the calculations to determine the distribution of household types.

People	Retired: 12.9%		Jobless: 8.2%		Fulltime: 64%			
Normalised	15%		10%		75%			
Household type	Dual retired	Single retired	Couple parttime	Family single worker	Family	Single	Couple	Family single parent
People per household	2	1	2	2	2	1	2	1
Assumptions/percentages	~64% of households lead by a retired person are single households.		~80% will be families with one stay-at-home parent.		20%:53%:21%:6%, but 1 parttime couple is already used , as well as 7 retired couples and 1 single retired and 8.6 families with two parents.			
%Households tot					20	53	21	6
SUMPRODUCT:								141
Normalisation #2					14	38	15	4
#Households	4	7	2	8	7	30	9	4
Percentages	5,6%	10,0%	2,7%	10,8%	9,2%	43,0%	12,7%	6,0%
Conclusion:	**Dual retired**	**Single retired**	**Couple parttime**	**Family single worker**	**Family**	**Single**	**Couple**	
	5%	**10%**	**3%**	**11%**	**15%**	**43%**	**13%**	

B Linear model performance

A linear approximation of the main simulation model was used for the two optimization strategies. Figure 21 shows an output comparison of the two models for the inside temperature for a typical week in winter. In the winter months, the difference was on average 0.25°C, with a standard deviation of 0.21°C. In the summer months, the difference was sometimes larger, as the cooling that was assumed in the main model was not implemented in the linear model (as this makes it nonlinear). This difference in the summer is insignificant to the results, as the heat pump is rarely activated in the summer.

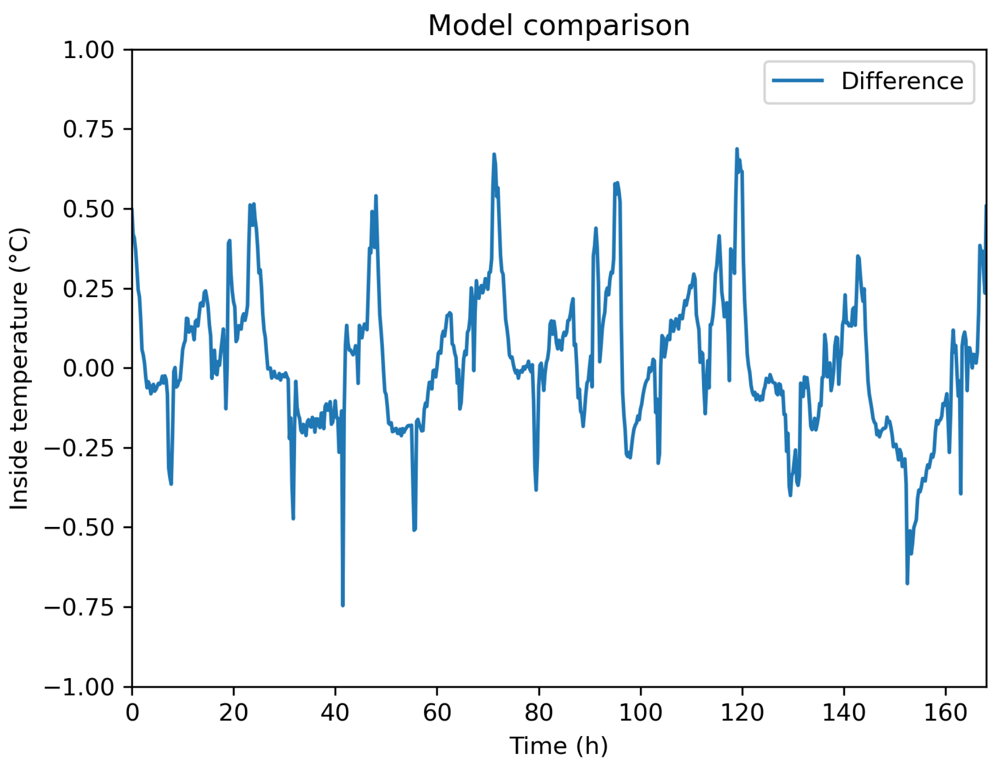

Figure 21: Example week to show the temperature difference between the linear model and the main (complex) model.