Reduced energy cost of heat-pump driven heating systems by smart use of thermal storage

Jonas Cleiren[1], Stef Jacobs[2, 3], Guillaume Van Caelenberg[1], Menno Janssens[1], Peter Hellinckx[3], Ivan Verhaert[2]
[1] Noven NV, Coupure Rechts 64 D, 9000 Gent, Belgium, firstname@noven.be.
[2] EMIB, Faculty of Applied Engineering - Electromechanics, University of Antwerp, Groenenborgerlaan 171, 2020 Antwerp, Belgium, firstname.lastname@uantwerpen.be.
[3] M4S, Faculty of Applied Engineering - Electronics ICT, University of Antwerp, Groenenborgerlaan 171, 2020 Antwerp, Belgium, firstname.lastname@uantwerpen.be.

Abstract

A day-ahead electricity price offers opportunities for demand response strategies in heat pump-based collective heating systems. However, a trade-off between energy cost and operational system efficiency (heat losses and production efficiency) needs to be made. This research identifies the cost saving potential for a real case study by applying various temperature control schemes in a collective space heating network. Results show that adjusting the temperature set point can yield daily cost savings of up to 40,2%. However, the optimal temperature increase depends on heat loads and price volatility of that day.

Highlights

- The potential of storage temperature increase based on time-varying electricity prices for energy cost savings has been established.
- In winter, the central storage tank and temprature set point increase should be larger than in autumn to achieve higher cost savings.
- In autumn or spring, the potential savings are heavily dependent on the price volality, expected heat demand and temperature settings.

Introduction

The main challenge of the energy sector is to provide renewable energy at an affordable cost without compromising the security of supply. The climate goals of the European Union by 2050 require increased use of renewable energy sources and energy efficient systems. Besides renovating the built environment, two more issues are important in this context.

The first issue is sustainable generation of electricity, for example by renewable sources such as wind turbines and PV panels. However, these make production weather-dependent, making it more difficult to balance production and demand compared to traditional generation units (based on coal, gas or nuclear). Therefore, flexibility through demand-side management strategies and energy storage are needed to adjust demand to production, without compromising comfort (Gelazanskas et al., 2014). This could make use of time-dependent electricity price signals, as they indicate whether there is a surplus or shortage of electricity and indirectly reflect the CO_2 emissions from the electricity generated (Luc et al., 2020).

The second issue is the electrification of thermal energy supply (Thomaßen et al., 2021). This can be done efficiently with collective heating systems. A collective heating network connects multiple end-users to common heat production units through large distribution pipes. Combining end-users with a common production unit facilitates the integration of Heat Pumps (HP) in the built environment (Lund et al., 2014), as economies of scale apply and the HP will operate more efficiently due to fewer fluctuations in heat demand. Moreover, collective heating systems have high thermal inertia and usually large thermal storage tanks, which is ideal for providing flexibility to the renewable electricity grid.

Both of the above points present opportunities for HP-based collective heating networks. Making smart use of the time-dependent electricity price, reflecting the CO2 intensity and flexibility needs of the electric grid, in controlling HPs can I) make building heat supply more sustainable, II) lead to lower energy costs for buildings and III) provide flexibility to the electric grid.

State of the Art

On the one hand, the scientific literature contains studies aimed at optimizing design and production efficiency in HP-based systems to indirectly save energy costs. For example, Wang et al (2022) reduced the energy costs up to 58% by optimizing the Coefficient of Performance (COP) of a coupled air and ground source HP system with energy storage for a hotel building. The design of booster HP-based 2-pipe heating system for apartment buildings and its design supply temperature were optimized by Jacobs et al (2021).

On the other hand, the state-of-the-art includes control optimizations that realize direct energy costs reductions based on time-dependent energy prices. For example, Saffiri et al (2018) and Cirocco et al (2022), both optimized the charging schemes for thermal storage in an industrial refrigeration plant that maximizes the use of renewable energy and aims for the lowest possible total cost of electricity. The tariff structure was Time-Of-Use (TOU). Saffiri et al (2018) investigated scenarios for shifting on-peak loads to off-peak moments where the DSM strategy can put the PV panel and/or the cold storage tank in 'Inactive mode' for the weekend, 'Charging mode', or 'Discharging mode'. It was concluded that greatest savings are possible when the PV panels and the cold storage tank are linked together. Cirocco et al (2022) validated a similar approach in a practical case, where a third operating mode was the 'intermediate' mode. During this mode, charging is done based on the predicted load of both cooling demand and PV electricity

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production. Siecker et al (2022) present an optimal switching strategy for an air-to-air heat pump to heat a two-bedroom residential building. The strategy, solved with Mixed Integer Linear Programming (MILP) technique, takes advantage of the building's thermal inertia to switch off the heating during high TOU electricity prices. The results show savings of 0.32 USD per day compared to a thermostat control. The heating and cooling demand in an apartment building of 8 dwellings was optimized by Schibuola et al (2015). The heat and cold are produced centrally and distributed by a collective network. Three control strategies were investigated based on the ON/OFF control of the central production units (PV panels, solar boiler, HP, storages, etc.). The control strategies include forced on and forced off signals, but the temperatures can never exceed the preset set points. Again, cost savings of up to 30% were achieved.

Problem statement

Thermal inertia in the system and storage tanks is highly related to temperature. In this respect, large cost savings are possible by increasing temperatures when electricity prices are low to use this heat in times of high prices. In this way, overall energy costs can be reduced while still delivering thermal comfort. However, this leads to increased heat losses and a lower COP of the central heat pump, due to higher temperatures. Therefore, total electricity consumption will increase to cover the additional heat losses and lower energy efficiency. Consequently, temperatures will not always increase when the electricity prices are low, but only when assumed relevant to a future heat demand. A proper control scheme that takes account of all those effects needs to be found.

Scope of paper

This research contributes to the literature by investigating the trade-off between overall energy cost and operational efficiency (i.e. energy efficiency and heat losses) of an existing heating system during demand response, while fulfilling energy demands of end-users. The aim of this work is to identify the potential cost savings by developing a rule-based supply temperature control scheme for an HP-based collective heating system only for space heating, here referred to as a "Collective Space Heating System". In particular, the focus lies on deciding I) when to exactly increase the temperatures to store thermal energy in the central storage tank, and II) which temperature set point increase ($\widehat{T_{SP}}$) is the optimal for different situations. The considered time-dependent electricity price scheme is a day-ahead price (DAP) signal as at 1pm this price is published and set for each hour of the following day. This provides opportunities to develop an optimisation strategy for planning electricity consumption in a cost-minimizing manner by anticipating hours with high prices. The difficulty of this work lies in accommodating the different time scales of the problem. The prices have an hourly time scale, the control system has a shorter time scale and the effects of temperatures on both heat losses and thermal inertia have a delayed and longer impact.

Method

To investigate the trade-off between overall energy cost and operational efficiency, a digital twin of a reference Collective Space Heating System ("NovUa") is built in the Hysopt simulation software. In this respect, different rule-based control (RBC) schemes for the increase in central storage temperature, based on a day-ahead price, are imposed on the central HP and storage tank.

The decision to employ an RBC approach in this research is driven by several factors. Firstly, this research is part of a project that investigates how to efficiently control such systems, first by considering rule-based controllers (RBC) and later optimizing this RBC with more advanced techniques. By initiating the study with a rule-based approach, a gradual progression towards innovative control methods can be achieved.

Secondly, the adoption of a simple RBC strategy enables the swift identification of potential cost savings. This serves as an initial accomplishment to demonstrate the effectiveness of the digital twin and control strategy in the real system. The implementation of the RBC strategy in actual operating conditions validates its feasibility and performance, yielding valuable insights.

Finally, the integration of a RBC strategy at this stage establishes a solid foundation for further optimization and fine-tuning of the control approach. By attaining a comprehensive understanding of system dynamics and constraints through the RBC implementation, subsequent iterations of the project can leverage this knowledge to develop and enhance more advanced control strategies.

Reference case: "NovUa"

The reference case is a mixed-use residential building (apartments and hotel) situated in West Flanders (Belgium), here called "NovUa" for privacy concerns. Currently, only the Collective Space Heating System of the hotel is operational with a design thermal power of 300 kW and design temperature regime of 45°C/35°C. The building is heated by a cascade of four non-modulating ground-source heat pumps (GHP), type *Nibe F1345-60*, with a total thermal power of 240 kW, and back-up boilers to deliver the necessary remaining heat during peak demand. The measured heat demand profile of the first week of January (2023) and of October (2022) are depicted in Figure 1. A three-way mixing valve controls the supply temperature based on a heating curve.

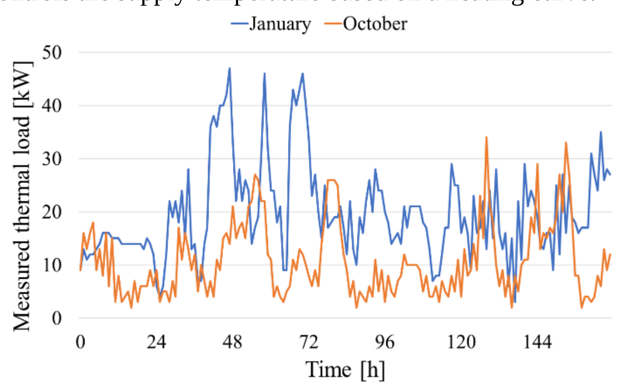

Figure 1: Total measured heat demand of two representative weeks, January (winter) and October (autumn).

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The cascade of GHPs controls the temperature in the central storage tank with a volume of 2 m^3. Its temperature set point corresponds to the heating curve, with a hysteresis of 2°C to ensure that the mixing valve can reach the temperature imposed by the heating curve.

Simulation framework: Hysopt

This research is conducted in Hysopt, a design and simulation software specifically developed for hydronic systems. The software employs an innovative design methodology called "Base Circuit", where pre-programmed circuits are linked to create a mathematical model of hydronic systems (Vandenbulcke et al., 2012). Unlike other simulation software, Hysopt combines thermal and hydraulic system calculations using a solver based on the Newton Raphson iteration method.

Hysopt includes a "system check" to ensure early detection of design faults. It provides an automated system typology to identify and warn about incorrect component positions. The software calculates flow rates, selects suitable pipes, and optimizes system components like pumps, valves, and heat exchangers.

The software enables the implementation of advanced control strategies and Dewey Decimal Classification (DDC) techniques. Energy consumption of production assets and auxiliary energy can be quantified. The simulations run on a 30-second step size, and the software utilizes Amazon cloud servers for efficient calculations. Compared to other modeling software, Hysopt's hydraulic solver is specifically tailored for large heating and cooling systems, resulting in faster simulations. The software not only provides simulation capabilities but also automates design calculations for accurate predictions.

Since this research focuses on assessing the potential of central storage temperature adjustments based on a DAP signal, the case study is simplified in two ways. First, by implementing the measured thermal loads of Figure 1 into the simulation model in Hysopt using a single end-unit instead of the entire distribution network (see Figure 2). The actual thermal behaviour of the Collective Space Heating Network is taken into account by adjusting the central return temperature based on the measured data.

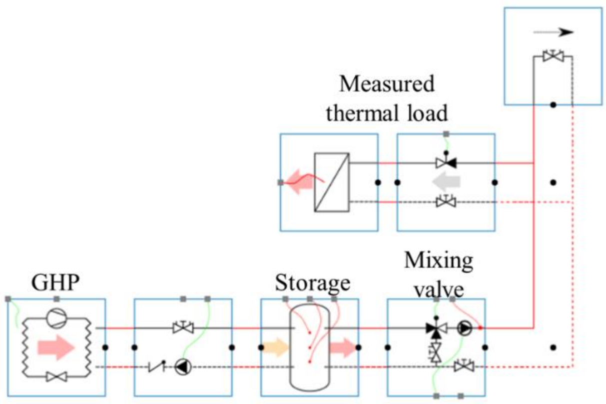

Figure 2: Simplified case study. A central 300-kW GHP heats the Collective Space Heating Network, represented by a single end-unit.

These two demand profiles were implemented to reflect the impact of different seasons, as they are a good representation of average heat demand during periods of high demand (winter) and periods of medium to low demand (autumn). The simulation approach resulted in similar heat demand compared to the actual measured heat load (see Figure 3).

Second, by replacing the cascade of the non-modulating GHPs with a single 300-kW GHP. This is mainly because all the specifications needed for accurate cascade control are a trade secret of Nibe. However, this does not affect the current study, as the goal is to identify the cost savings potential and the effects of storage temperatures on I) COP are also captured in a single GHP and on II) storage losses are captured in the storage tank model.

Demand response strategy: "price-dependent storage temperature control"

To identify the potential cost savings of increasing the storage temperature based on a time-varying electricity price, different temperature control schemes are imposed to the digital twin and compared to the reference control strategy (i.e. following the heating curve). In this respect, two parameters are considered for the different control schemes: the temperature set point increase ($\widehat{T_{SP}}$) and the duration of set point increase ($\widehat{\Delta t}$).

The $\widehat{T_{SP}}$ is always relative to the imposed set point of the heating curve (and respecting the 2°C hysteresis). Since only increases in temperature set point are considered for this study, the supply temperature in the distribution pipes will never be lower than with the reference control. The required temperature for end-users is therefore always guaranteed, and so is thermal comfort.

Future heat demand is not yet taken into account in this study's control scheme. It is solely based on the day-ahead price itself. The moments of largest price rise are identified, and just before these hours, the temperature increase always ends. So the period of temperature set point increase ($\widehat{\Delta t}$) refers to the period right before the time of this largest price rise. Figure 4 visualises the two adjusted parameters in the control scheme in red. In this example, it can be noted that the electricity price starts increasing at 6am. Thus, the temperature increase is imposed a period before 6am.

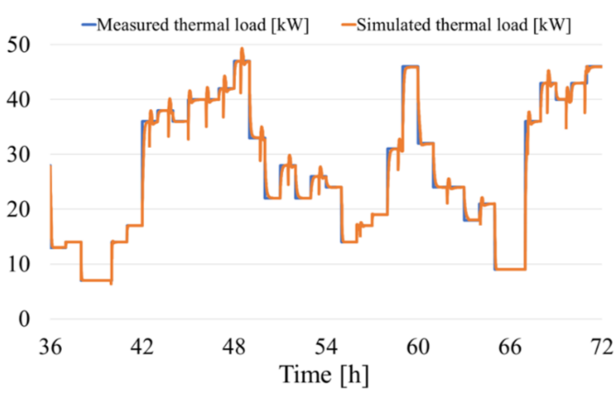

Figure 3: Measured heat load vs. simulated heat load for a few days in January 2023.

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Sensitivity analyses

The potential savings of increasing the storage temperature during times of low electricity price are highly dependent on I) the price volatility, II) thermal demand, III) the used $\widehat{T_{SP}}$, IV) the used $\widehat{\Delta t}$ and V) the storage tank volume. Therefore, these five parameters are considered when assessing the cost saving potential.

To cover the first two parameters, this study considers two day-ahead price day schemes, i.e. for 5 October 2022 and for 5 January 2023 (electricity prices are shown in Table 1), and two one-week thermal load profiles. The assessment uses the same one-day price scheme each day for the entire considered week, as this is a typical representation of electricity prices in the respective seasons. Moreover, the goal is to evaluate the demand response strategy for different heat demand profiles. Therefore, the results are interpreted for each day separately and also for the whole week (i.e. day 2 to 7, as the first day is neglected due to initialisation). The data of October shows higher volatility with lower prices at noon due to solar electricity surpluses compared to January. The average price (€143,11/MWh) and standard deviation (€67,81/MWh) in October are higher than in January (€120,09/MWh and €57,86/MWh, respectively).

Second, the applied $\widehat{T_{SP}}$ are {+5°C; +10°C; +15°C; +20°C} compared to the heating curve set point of the reference case. The higher the increase, the lower the COP and the greater the losses in storage tank, but more heat can be stored at lower cost for use during high prices.

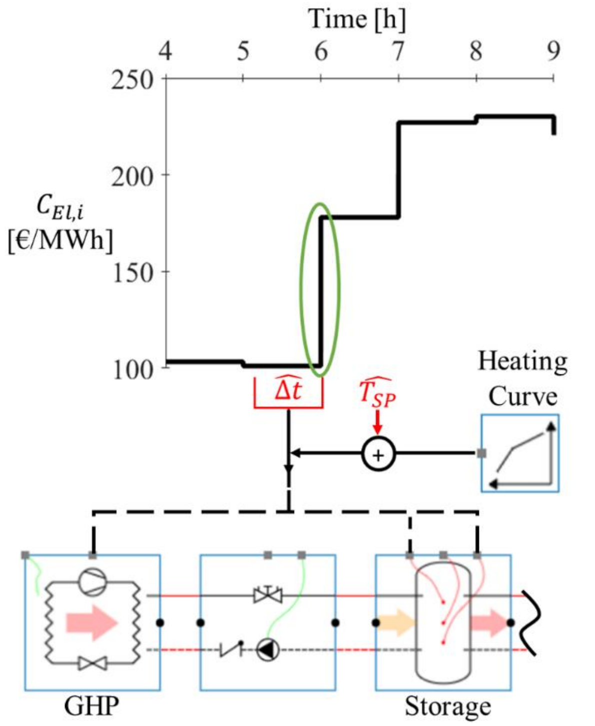

Figure 4: Example of the "price-dependent storage temperature control". In green, the largest increase in day-ahead electricity price ($C_{El,i}$) is highlighted at 6am. A certain period ($(\widehat{\Delta t})$ before 6am, the temperature set point is increased by $\widehat{T_{SP}}$ compared to the heating curve set point.

Third, the applied $\widehat{\Delta t}$ are {15min; 30min; 45min; 60min} before the largest price rises. For the simulation the setpoints are increased before 6 am, as here the largest relative price increases of the morning were found. For January, the relative price increase is 90,61% compared to the price of 5am and for October it is 75,98%. The motivation for a storage temperature increase in the morning is to use all extra heat for the heat demand of that same day.

Finally, the storage tank volume is increased from 2 m³ to 6 m³, as more thermal energy can be stored at lower temperatures. This could therefore lead to greater cost savings, because the $\widehat{T_{SP}}$ can be reduced or even more energy can be stored which means less recharging cycles at higher electricity prices. Note that to assess the impact of increased storage volume, the "price-dependent storage temperature control"-variants are compared with the reference control at a 6 m³ storage tank.

Key Performance Indicators

The "price-dependent storage temperature control" is analysed for each day separately and for the whole week from both economic and ecological perspectives.

The economical assessment considers the relative electricity cost savings (CS_{rel}^{El}) [%] compared to the reference case where the storage temperature is controlled according to a heating curve (see Equation (1)).

$$CS_{rel}^{El} = \sum_{i=1}^{k} \frac{C_{El,i} \cdot (E_{el,i,ref} - E_{el,i})}{C_{El,i} \cdot E_{el,i,ref}} \cdot 100 \qquad (1)$$

Table 1: Day-ahead price ($C_{El,i}$) for 5 October 2022 and 5 January 2023, respectively.

Day ahead-price signal			
October 2022	€/MWh	January 2023	€/MWh
5/10/2022 0:00	192,31	5/01/2023 0:00	34,78
5/10/2022 1:00	177,19	5/01/2023 1:00	31,42
5/10/2022 2:00	157,72	5/01/2023 2:00	33,10
5/10/2022 3:00	110,97	5/01/2023 3:00	14,56
5/10/2022 4:00	122,32	5/01/2023 4:00	22,19
5/10/2022 5:00	101,15	5/01/2023 5:00	41,20
5/10/2022 6:00	178	5/01/2023 6:00	78,53
5/10/2022 7:00	227,02	5/01/2023 7:00	127,98
5/10/2022 8:00	234,14	5/01/2023 8:00	141,02
5/10/2022 9:00	190,5	5/01/2023 9:00	147,18
5/10/2022 10:00	107,23	5/01/2023 10:00	149,81
5/10/2022 11:00	57,18	5/01/2023 11:00	147,46
5/10/2022 12:00	32,38	5/01/2023 12:00	143,17
5/10/2022 13:00	50,95	5/01/2023 13:00	143,79
5/10/2022 14:00	24,97	5/01/2023 14:00	151,03
5/10/2022 15:00	36,89	5/01/2023 15:00	159,48
5/10/2022 16:00	81,93	5/01/2023 16:00	172,73
5/10/2022 17:00	180,64	5/01/2023 17:00	182,34
5/10/2022 18:00	209,6	5/01/2023 18:00	194,67
5/10/2022 19:00	241,1	5/01/2023 19:00	177,98
5/10/2022 20:00	188,14	5/01/2023 20:00	163,99
5/10/2022 21:00	190,67	5/01/2023 21:00	152,00
5/10/2022 22:00	182,4	5/01/2023 22:00	144,64
5/10/2022 23:00	159,43	5/01/2023 23:00	127,00

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Where, $C_{El,i}$ is the day-ahead price for hour i [€/MWh] and $E_{el,i}$ the total electricity consumption of that hour [MWh]. $E_{el,i,ref}$ is the reference electricity consumption per hour. However, also the absolute cost savings (CS_{abs}^{El}) are given as in (2).

$$CS_{abs}^{El} = \sum_{i=1}^{k} C_{El,i} \cdot (E_{el,i,ref} - E_{el,i}) \tag{2}$$

For the ecological assessment, the energy performance of the Collective Space Heating System is assessed with the total electrical energy consumed (E_{El}^{tot}) [kWh], the total thermal losses (E_{loss}^{tot}) [kWh] and the Seasonal Performance Factor (SPF). The E_{El}^{tot} is a result from the Hysopt software, where E_{El}^{tot} takes account of the COP performance map. The E_{loss}^{tot} are calculated afterwards by subtracting the supplied energy, according to the measured heat load, from the E_{El}^{tot} . Thus the E_{loss}^{tot} represents the sum of storage losses and distribution losses of the 15-metre-long pipes in the central boiler room. The SPF is the ratio between the heat supplied by the central energy production room (i.e. measured at the mixing valve) and E_{El}^{tot}. This ratio thus includes the heat demand, E_{El}^{tot} and E_{loss}^{tot}.

It should be noted that the economical assessment already implicitly includes the operational efficiency. However, the ecological standpoint is of interest to quantify the additional electricity demand of the Belgian power system, in case this demand response strategy would be implemented in many buildings.

Results and discussion

First, the effects of increasing temperature set points and adjusting periods with higher set points in different seasons are being discussed. Afterwards, the results of increased storage tank are presented.

Season-dependent performance

Figure 5 shows CS_{rel}^{El} and SPF of the presented demand response strategy for different $\widehat{T_{SP}}$ and $\widehat{\Delta t}$ in both January and October.

On the one hand, the relative cost saving, CS_{rel}^{El}, is lower in the winter week (between -0.62% and 6.07%) than in the autumn week (between 0.84% and 8.03%) for different $\widehat{T_{SP}}$ and $\widehat{\Delta t}$. This has two main reasons, namely higher price volatility and lower heat demand in October. Due to lower heat demand, the cheaper stored thermal energy in the central storage tank is in use longer in October and the moments of following recharging cycles are shifted in time. Due to the price reduction around noon, the next recharging cycle is at lower energy cost than with the reference control, so a higher relative saving is obtained. For January, the next recharging cycles are all at a higher electricity price. Despite the lower relative cost savings, the higher heat demand in January leads to slightly greater absolute cost savings (CS_{abs}^{El}) of €5.98 a week, compared to €5.16 in October.

On the other hand, the SPF is lower in autumn than in winter (average of 3,60 for January and 3,47 for October). The smaller heat demand also results in relatively greater standing losses. The weekly E_{loss}^{tot} in January is on average 451,74 kWh, which is 15,08% of the total heat demand (i.e. 2995 kWh) for the different $\widehat{T_{SP}}$ and $\widehat{\Delta t}$, while in October the heat losses are 17,55% of the 1590 kWh demanded heat. For this reason, the SPF is better in the winter week despite lower production efficiencies.

Overall, the highest savings appear to be at higher $\widehat{T_{SP}}$. In both months, the highest CS_{rel}^{El} were found with $\widehat{T_{SP}}$ = +20°C. Therefore, in an attempt to increase the SPF and cost savings, the storage tank volume is also increased from 2 m³ to 6 m³ for possibly larger storage capacity at lower temperatures.

Increased central storage volume

Figure 6 shows that increasing the storage volume generally increases the potential cost savings in both winter and autumn weeks, but a larger volume involves higher risks at increased energy costs in autumn.

In January, the maximum potential CS_{rel}^{El} for a day can increase from 10,8% with 2 m³ to 30,1% with 6 m³ storage volume. Again, the highest savings were both yielded at $\widehat{T_{SP}}$ = +20°C, but, as can be noticed in Figure 7, the optimal $\widehat{\Delta t}$ generally shifts towards 30 minutes and 45 minutes for January, instead of 15 minutes with 2 m³. The

CS_{rel}^{El} [%]	January 2 m³				October 2 m³			
	15 min	30min	45min	60min	15 min	30min	45min	60min
+5°C	1,10%	-0,08%	0,03%	-0,62%	0,87%	2,64%	0,74%	0,84%
+10°C	2,24%	1,55%	0,56%	0,49%	4,68%	4,70%	4,04%	1,62%
+15°C	4,14%	2,99%	2,36%	1,45%	7,92%	5,09%	4,97%	4,42%
+20°C	6,07%	5,13%	4,68%	3,49%	7,31%	8,03%	5,90%	5,31%

SPF [-]	January 2 m³				October 2 m³			
reference	3,64				3,58			
	15 min	30min	45min	60min	15 min	30min	45min	60min
+5°C	3,65	3,64	3,63	3,62	3,53	3,56	3,56	3,53
+10°C	3,62	3,61	3,60	3,63	3,49	3,52	3,52	3,49
+15°C	3,59	3,57	3,61	3,60	3,48	3,44	3,44	3,44
+20°C	3,55	3,55	3,55	3,56	3,37	3,37	3,37	3,40

Figure 5: CS_{rel}^{El} and SPF for different $\widehat{T_{SP}}$ and $\widehat{\Delta t}$ for the considered week in January and October. The colour gives an indication on the performance, namely the greener the better for both KPIs.

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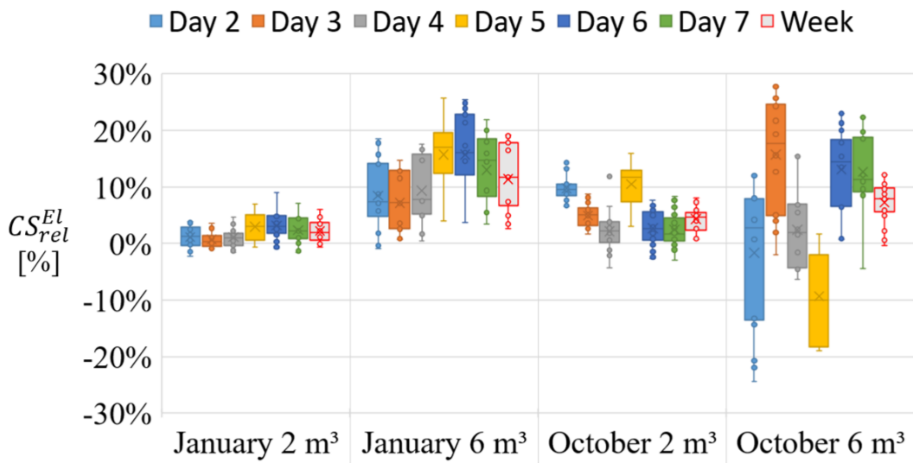

Figure 6: Boxplot of potential CS_{rel}^{El} for each $\widehat{T_{SP}}$ and $\widehat{\Delta t}$ on each day of the first week in January and October, and for both 2 m³ and 6 m³ central storage. The week represents the respective average CS_{rel}^{El} from day 2 to 7.

main reason is again the high heat demand. The total consumed electricity, E_{El}^{tot}, in January varies between 820,96 kWh and 842,85 kWh, while the reference control consumes 823,26 kWh for 2 m³ storage. In case the storage volume is 6 m³, the range of E_{El}^{tot} is between 762 kWh and 830,77 kWh, while the reference control uses only 762,56 kWh.

On the contrary, during days with small heat demands, such as day 5 in October (see Figure 1), an increased storage size has only a negative effect. On that day, according to Figure 7, the maximum CS_{rel}^{El} is only 2% at a $\widehat{T_{SP}}$ = +15°C during 30 minutes and the electricity costs could even increase by 59% compared to the reference control (i.e. heating curve). For these reasons, an adjustable buffer volume to make the storage capacity flexible can be useful to track the highest cost savings potential throughout the year.

In Figure 6 and Figure 7, it is also shown that the potential cost savings are highly dependent on the day, $\widehat{T_{SP}}$ and $\widehat{\Delta t}$. This can easily lead to negative or suboptimal savings, mainly due to varying demand. For example, on day 3 in October at a storage volume of 6 m³, the highest savings (39,4%) are achieved with a $\widehat{T_{SP}}$ of at least 10°C and a $\widehat{\Delta t}$ of 15 minutes. However, on day 5 of October these settings result in savings of -43%, meaning that the energy costs are even greater than for reference control. However, this 43% increase only results in €2 extra energy costs, as the heat demand for that day is really low (only 164 kWh and the average daily heat demand is 265 kWh/day in October). Furthermore, the price volatility is larger in October than in January. For this reason, one extra moment of set point increase might be considered to reduce the energy costs even more, as the largest relative cost increase for October is at 4pm (122.09%).

In general, the relative savings in October are the highest (and positive) when a higher heat demand occurs and low (or even negative) when nearly no heat demand exists. Therefore, choosing the temperature and duration of the setpoint increase solely based on electricity prices without considering expected heat demand is not advisable in autumn. In winter, the heat demand is more constant, and thus increasing the temperature before each large price rise is most likely to result in cost savings.

Although the potential daily savings are higher for October, the potential savings on a weekly basis are the highest for January with a central storage volume of 6 m³ and a $\widehat{T_{SP}}$ of +15°C for 30 minutes. In this case, the relative cost saving was 19,25% which means an absolute cost saving of €17,71 for that week. To realise this cost saving, the E_{El}^{tot} increased from 763 kWh to 794 kWh for that day due to lower SPF (3,77 compared to 3,93).

It can also be noted that when a 6 m³ storage is used, similar cost savings occur when the temperature set point is increased for only 15 minutes, regardless of the temperature increase. Therefore, the 15 minutes are insufficient to heat a 6 m³ storage tank with the current heat pump capacity.

Conclusion

The performance of heat pump-based collective heating systems is highly dependent on the temperatures used. Therefore, the temperature is usually as low as possible and the heat pump is switched on or off based on price or temperature tresholds. However, a time-varying electricity price, such as the day-ahead price, offers great opportunities for energy costs savings while still meeting thermal comfort requirements. At lower prices, the supply temperature can be increased and be stored for later use during high prices. This lowers the heat pump's COP and increases heat losses, but at lower costs. Therefore, a trade-off has to be made between total energy cost and operational efficiency of the system. Furthermore, a lower day-ahead price usually indicates a surplus of intermittent electricity sources, such as wind or solar generation. Thus, the increased energy consumption does not necessarily lead to more CO_2 emissions.

The cost savings were identified for a real case study "NovUa" by means of a digital twin in HySopt, based on measurements of the building's thermal load in January and October. The applied demand response strategy is the "price-dependent storage temperature control", where the storage temperature set point is increased by $\widehat{T_{SP}}$ (compared to heating curve) for a specified period ($\widehat{\Delta t}$).

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The main results showed that for a 2 m³ sized central storage tank, the relative cost savings (CS_{rel}^{El}) are generally lower, but more constant, than for 6 m³. The highest savings appear to be at $\widehat{T_{SP}}$ of +15°C and +20°C, for a small $\widehat{\Delta}$t. However, this is highly dependent on the heat demand and the price volatility of the day. A 6 m³ storage leads to smaller daily potential relative savings in winter than in autumn, but both the absolute cost savings and the weekly savings are larger in winter.

The weekly cost savings can go up to 8,0% with 2 m³ storage and 19,3% with 6 m³ storage, while the daily cost savings vary between -10% and 16,3%, and -59% and 40,2% for small and large storage, respectively. To achieve the highest weekly cost savings, the electricity consumption increased by 6,3% and 4% for 2 m³ and 6 m³ storage, respectively. This means that larger cost savings are possible with larger storage tanks, while the increase in electricity use is relatively smaller.

Since the cost savings heavily depend on the future heat demand and on the available storage volume, these might be subject for further optimisation. The storage volume might be adaptable to the needs according to future heat demand expectation, e.g. by having multiple storages in parallel with bypass valves. Optimising the control strategy can be further elaborated using data-oriented control techniques (techniques solely relying on data, like Machine Learning techniques) or Model Predictive Control to decide when to increase the temperature to which set point. Other future work to optimise the "price-dependent storage temperature control" should focus on:

- Consider temperature set point reductions when the electricity price is high and no heat demand is expected in the near future.
- Enlarge the thermal inertia by also including the distribution pipes by linking the set point of the mixing valve (see Figure 2) to the set point increase of the storage temperature.
- Validate the demand response strategy by implementation in real buildings and compare the simulated behavior with the actual behavior of the Collective Space Heating System. In addition, this also allows the required level of detail of the heat pump model to be determined.

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Appendix: Relative cost savings for all simulated variant

		January 2 m³				January 6 m³				October 2 m³				October 6 m³			
		15min	30min	45min	60min	15min	30min	45min	60min	15min	30min	45min	60min	15min	30min	45min	60min
Day 2	+5°C	1,6%	-1,1%	0,6%	-0,7%	1,5%	0,3%	1,4%	0,4%	4,9%	13,8%	9,9%	9,1%	-8,0%	-7,8%	-8,9%	-21,3%
	+10°C	-0,2%	0,3%	-0,6%	-2,1%	-0,6%	8,2%	7,5%	7,6%	9,8%	15,5%	7,9%	10,9%	-8,0%	-33,9%	-41,2%	-41,6%
	+15°C	4,7%	2,7%	2,6%	0,5%	-0,7%	16,1%	13,7%	15,1%	14,1%	10,5%	9,4%	8,6%	-8,0%	-24,6%	-43,8%	-48,2%
	+20°C	6,4%	5,2%	4,8%	3,2%	-0,7%	12,5%	14,1%	12,1%	13,9%	6,4%	2,8%	8,0%	-8,0%	-4,9%	9,7%	8,8%
Day 3	+5°C	-2,1%	1,0%	0,4%	-2,2%	5,8%	-3,2%	-2,5%	-1,8%	3,8%	0,1%	-0,7%	0,4%	20,6%	13,3%	14,5%	11,6%
	+10°C	2,0%	1,7%	-0,9%	1,3%	4,7%	4,8%	4,3%	4,4%	4,0%	2,8%	5,8%	4,5%	39,4%	29,2%	34,3%	33,0%
	+15°C	2,2%	-0,4%	-0,2%	-0,6%	3,8%	10,5%	10,6%	11,9%	7,5%	7,7%	7,0%	3,8%	39,4%	31,0%	18,1%	19,5%
	+20°C	2,1%	2,9%	2,5%	-0,3%	3,8%	8,6%	10,8%	8,9%	5,8%	7,9%	7,0%	6,6%	39,4%	23,2%	0,0%	-7,3%
Day 4	+5°C	1,5%	0,9%	1,9%	3,0%	4,0%	3,5%	4,3%	3,3%	-3,4%	6,2%	0,2%	-2,6%	5,5%	-4,3%	-1,1%	-7,2%
	+10°C	3,6%	2,8%	0,2%	0,3%	3,5%	11,4%	11,4%	11,5%	4,9%	5,4%	3,4%	1,6%	-15,6%	3,6%	3,3%	-17,9%
	+15°C	4,8%	3,0%	2,4%	2,4%	3,8%	20,2%	20,9%	16,1%	6,2%	4,3%	-2,0%	5,9%	-15,6%	-10,8%	13,8%	15,0%
	+20°C	5,7%	5,7%	5,6%	5,6%	3,8%	19,3%	16,7%	17,5%	6,3%	15,2%	6,6%	5,6%	-15,6%	-8,9%	-5,8%	-6,6%
Day 5	+5°C	1,2%	-4,7%	-4,0%	-4,6%	6,6%	7,5%	9,1%	10,1%	6,5%	2,1%	4,1%	8,9%	-21,5%	-11,8%	-23,6%	-28,2%
	+10°C	-1,1%	-1,5%	1,1%	1,4%	20,9%	19,0%	19,9%	19,6%	16,3%	14,3%	8,6%	-10,0%	-43,0%	-58,8%	-59,0%	-14,4%
	+15°C	2,1%	4,2%	2,3%	-1,1%	21,0%	27,9%	27,0%	25,8%	3,5%	-1,1%	14,3%	9,5%	-43,0%	2,0%	-0,5%	-11,7%
	+20°C	7,6%	3,9%	1,9%	0,2%	21,0%	27,6%	22,7%	24,1%	14,1%	11,5%	12,8%	13,7%	-43,0%	-19,6%	-24,8%	-23,3%
Day 6	+5°C	5,6%	1,7%	1,9%	1,1%	6,5%	6,3%	6,7%	6,3%	-2,4%	-6,0%	-3,8%	-1,3%	23,5%	18,4%	20,5%	21,1%
	+10°C	5,6%	4,9%	4,6%	1,1%	19,5%	18,8%	18,3%	17,6%	-0,5%	0,8%	-1,2%	2,2%	18,8%	37,2%	40,2%	40,2%
	+15°C	7,9%	7,7%	4,2%	4,0%	19,5%	25,4%	26,5%	24,2%	9,5%	4,8%	6,5%	2,3%	18,8%	-1,0%	0,3%	0,0%
	+20°C	10,8%	7,8%	8,2%	7,6%	19,5%	22,5%	30,1%	22,7%	2,8%	4,1%	5,8%	-1,5%	18,8%	32,3%	20,6%	21,3%
Day 7	+5°C	0,5%	0,9%	-1,2%	-0,3%	5,5%	4,5%	4,6%	6,1%	-1,4%	2,9%	-0,9%	-3,3%	0,7%	8,5%	6,2%	4,6%
	+10°C	3,7%	1,1%	0,2%	1,2%	2,9%	13,1%	14,6%	13,5%	0,4%	-2,4%	2,3%	-2,0%	25,8%	14,1%	14,1%	4,0%
	+15°C	4,0%	2,6%	3,7%	4,0%	2,6%	20,2%	20,1%	19,6%	6,9%	2,9%	-0,3%	0,4%	25,8%	20,7%	19,6%	18,8%
	+20°C	5,9%	6,0%	5,6%	5,7%	2,6%	21,0%	24,8%	17,8%	6,0%	4,7%	2,6%	3,4%	25,8%	4,5%	-11,8%	1,4%
Week	+5°C	1,1%	-0,1%	0,0%	-0,6%	4,9%	2,7%	3,4%	3,6%	0,9%	2,6%	0,7%	0,8%	8,1%	6,3%	5,8%	2,2%
	+10°C	2,2%	1,5%	0,6%	0,5%	7,6%	11,9%	12,0%	11,7%	4,7%	4,7%	4,0%	1,6%	12,1%	9,5%	10,5%	8,7%
	+15°C	4,1%	3,0%	2,4%	1,4%	7,4%	19,3%	19,0%	18,2%	7,9%	5,1%	5,0%	4,4%	12,1%	7,9%	6,0%	4,9%
	+20°C	6,1%	5,1%	4,7%	3,5%	7,4%	17,8%	19,1%	16,4%	7,3%	8,0%	5,9%	5,3%	12,1%	9,6%	-0,4%	0,6%

Figure 7: CS_{rel}^{El} for different $\widehat{T_{SP}}$ and $\widehat{\Delta t}$ for each day of the considered week in January and October and for the 2 m³ and 6 m³ central storage tank. The greener, the higher the cost savings are.

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