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Demand response events in district heating: Results from field tests in a university building

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Abstract

Demand side management will play a major role in future energy systems. However, while they have been explored in some depth for electricity grids, a similar progress has not been made for district heating networks (DHN). To this end, the current work field-tested the effect of demand side management, in the form of price based, demand response (DR) events, in the DHN catering to a university building. Responding to variations in a pricing model, the temperature of inlet water was varied from the heating water substation. Using combinations of parameters, 11 different DR scenarios were executed. To gauge the effect of the DR interventions, inlet water temperature, room air temperature, and occupant satisfaction were monitored. Depending on the constraints imposed, significant variations in the inlet water temperature and peaks and drops in the room air temperature were noted. The different DR scenarios did not greatly alter occupant satisfaction levels. The study was able to provide useful data from field tests of DR events in a DHN. The data also showed that price based DR events may be triggered and executed without significantly impacting occupant satisfaction with thermal comfort of the premises.

Keywords: demand response, district heating, thermal comfort, smart grid, field study

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1. Introduction

In an energy network, while high resolution management on the supply side is the modus operandi, demand side management (DSM) is emerging as an useful aide (Gelazanskas and

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Gamage, 2014; Pedersen et al., 2017). The future is thus leading towards smart energy networks that can deliver energy in a controlled manner, from points of generation to active points of consumption (Siano, 2014). In recent years, the idea of DSM has moved from the concept of controlling just the electrical energy to controlling both electrical and heat energy flows, i.e., Dual Demand Side Management. Such management would be more effective at exploiting the thermal storage potential in a district (Müller et al., 2015; Paiho et al., 2018). As renewable energy production and prosumers gradually become a greater part of them (Aslani et al., 2013), future energy networks would need increased flexibility (Paiho et al., 2018). In the changing energy paradigm, buildings will need to be considered as having an active role instead of being passive consumers. This evolution requires controls that can adapt to real-time conditions, both weather wise and energy market wise (Reynolds et al., 2017). For smart districts, a top priority would be to manage and exploit the inherent flexibility of buildings, shifting consumption times and achieving smooth integration of alternative energy sources (Good et al., 2017).

Demand response (DR) actions may be defined as the changes in energy use, vis-a-vis normal levels, effected on the demand-side, in response to changes in energy pricing, incentives from the supplier, or a possible threat to system reliability (Gelazanskas and Gamage, 2014; Gils, 2014). Studies point to all consumer sectors in Europe showing significant DR potential (Gils, 2014).

A building's HVAC system can serve as an ideal candidate for DR measures due to the thermal mass of buildings, the energy intense nature of such systems, and the fact that they already function as at least partly automated systems, integrated with the building management system (BMS) (Motegi et al., 2007). District heating (DH) has been in use as a secure and efficient way to heat cities, with combined heat and power (CHP) plants providing the base thermal load while peak needs are attended to by boilers (Verda and Colella, 2011). About 90% of heating needs in the larger cities of Finland is taken care of by DH networks (DHN) relying on CHP production, while peak load use has to be handled by heat only boilers (Syri et al., 2015).

DHNs are the go to method for indoor heating in Finnish urban areas, and they need to evolve both in terms of generation efficiency and operational management and distribution (Abdurafikov et al., 2017). They are projected to play an important role in the transition towards sustainable energy systems, with integrated renewable energy generation capacity (Lund et al., 2014). Such smart districts can be a crucial tool in addressing the "energy quadrilemma" that the future holds — balancing affordability, sustainability, energy security, and social conformance (Good et al., 2017). Demand response techniques, relying on demand side flexibility, can help reduce peak capacity requirements and plant emissions, pipe sizing from initial investment costs, and operational costs are reduced by being able to cover a larger client base, even on an existing DHN (Aduda et al., 2017; Kreuder and Spataru, 2015; Wernstedt et al., 2007). The EU's encouragement of eco-districts and zero energy objectives act as positive drivers towards smarter DHNs (Koutra et al., 2018). Smart DHNs may be imagined as parallels of their electric counterparts (Lund et al., 2014).

Suitable DR strategies need to achieve the energy saving targets, without adversely affecting occupant comfort. The IEA EBC Annex 67 defines energy flexibility of a building as a building's "... ability to manage its demand and generation according to local climate conditions, user needs, and grid requirements. Energy Flexibility of buildings will thus allow for demand side management/load control and thereby DR based on the requirements of the surrounding grids." (Reynders et al., 2018). In terms of energy pricing, a simpler presentation of flexibility factor could be the opportunity to shift energy usage from higher price periods to lower price periods (Le Dreau and Heiselberg, 2016). Simulations have shown that added thermal storage capacity can aid in reducing peak DH loads (Knudsen and Petersen, 2017). Heating demand, even over a single day, can have considerable variations. By effecting periodic, small variations on the demand side, building thermal mass can be utilized for thermal energy storage, thus aiding the system to overcome variable needs (Kensby et al., 2015). Structurally heavy buildings, due to their larger thermal mass are more energy flexible, making it easier for them to overcome variations in heat deliveries while keeping their indoors within comfort needs (Kensby et al., 2015). DR in DHNs can easily take advantage of the already existent thermal mass of buildings as a means of storing thermal energy, facilitating easier integration of renewable energy sources with fluctuating generation profile (Lund et al., 2016).

Compared to the number of works that have looked at DR measures in electric grids, only meagre numbers have touched on DR for DHNs. Fewer still have looked at field implementation of DSM on performance of DHNs. There is a lack of scientific literature that examines the effect of demand response control on real existing buildings and the occupants. Only a recent study by Sweetnam et al. (Sweetnam et al., 2018) looked at demand shifting in a DHN catering to 28 residences in England. The demand shifting strategies could successfully improve the ratio of the mean to maximum heating load of participating residences from 0.29 to 0.44, with only some of the occupants noting the altered indoor thermal conditions (Sweetnam et al., 2018).

The electricity market in Finland has undergone a major change over the past couple of decades, moving towards free and open market. Though it is not so as of now, it is only logical to expect that the DH market will soon follow suit. Open DH pricing is already being tried out in neighbouring countries (Syri et al., 2015). Like the electric grid, in heating dominated climates, DHNs are also a vital part of building energy system and an essential part of building performance. Solutions proposed for DHN demand response need to be field tested before being put to practice (Robert et al., 2018). Keeping this in mind, the current work takes the step of exploring the effects of DR actions applied to a DHN. Demand response strategies could fall under one of two broad categories: those which adjust the indoor conditioning set-point temperatures and those which make adjustments to the heating system (Motegi et al., 2007). In this work, strategies under the second category were explored, that is adjustments were made to the heating water temperature.

Two different DR algorithms were implemented, with a variation of parameter settings, leading to a total of eleven scenarios. One group of DR algorithms affected only the inlet temperature of the water radiator system while the other group affected both water inlet temperature and supply air temperature from selected air handling units (AHUs). Being based on dynamic pricing information, these can be classified as DR events (Motegi et al., 2007). Based on if the energy price was falling, keeping constant, or rising, the controls were effected on the water and air temperatures. A previous work had shown energy and cost savings for control based on trends of changes to the price signal (increasing or decreasing), similar to the ones used in the current work, in electrically heated single-family houses (Alimohammadisagvand et al., 2017).

The effects were limited to one of the wings of a building on the Aalto University's Espoo campus. A three level monitoring campaign was carried out during the entire survey duration:

- Inlet heating water conditions: Effect of the DR algorithms on the temperature of the inlet water's temperature
- Indoor thermal conditions: Effect of the DR algorithms on the room temperatures being maintained
- Occupant satisfaction: Effect of the DR algorithms on the subjective satisfaction of the occupants using the said spaces

The goal was to examine how much deviations could be incurred in the inlet water temperature and how, if at all, that affected occupant perceptions. This study provided a unique opportunity to field test DR strategies and evaluate their effects on the building and the occupants. As such, it contributes to a rather sparsely populated field of knowledge. We believe that this work brings valuable, new information to the field even though constraints meant that the scenarios were all tested for a single building, with variable users, and in changing weather.

2. Methods

2.1. Building description

The study was conducted in the U-Wing of a large building on Aalto University's Espoo campus, near Helsinki, in Finland. The building was originally built in 1964 while U-Wing was built in 1975. All the load bearing structures of the building are massive concrete features. While the building's gross floor area is 48,000 m^2, U-Wing itself has a heated floor space of 13,800 m^2. The Wing has six floors and comprises mainly of teaching facilities, meeting spaces, cellular offices, and open-plan offices.

U-Wing was refurbished in 2014 when ventilation, heating, and building management systems were upgraded. The original 2-pane windows were renovated by replacing their inner window pane by an argon filled, low-emissivity glazing element. The new glazing elements of the windows facing south or west were also equipped with solar protection. The renovated windows have a U-value of 1.0 W/m^2K. Solar heat transmittance (g-value) of south and west facing windows is 0.44 while for the rest of the windows it is 0.57. The renovation did not affect building insulation levels. The U-values of the external walls, the roof and the base floor are 0.36, 0.3 and 0.8 W/m^2K, respectively. It was assumed that the concrete core structure of U-Wing would be advantageous by providing thermal mass for implementation of the planned DR strategies, improving demand side flexibility.

The Wing is equipped with mechanical supply and exhaust ventilation system, with regenerative heat recovery. It is a variable air volume (VAV) system, controlling air flow rates based on the dual inputs of room air temperature and carbon dioxide concentration. There are a total of 21 AHUs in the Wing and the total maximum supply and exhaust air flow rates of the wing are 26 and 27 m^3/s, respectively. A schematic of the substation that serves the Wing has been provided in Figure 1.

2.2. Objective measurements

The sensing and controls aspects were handled by the BMS from Fidelix Oy. This BMS was already responsible for day-to-day management of building HVAC systems. Room air temperatures were measured by Produal Temperature Meters (model TEHR NTC10-P, accuracy: ± 0.2 ℃ at 25 ℃). Apart from room conditions, the heating water inlet and outlet temperatures were also measured. The BMS collected and stored all temperature measurements, with a frequency of once every 15 minutes.

During one of the weeks when DR studies were not under way, on the Friday, at about 10 pm, when the building is not likely to have any occupants, the inlet water temperature from

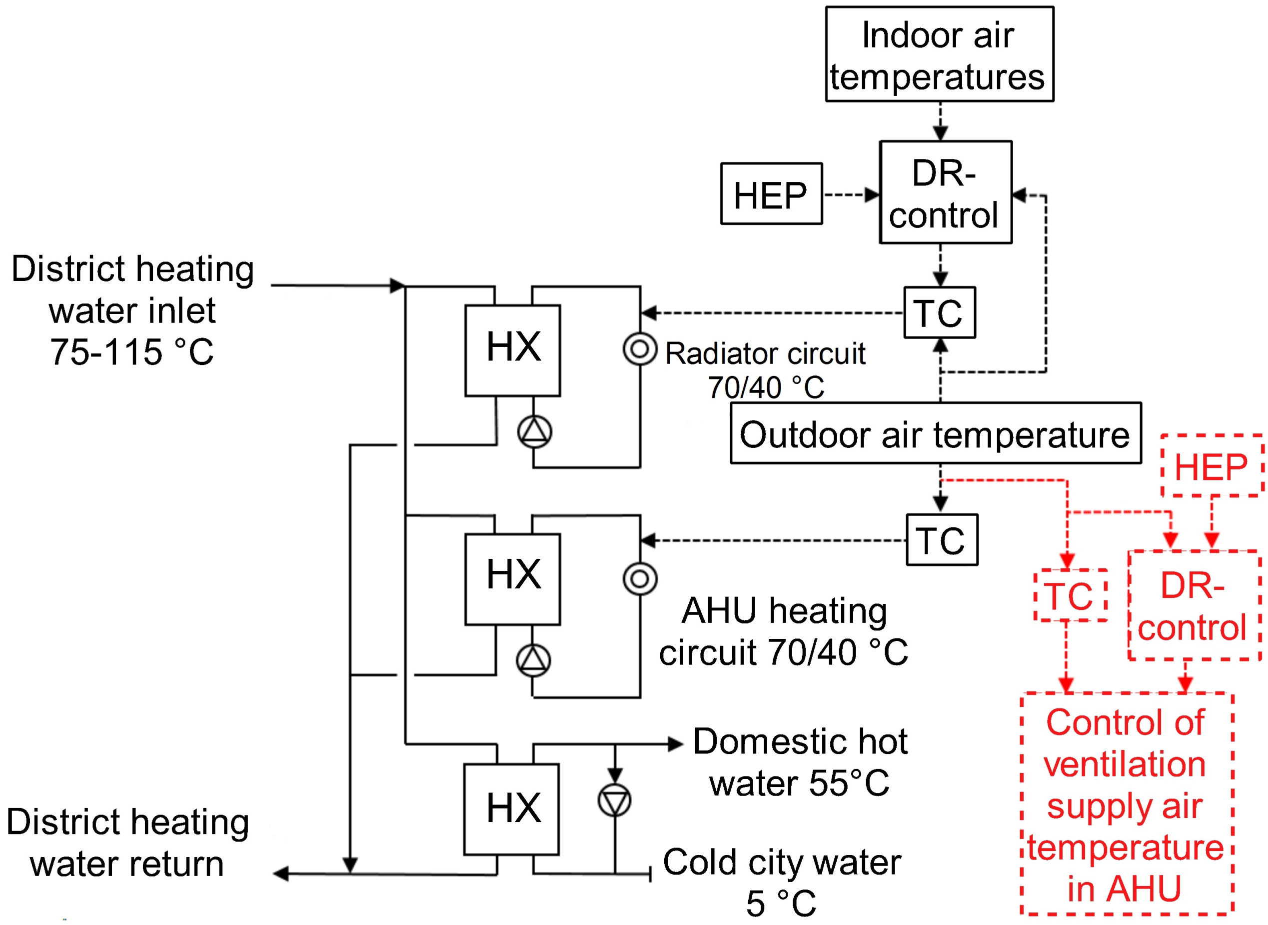

Figure 1: A schematic of the substation serving U-Wing, as part of the DHN (in black) and a schematic of demand response control of ventilation (in red). In the figure, "HEP" denotes hourly district heat price, "HX" heat exchanger, "DR-control" demand response control of inlet water temperature of radiator circuit or ventilation supply air temperature and "TC" temperature control.

the substation was decreased by ∼10 ℃ in one step. Temperature was gradually brought up to values required by the standard control curve starting from Sunday afternoon, so that the spaces would be ready for occupants on Monday morning.

Thermocouples were used to log the hot water pipe temperature at the point in the wing which was closest to the DH substation (in the basement) and at a point which was farthest from the source (on the fourth floor). Temperatures were logged using a Testo temperature logger (Model 176T4, accuracy ± 0.3 ℃) and K-type thermocouples, with 1 minute time step. The time it would take for the step change to reflect at the farthest point would provide an idea regarding the hot water distribution network's responsiveness to changes in water temperature.

2.3. Occupant feedback

During all survey periods, occupants and users of the Wing were requested to participate by providing their feedback on the indoor temperature conditions. An example of the feedback platform set up in the lobby of the Wing has been presented in Fig. 2. Along with one such platform, the notification in Fig. 2 was displayed in 40 locations across all floors, along with a QR-code for a webpage where occupants could provide feedback and comments.

Figure 2: An image of the occupant feedback platform set up, along with the notification

2.4. Price trends for heating energy

In testing the DR scenarios for this study, an inherent assumption was that dynamical pricing would be available for DH and a moving 24 hours, hourly price, would be known in advance, at any point in time. The hourly price was estimated for a year, based on the price data for district energy sources and the weather data from the Finnish test reference year 2012 (Kalamees et al., 2012). The price estimates are dynamic and representative of a typical DH producer in Finland. The price includes energy and transfer costs and a value-added tax of 24%. The price estimates were then used in implementing the DR algorithms. In Finish DHNs, during peak periods, peak-load plants, consisting of heat only boilers are made operational to handle the increased demand. This increases both the price and emissions.

The DR algorithms try to reduce the inlet water temperature when the price trend is on the fall, thus, trying to lessen the burden on the DHN when prices are already high. Conversely, they try to increase the inlet water temperature when the price trend is rising, thus trying to load the building thermal mass while the prices are still low and before they rise and get too high. When the price trend holds flat, no action is taken and the standard inlet water temperature was used. With a falling price trend, to reduce the water temperature, a control signal (CS) of -1 was generated. For a rising price trend, to increase the water temperature, a CS of $+1$ was generated. From a comparison of algorithms which use fixed energy price limit vs ones that use energy price trend, performed in a previous work (Alimohammadisagvand et al., 2017), it was realised that use of energy price trend could minimize energy cost more effectively. Hence, the current work relied on using energy price trends based algorithms.

When the Behrang–Siren (BS) algorithm (Alimohammadisagvand et al., 2018) was used, CS was calculated using the hourly energy price (HEP), the HEP averaged over hours p to q ($\mathrm{HEP}_{\mathrm{avg}}^{+\mathrm{p},+\mathrm{q}}$), and the selected parameters marginal value, up (positive, MVU) and marginal value, down (negative, MVD). The pseudo code for generation of CS, using the BS algorithm, is provided below:

IF,
  $\mathrm{HEP} < \mathrm{HEP}_{\mathrm{avg}}^{+1,+24} + \mathrm{MVD}$
  OR
  $\mathrm{HEP}_{\mathrm{avg}}^{+6,+12} > \mathrm{HEP}_{\mathrm{avg}}^{+6,+24} + \mathrm{MVU}$
THEN, CS = +1
ELSEIF HEP > $\mathrm{HEP}_{\mathrm{avg}}^{+1,+24}$, THEN CS = −1
ELSE CS = 0
END IF

With a low marginal value, price is more often classified as cheap and the price trend as rising, and vice versa for a high marginal value. Two marginal values were chosen for these studies: low (±7 €/MWh) and high (±75 €/MWh).

For the Dreau and Heiselberg (DnH) method (Le Dreau and Heiselberg, 2016), CS was based on current HEP and the first quartile $\mathrm{HEP}_{\mathrm{1st\ quartile}}^{\mathrm{period}}$ and third quartile $\mathrm{HEP}_{\mathrm{3rd\ quartile}}^{\mathrm{period}}$ of the historical price period. The length of the historical period is a chosen parameter. Determination of DnH CS used the following pseudo code:

IF,
  $\mathrm{HEP} < \mathrm{HEP}_{\mathrm{1st\ quartile}}^{\mathrm{period}}$
THEN, CS = +1
ELSEIF HEP > $\mathrm{HEP}_{\mathrm{3rd\ quartile}}^{\mathrm{period}}$, THEN CS = −1
ELSE CS = 0
END IF

Two different length of historical period were used in this study: two weeks and three days. Sampling historical price data over a smaller duration (3 vs 14 days) gives more dynamism to the price trend estimates by being able to focus on the more recent patterns. Shorter time period means conservation and loading take place more frequently, making the building able to quickly adapt with fluctuations in the price and utilize available thermal mass as a storage. This makes for an energy flexible building as heating need is transferred from higher to lower price periods. Similarly, a lower marginal value offers a more dynamic view of the pricing trend, allowing for more flexibility in terms of deciding deviations of inlet hot water temperature.

The hourly prices and the price trend calculated using the DnH algorithm has been provided in Fig. 3, as an example. From April through mid of November, hourly prices were quite stable. However, from end of November to end of March, prices varied a lot more, with peaks and ebbs.

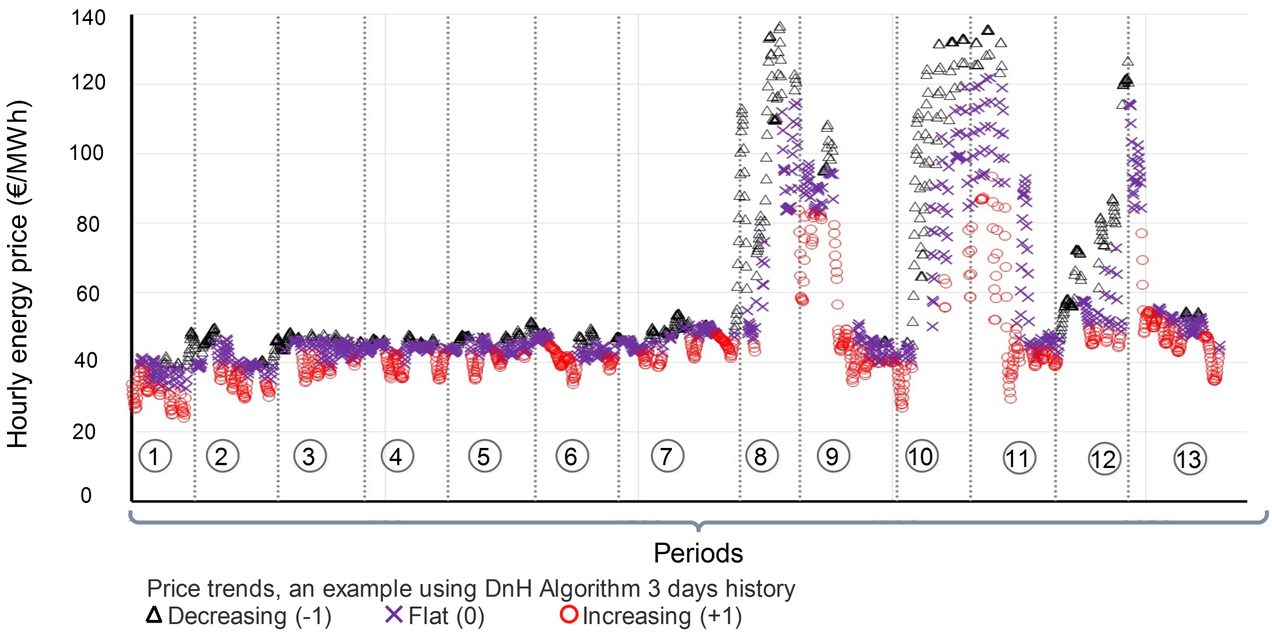

Figure 3: Hourly energy price variations during each of the 13 periods along with the price trend calculated using Dreau and Heiselberg algorithm

2.5. The demand-response algorithms

For this work, temperature of the inlet water is adjusted at the DH substation catering to the entire Wing. So, when we refer to the strategy as a centralized DR strategy, it implies a centralized, building level control of heating. The entire DHN was not being centrally regulated. During any of the scenarios, the heating water supplied to every radiator in the Wing was altered. Eleven different scenarios were implemented over 11 different periods. They were interspersed with two periods during which the controls were left at their standard values. The precise controls were handled by the BMS. The water radiators themselves are equipped with thermostatic regulator valves (TRVs). The TRVs can prevent overheating of the space but are not suitable for fine control of the room air temperature.

Each scenario allowed a certain degree of deviation from the standard water inlet temperature — the water temperature the DHN would have supplied without any interference, Fig. 5 a) — was allowed. For the first nine periods, the deviation allowed was determined as a fraction of the radiator heat output (Martin, 2017). This fraction was kept between ±10 to ±25%. However, during Periods 12 and 13, greater deviations between the standard and actual inlet water temperature were allowed. Deviations of +10/−20 ℃ were allowed for inlet water temperature between actual and standard values.

Periods 7 through 12 controlled the supply air temperature from some of the AHUs, in addition to controlling the inlet water temperature. During Periods 7–11, AHUs 3, 4, 5, and 15 were controlled. For these AHUs, when price trend was increasing, a supply air temperature of 22 ℃ was used while supply air temperature was 18 ℃ when price trend was on the fall. For the rest of the times, the standard control curve for supply air temperature was used (Fig. 5). During Period 12, only AHU 15 was being controlled. For this period, for falling price, supply air temperature was 2 ℃ less than the standard value while it was 2 ℃ more than standard value when price trend was rising. The standard control curve was used when price trends remained flat. The way deviations in inlet water temperature and supply air temperature were implemented has been expounded upon in the flowchart provided in Fig. 4. Fig. 4 provides the generic control flow, applicable to all the scenarios, following the calculation of the CS explained in Section 2.4. The change of supply air temperature, for the AHUs, as denoted in the flowchart, did not apply for Periods 2-5 and for Period 13. As a precaution, to ensure that the algorithm was implemented only during winter/heating period, the control flow starts off with checking if the moving average outdoor air temperature was below a specified limit. The limit, in this study, had been chosen to be 0 ℃.

Periods 1 and 6 were run with standard controls and were treated as reference periods. The other periods and their respective DR Scenarios have been listed below.

- Period2 – BS algo, marginal value ±75 €/MWh, deviations of up to ±10% (BS, ±€75, ±10%)
- Period3 – BS algo, marginal value ±7 €/MWh, deviations of up to ±20% (BS, ±€7, ±20%)
- Period4 – DnH algo, 14 days history on prices, deviations of up to ±20% (DnH, 14D, ±20%)
- Period5 – DnH algo, 3 days history on prices, deviations of up to ±20% (DnH, 3D, ±20%)

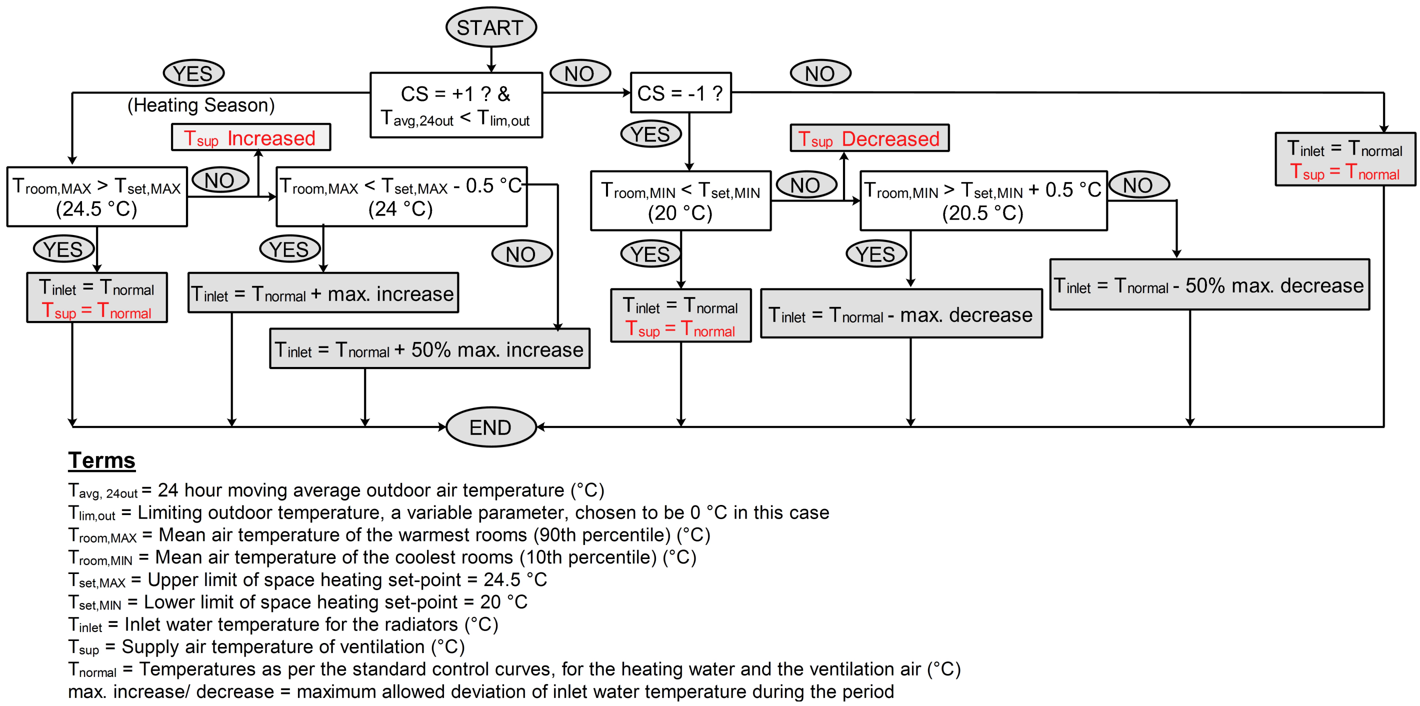

Figure 4: Flowchart for the implementation of controls during the scenarios for the inlet water temperature and supply air temperature

- Period7 – BS algo, marginal value ±75 €/MWh, deviations of up to ±10%, AHU supply T_{air} affected (BS, ±€75, ±10%, AHU)
- Period8 – BS algo, marginal value ±7 €/MWh, deviations of up to ±20%, AHU supply T_{air} affected (BS, ±€7, ±20%, AHU)
- Period9 – DnH algo, 14 days history on prices, deviations of up to ±20%, AHU supply T_{air} affected (DnH, 14D, ±20%, AHU)
- Period10 – DnH algo, 3 days history on prices, deviations of up to ±20%, AHU supply T_{air} affected (DnH, 3D, ±20%, AHU)
- Period11 – DnH algo, 3 days history on prices, deviations of up to ±25%, AHU supply T_{air} affected (DnH, 3D, ±25%, AHU)
- Period12 – DnH algo, 3 days history on prices, deviations of up to +10/−20 °C, AHU supply T_{air} affected (DnH, 3D, +10/−20, AHU)
- Period13 – DnH algo, 3 days history on prices, deviations of up to +10/−20 °C (DnH, 3D, +10/−20)

During loading (conservation), inlet water temperature was increased (reduced) to a value within the pre-set limits over and under the standard inlet temperature. At the room level, heat output is controlled by TRVs and their set-points remain fixed through the entire study. During loading, the valves can reduce water flow to keep room air temperature within the upper bounds. During conservation, the TRVs open up to allow greater flow rate so as to keep indoor air temperature over the lower bound.

2.5.1. Constraints on the algorithms

The scenarios had to be run within constraints of comfort. All algorithms aimed at keeping room air temperature within 20-24.5 ℃, i.e., within the recommended winter comfort zone (Comite'Europe'en de Normalisation, 2007). To ensure that all the occupied rooms kept within the required comfort zone, the algorithms depended on the mean air temperature of the coldest and warmest rooms. The coldest rooms were defined as rooms whose temperature was lower than 90% of the permanently occupied rooms of the Wing and the warmest rooms were defined as rooms whose temperature was higher than 90% of the permanently occupied rooms in the Wing. When mean air temperature of the coldest rooms fell below 20 ℃, or mean air temperature in the warmest rooms rose over 24.5 ℃, the standard control curve for inlet water temperature was used. This has also been illustrated in Fig. 4.

As is normal for DH systems, the standard operation curve is a function of outdoor conditions (Khabdullin et al., 2017). This curve has been depicted in Fig. 5 a). The standard control curves for the four AHUs affected during the DR runs have been provided in Fig. 5 b)–e). The standard control curves determine inlet temperature and supply air temperature as a function of the outdoor temperature.

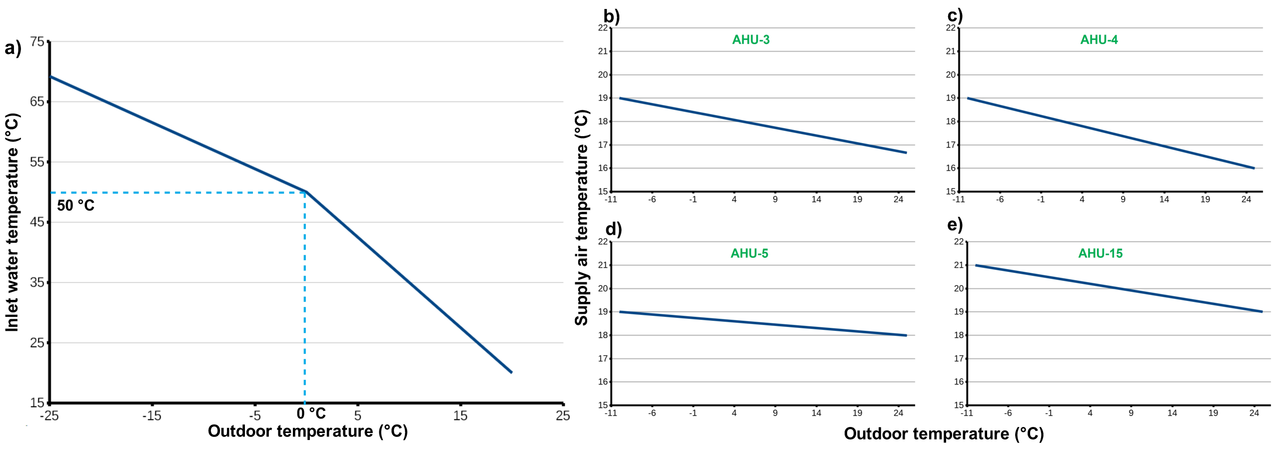

Figure 5: a) Inlet water temperature control curve. Supply air temperature control curves: b)AHU-3 c)AHU-4 d)AHU-5 e)AHU-15.

2.6. Analysis of data

As described in Introduction, the monitoring campaign may be divided to three distinct “levels”: the heating water, the room indoors, and the occupants. For each Period, the data at these three levels were processed separately. The focus of the analysis may be divided into the following objectives:

- Deviations between actual and standard values of heating water inlet temperature during implementation of DR algorithms
- Deviations between actual and standard temperature of AHU supply temperature during the Periods when AHU supply temperature was controlled
- Deviations between temperature of occupied spaces and the targeted comfort range of [20, 24.5] ℃
- Occupant response to the prevalent temperature conditions during the different Periods

Temperature deviations, both for supply air temperature and inlet water temperature were calculated as (actual – standard). The standard values were obtained based on the respective control curves (Fig. 5). Positive deviations were when the actual inlet water temperature was greater than the standard value and negative deviations imply the standard value being greater than the actual inlet water temperature. For a convenient representation of the cumulative deviations during each Period, both over and under the standard values, the sum-total of positive and negative deviations were converted into degree-hours (℃ · hr). It was assumed that a deviation lasted for the entire time step of the measurement (15 minutes). Thus, the summation of positive (or negative) deviation in temperature across the whole period, divided 4 (=60/15) gave the deviation value in terms of degree-hours.

Data pre-processing and analysis was conducted in the R statistical environment (R Core Team, 2016).

3. Results

3.1. Outdoor conditions during the study

The minimum, mean, and maximum outdoor temperatures for each period have been summarized in Table 1. The last two Periods were the coldest and over the entire study duration, a wide range of outdoor conditions was experienced (-10 to 13.5 ℃).

3.2. Temperature of heating water

As described in Section 2.2, the responsiveness of the network to water temperature changes had been tested. Transmission delay, the delay in heat transmission across a network due to thermal inertia, can become an important factor if its time scale becomes similar to the time scale of DR events. Simulations have yielded a time scale of the order of hours for district sized systems (Gu et al., 2017). The recorded temperatures for the network piping around the step-change has been provided in Fig. 6.

Table 1: Outdoor temperature conditions during the survey

Period	**Dates**	**Min** (°C)	**Mean** (°C)	**Max** (°C)
1	2–6 Oct 2017	4.9	9.5	13.5
2	6–13 Oct 2017	1.0	8.1	12.5
3	13–20 Oct 2017	1.1	7.9	15.3
4	20–27 Oct 2017	−1.2	1.8	7.3
5	27 Oct–3 Nov 2017	−1.5	2.1	6.2
6	3–10 Nov 2017	1.3	6.0	8.9
7	10–20 Nov 2017	1.1	4.2	7.0
8	20–24 Nov 2017	0.4	2.3	7.5
9	24 Nov–2 Dec 2017	−0.1	3.7	7.5
10	2–8 Dec 2017	−3.2	2.0	6.0
11	8–15 Dec 2017	−0.3	2.2	5.8
12	16–22 Mar 2018	−10.1	−1.6	6.2
13	26 Mar–3 Apr 2018	−6.7	−0.4	5.3

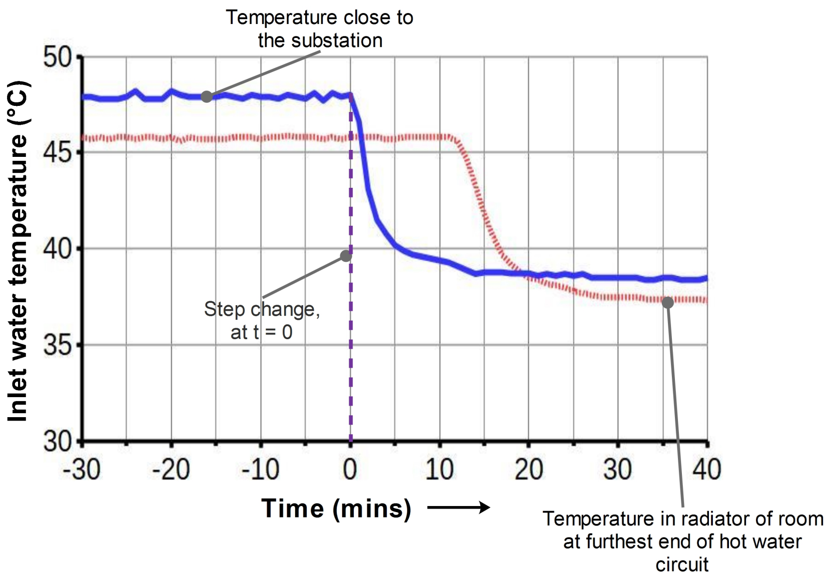

Figure 6: Temperature variation in the hot water distribution network at two locations — once closest to the substation and one furthest from it — around a step change in the water temperature

It may be clearly noted that the response to a sudden reduction in water temperature travelled through the network without a significant delay. With the temperature logging frequency being at one minute, the lag in response at the furthest end was between 12 to 15 time steps, i.e. under 15 minutes. This lag time may be put in context considering the monitoring during the Periods used a 15 minute time step.

As required by the premise of this study, the DR algorithms caused the inlet water temperature to deviate from its standard value. For each Period during which a DR control algorithm was being implemented, the actual inlet water temperature and the standard values for the inlet water temperature have been provided in the collage of plots in Fig. 7.

To better understand the effect of the control algorithms on inlet water temperature, the ranges of the deviations of water temperature from the standard during each period and the

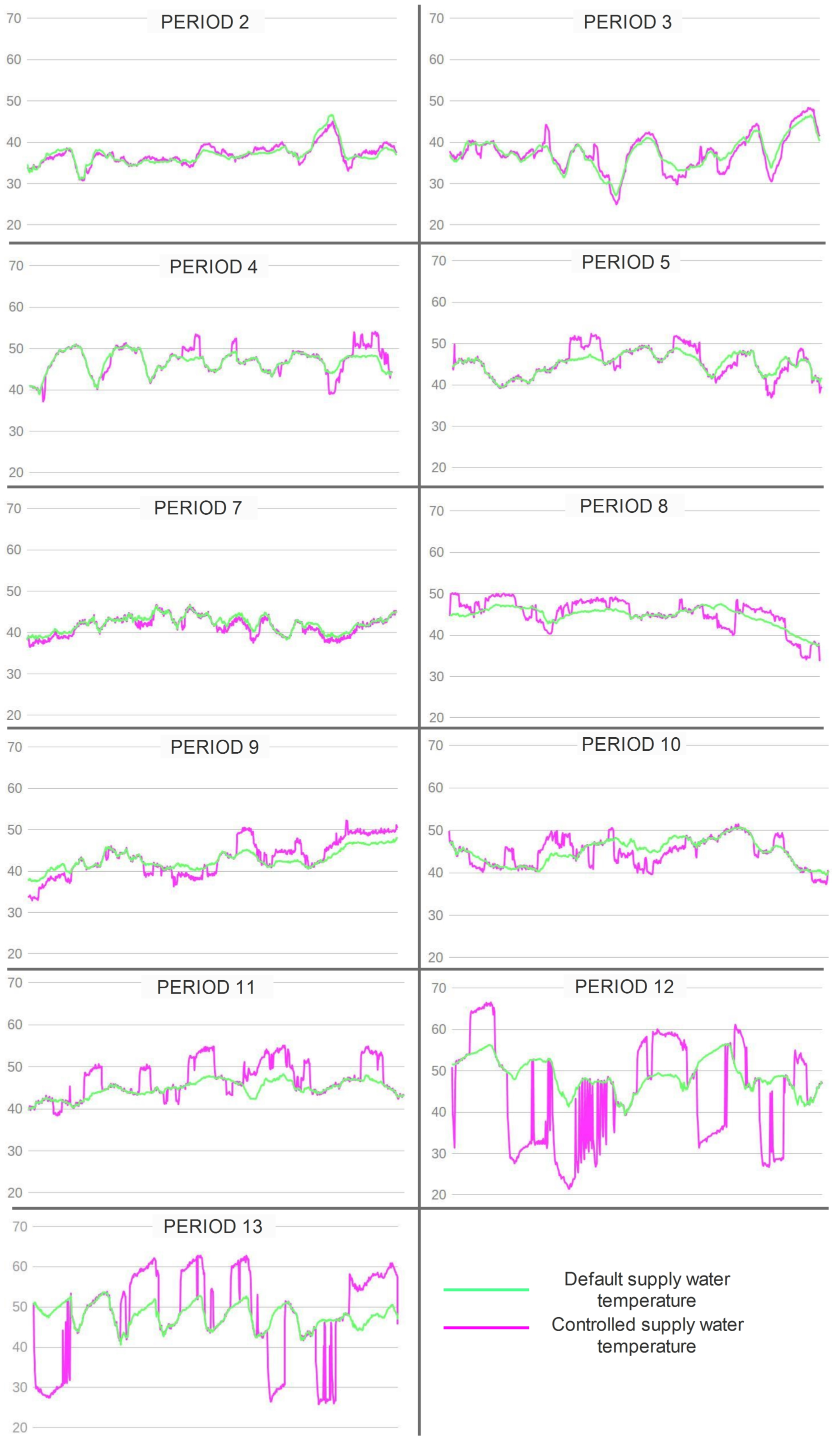

Figure 7: Standard and actual temperature of heating inlet water during each period when DR algorithms were introduced

range of the inlet water temperature have been shown in Table 2. Periods 12 and 13 show their distinction since the allowed deviations in these two DR algorithms had been higher than that for the previous situations. As discussed in Section 2.5, Periods 12 and 13 allowed deviations of up to $+10/-20$ ℃ from the standard curves, unlike the previous periods which allowed deviations only as a fraction of the radiator heat input.

Further, Table 3 provides instances of positive and negative deviations from the standard

Table 2: Ranges for heating water inlet temperature and deviations during each period

Period	P2	P3	P4	P5	P7	P8	P9	P10	P11	P12	P13
Range of deviation (°C)	−2.7 2.1	−3.8 5.7	−5.2 5.8	−5.5 5.7	−3 0.8	−5.8 5.2	−4.9 5.8	−6.1 5.5	−3.6 7.3	−21.1 10.7	−20.7 10.9
Range of inlet water temperature (°C)	30.8 45.1	25.0 48.4	37.2 54.1	36.9 52.4	36.5 46.8	33.7 50.2	32.9 52.3	37.3 51.5	38.4 55.1	21.4 66.6	25.8 62.8

inlet water temperature for each Period. Each instance here corresponds to one time step, i.e., 15 minutes.

Table 3: Instances of deviations between standard and actual heating water inlet temperature. Each instance corresponds to one time step of 15 minutes. The percentage values given below the instances correspond to percentage of time corresponding to a particular nature of deviation

Deviation	P2	P3	P4	P5	P7	P8	P9	P10	P11	P12	P13
Positive	344 (51.2%)	347 (51.6%)	304 (52.1%)	303 (45.2%)	220 (23.7%)	260 (62.8%)	380 (51.1%)	235 (39.2%)	405 (59.6%)	243 (40.9%)	411 (54.4%)
Negative	302 (44.9%)	227 (33.8%)	250 (42.9%)	297 (44.3%)	643 (69.1%)	141 (34.1%)	316 (42.5%)	312 (52.1%)	213 (31.3%)	318 (53.5%)	298 (39.5%)
Null	26 (3.9%)	98 (14.6%)	29 (5.0%)	71 (10.6%)	67 (7.2%)	13 (3.1%)	48 (6.5%)	52 (8.7%)	62 (9.1%)	33 (5.6%)	46 (6.1%)

Period 7 DR showed the maximum fraction of negative deviation while Period 11 got the maximum positive deviation. Cumulative deviation was positive for all Periods except 7, 10, 12, and 13.

Table 4: Deviations between standard and actual heating water inlet temperature, expressed as degree-hours (°C · hr)

Deviation	P2	P3	P4	P5	P7	P8	P9	P10	P11	P12	P13
Positive (°C · hr)	68.9	101.1	90.7	118.5	14.5	126.6	206.5	101.6	384.0	382.7	671.5
Negative (°C · hr)	-67.4	-93.0	-50.3	-81.0	-156.2	-78.7	-132.7	-148.0	-40.9	-1066.8	-701.1

For cumulative deviations between standard controls and the specific DR control implemented during a period, the degree·hours were calculated for each of the 11 periods. As may be garnered from Table 4, the cumulative deviations (both positive and negative) were particularly noticeable for Periods 9 through 13. All five of these periods implemented variations of the DnH algorithm. And except for Period 9, the other four Periods used a 3 Day history to inform their price trend control signal.

3.3. AHU supply air conditions

As discussed in Section 2.5, during Periods 7 through 12, in addition to affecting the inlet water temperature, the supply air temperature from some of the AHUs serving the Wing were also affected. This too led to deviations from the standard control curves. The deviations were analysed similar to the deviations of the inlet water temperature and have been presented in

Table 5. Values were considered only for the hours when the AHUs were operational. Along with the instances of deviation, each deviation corresponding to a fifteen minute time step, the cumulative deviation in terms of ℃ · hr have been provided.

Table 5: Deviations between standard and actual supply air temperatures from the AHU during the six periods when the DR events affected the AHUs

AHU	**Deviation**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**
3	Positive	161	61	153	63	91	–
	Negative	242	99	167	177	189	–
	Positive (℃ · hr)	42.1	23.1	91.1	30.2	43.1	–
	Negative (℃ · hr)	-9.0	-6.2	-5.9	-12.5	-7.6	–
4	Positive	300	112	270	110	126	–
	Negative	102	46	90	90	152	–
	Positive (℃ · hr)	53.6	57.7	151.5	34.4	48.3	–
	Negative (℃ · hr)	-1.8	-1.3	-1.8	-4.4	-5.2	–
5	Positive	110	68	138	63	72	–
	Negative	140	91	63	137	75	–
	Positive (℃ · hr)	31.5	48.9	88.8	30.1	16.9	–
	Negative (℃ · hr)	-14.8	-13.5	-8.7	-26.3	-13	–
15	Positive	176	145	257	131	199	119
	Negative	551	141	310	296	301	328
	Positive (℃ · hr)	14	23.2	51.1	33.8	51.3	18.1
	Negative (℃ · hr)	-233.1	-56.9	-115.2	-101.5	-101.7	-124.8

3.4. Room temperature conditions

3.4.1. Summary of indoor air temperature

The recorded indoor air temperature data covered all the rooms in U-Wing. However, some of these spaces were hallways, were in the basement, housed equipment/machineries etc. Excluding such rooms, which were not meant for occupancy, left 115 rooms. The temperature data for these rooms was analysed together to provide a summary view of indoor thermal conditions during the observation periods. The data has been summarized using the plot in Fig. 8. The plot provides the mean, minimum, and maximum temperature at each instant of record across all 13 Periods, for the 115 rooms. Additionally, the indoor air temperature control signals, used for determining if a DR algorithm should be operational or if the standard inlet water temperature should be used (Section 2.5.1), have also been provided. The plot also demarcates the 20-24.5 ℃ zone that had been used during the study as the comfort temperature range for occupants.

It may be noted from Fig. 8 that the Wing's maximum and minimum temperature show a broad range of variation. The current work was not intended towards narrowing down to the causes of such variations but, some possible reasons could be: higher/lower heat load than designed, balancing problem of water network, too high/low airflow rate for demand in certain spaces.

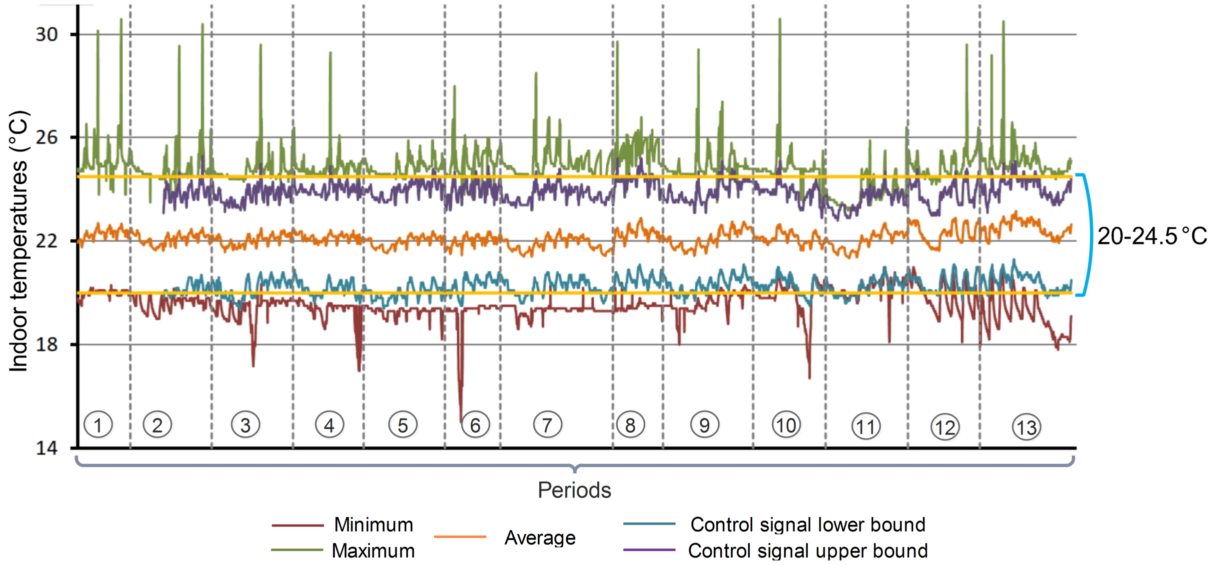

Figure 8: Summarized indoor temperature conditions of the observed rooms

As discussed in Section 2.5.1, the DR algorithms were constrained by the room temperature of the occupied spaces. The average temperature of the warmest rooms (90th percentile) could yet exceed 24.5 ℃ and the average temperature of the coolest rooms (90th percentile) could fall below 20 ℃. While such deviations in these two control signals have been graphically presented in Fig. 8, the instances of such deviations have been summarised in Table 6.

Table 6: Number of instances where the average temperature of the coldest and warmest rooms deviated out of the comfort bounds of [20, 24.5]℃

Deviation	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**
Over 24.5 ℃	9	16	11	13	15	70	41	19	4	33	76
Below 20 ℃	228	140	303	69	174	4	99	108	153	13	44

3.4.2. Non-compliant rooms

We defined a "non-compliant room" as one that overheats or overcools during the operation of a particular DR algorithm, for 10% of the time. Rooms are identified based on if the 10th percentile of their recorded temperatures was below 20 ℃or if the 90th percentile was over 24.5 ℃. Rooms which just housed machineries/equipment or were hallways/lobbies, have been excluded from this listing.

A summary list is presented in the Table 7. The list also includes the lowest and highest temperatures reached in the respective Period. The room in which this condition was reached has been underlined. The room numbers have been replaced with an alphanumeric code of the form NWXYZ. The code has been expounded upon in Table 7. For example, 2CRWV is a room assigned the serial number 2 which is a classroom (C), with radiators (R), external windows

(W), and its ventilation system is connected to one of the AHUs affected by the DR algorithm (V).

Table 7: Period-wise list of non-compliant rooms

Period	**No. of rooms**	**Issue**	**Room codes**	**Low/high Temp. (°C)**
1	7	Cool rooms	19PR-, 13OR-	19.6
		Warm rooms	6ARW-, 22CRW-, 2CRWV, 4CRW-, 5ARW-	26.5
2	7	Cool rooms	9P-, 11MR-, 13OR-, 14M-	19
		Warm rooms	6ARW-, 2CRWV, 5ARW-	26.3
3	12	Cool rooms	9P-, 7OR-, 8M-, 10OR-, 11MR-, 13OR-, 14M-, 15M-	18.8
		Warm rooms	6ARW-, 5ARW-, 22CRW-, 2CRWV	26
4	11	Cool rooms	20CR-, 9P-, 12IR-, 23CR-, 13OR, 14M-, 15M-	17
		Warm rooms	6ARW-, 22CRW-, 2CRWV, 5ARW-	26
5	12	Cool rooms	25CR-, 9P-, 21CR-V, 24CR-V, 13OR-, 14M-, 15M-, 16OR-	18.8
		Warm rooms	6ARW-, 22CRW-, 2CRWV, 5ARW-	25.9
6	11	Cool rooms	1MR-, 28MR-V, 23CR-, 24CR-V, 13OR-, 14M-, 15M-, 16OR-	15
		Warm rooms	5ARW-, 6ARW-, 2CRWV	26.1
7	11	Cool rooms	21CR-V, 9P-, 27MR-V, 24CR-V, 13OR-, 14M-, 15M-, 16OR-	18.6
		Warm rooms	6ARW-, 5ARW-, 18CRW-	26.8
8	8	Cool rooms	13OR-, 14M-, 15M-, 16OR-	19.2
		Warm rooms	5ARW-, 18CRW-, 6ARW-, 2CRWV	26.3
9	8	Cool rooms	9P-, 27MR-V, 13OR-, 14M-, 15M-, 16OR-	19.2
		Warm rooms	6ARW-, 5ARW-	26
10	4	Cool rooms	21CR-V, 13OR-	16.7
		Warm rooms	6ARW-, 5ARW-	25.8
11	1	Cool rooms	28MR-V	19.7
		Warm rooms		
12	6	Cool rooms	14M-, 26MR-	18.7
		Warm rooms	6ARW-, 2CRWV, 5ARW-, 17I-W-	26.0
13	8	Cool rooms	21CR-V, 14M-, 26MR-	17.8
		Warm rooms	6ARW-, 2CRWV, 3CRW-, 5ARW-, 17I-W-	25.9

Room alphanumeric codes: NWXYZ
N - Serial number
W - room type (A = auditorium, C = classroom, I = IT classroom, M = meeting room, O = open plan office, P = personal office)
X - radiators present or absent (R or blank)
Y - external windows present or absent (W or blank)
Z - supply air temperature affected by DR scenarios (V or blank)

Periods 10 and 11 had DR settings that were particularly effective at preventing rooms from getting too warm or too cool. As would be seen in the following section, Period 10 also had the most positive occupant feedback. On the other hand, Periods 3, 4, 5, and 7 had DR algorithms that lead to over 10 rooms deviating from thermal comfort goals. It is apparent that all the rooms classified as warm rooms had external windows.

There could be such rooms which were usually deviant from the thermal conditioning goals during most of the Periods (for example, rooms 5ARW-, 6ARW-, 13OR-, 14M-, and 2CRWV made it to the list during 7 Periods or more). On the other extreme, we had rooms that showed up only during one or two Periods. Counting such occurrences, we saw that during Period 3, we had three rooms which do not come to the list on any of the other Periods and one room which comes to the list only during one other period (Period 2). Hence, Period 3 DR algorithm may be considered to be particularly concerning for thermal comfort.

Of particular interest in Fig. 8 and Table 7 are the trends during Periods 12 and 13. The DR scenarios implemented for these two period allowed for a much larger deviation in the inlet water temperature. However, the results for room indoor temperatures show that the mean temperature pattern did not drastically deviate from the other periods. From Table 7 it may also be noted that there were not an excessive number of non-compliant rooms during these two Periods, as compared to the rest of them.

In a DHN, unbalanced heat distribution can lead to some spaces getting overheated and some underheated, thus compromising occupant comfort (Bojic and Trifunovic, 2000). Observation of such a pattern would of course suggest that the system needs to be rebalanced or valves and heat exchangers in the substation be renovated.

3.5. Occupant satisfaction

During certain Periods of implementations, mainly at the beginning of the study, very few feedbacks were received, as depicted in Table 8. This may be attributed to occupants taking the first few weeks to get acquainted with the feedback required, the method of feedback, and the location of the terminals and using the web portal.

Because of the large floor area and considering that the Wing is used by hundreds of occupants during each Weekday, it was not possible to follow up with all of them. However, considering the fact that the information regarding the feedbacks being requested had been widely circulated, it was expected that occupants would provide feedback. The expectation was that especially occupants dissatisfied with the thermal conditions would be sharing their opinion, helping us obtain and indication of if the different DR control actions impacted occupant perception.

Periods 9, 10, 12, and 13 fared particularly well with the occupants, each securing over 65% positive feedback. At the same time, it is of note that Periods 12 and 13 had quite high acceptance among occupants in spite of the fact that much larger deviations in inlet water temperatures were allowed during these two periods. As given in Table 2, inlet water temperature deviation during the last two periods was markedly higher than for the rest of the DR scenarios. Together with the findings in Section 3.4, it would appear that the DR scenarios can be implemented without affecting major alterations in the indoor thermal conditions and without increasing occupant discomfort.

Table 8: Occupant satisfaction feedback during different periods

Period	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
Negative ☹	8	11	1	1	3	2	55	35	54	61	46	13	5
Positive ☺	9	3	1	0	1	0	66	39	107	127	51	36	12

4. Discussions

Considering the meagre literature that exists regarding examining the workings of DR algorithms on a DHN, as observed in an actual building, the current work took an important step forward. To evaluate the performance of the several DR algorithms implemented, a three level monitoring was used. These levels were how the DR algorithm affected the inlet water temperature for heating, how it affected the indoor conditions in the influenced rooms, and how it affected occupant perception. It is pertinent to keep in mind that a "smart" control algorithm, like the ones used in this study, can be nearly 30% more effective at saving peak energy demands and at maintaining thermal comfort levels too, than a simple on/off control (Ahn and Cho, 2017).

Though such a DR system for DHNs is not currently in market, it is raising great interest. As a pilot study in this field, the current work managed to successfully implement and study on the field DR algorithms for DHN. This direction of investigation could complement the recent progress that has been made in the direction of a reliable, ease to use tool for modelling heat demand of district scale networks (Talebi et al., 2017, 2018).

The study also set-up the frame work for a meticulous monitoring system that looked at the performance of DR algorithms from multiple levels, ensuring the algorithms may be adjudged in a more careful manner. This platform is set to play a major role in upcoming similar studies. Such smart energy management systems have also been credited in previous works to have greatly aided the end user in making decisions regarding optimal energy use (Ogunjuyigbe et al., 2015).

Limiting heat loss to the outdoors can have a significant effect on DR applicability for buildings using water radiator systems (Pedersen et al., 2017). In the current case, U-Wing had undergone refurbishment within the last four years, making it a suitable study case.

While this work field tested a centralized building level control of demand control, and centralized schemes have been reported to have their advantages in terms of energy savings (Pedersen et al., 2017), future works would need to also examine decentralized approaches, i.e., moving down to the room level. Control at the room level can provide better accuracy and avoid peaks and valleys. As seen in the current work (Section 3.4.2), using the centralized building level control, during certain Periods, rooms that typically did not have an issue came up to feature in the list of non-compliant rooms. The room air temperature in these rooms could have been better managed with a decentralized approach, possibly even improving occupant comfort. For district level energy systems, centralized scheduling may give the best coordination but decentralization of DR efforts can give improved scalability and more options (Harb et al., 2015). In this regards, IoT thermostats may be expected to play a major role (Marantos et al., 2019). The IoT thermostats, with ventilation control, unlike TRVs, can accurately control temperature ups and downs at the room level. The higher resolution control, extending to the room level, can also help better address peak power (heating and cooling) issues.

Some of the challenges that face the future of DH would be lower energy demands of the newer, better insulated buildings while peak power demand does not reduce as much, more efficient energy conversion plants that are able to operate at lower temperatures (Tereshchenko and Nord, 2018) and incentives for thermal energy generation from renewable sources, similar to ones available for generating electricity from renewable sources (Aste et al., 2015). Hence, the inlet water temperature adjustments considered, in sync with energy pricing, in this case study have a bearing upon design of future DHNs.

Demand side management often aims at reducing peak energy consumption but in this effort, new peaks may be created. This is particularly a concern with the rebound expected after conservation measures are withdrawn (Motegi et al., 2007). Future systems, in addition to reducing energy use peaks, would also need to consider trying to sync demand with energy generation (Gelazanskas and Gamage, 2014) and this effort, they could use additional indicators, beyond energy price (Nyholm et al., 2016).

Our observations were spread across 13 periods. During this time, the outdoor conditions varied significantly. Hence, it was advisable to compare the performance of the DR algorithms with the standard algorithms used for control of inlet water temperature and AHU supply air temperature. Over time, internal load profile would also have change but this may not have got to a noticeable level due to the large floor area of the Wing and the varied room types it houses. A useful, practical finding was that the inlet water temperature changes effected at the substation were rapidly reflected in all rooms of the Wing, indicating the system was able to respond fast to DR events. Reduced temperatures, system-wide, in a DHN, are an important aid to achieving savings in future energy systems, with benefits being realized both during operation and in the energy production process (Lund et al., 2018). This is the current direction of progress towards fourth generation DH.

Periods 12 and 13 had DR algorithms that allowed significant deviations from the standard control curves, as compared to the other periods. This can be seen from the results presented in Section 3.2. During these periods, instead of allowing water temperature deviations based on a percentage of the radiator output, water temperatures were allowed to deviate by +10 to −20 ℃. This can be a useful pointer for implementation of DR algorithms in the future. Even with the larger allowed deviations during the last two Periods, room air temperature did not fare any worse than the other periods, as presented in Table 7.

While technical concerns may come with lowering temperature of heating water in a DHN, they do not appear to be insurmountable (Hasan et al., 2009; Ovchinnikov et al., 2017). Beyond technical considerations though, a major concern would be comfort of occupants. Across the different periods, the DR events did not cause any major deterioration to occupant indoor thermal comfort experience, as seen in Table 8. This was also the case for Periods 12 and 13 which allowed much greater reductions in heating water temperature. It may be noted here that previous studies also indicate changes of ∼2 ℃ to air temperature being unlikely to impact comfort of occupants (Aghniaey et al., 2018, 2019).

These control strategies still had majority of respondents providing a positive rating. Simultaneously, the wide range of thermal preference individuals over the entire Wing may have (Xu et al., 2009), could also have contributed towards keeping cumulative satisfactions high as the space temperature varied during the DR events. Since the occupant feedback system used in this work was rudimentary, subsequent works would need to extend the occupant feedback mechanism to obtain more continuous input from occupants, on multiple headings concerning their comfort perception and preferences. In future studies, it would also be interesting to see occupant satisfaction levels when the implementation is done over the entire DH network. Simulation results suggest that more building types with diverse usage profile, can provide greater opportunities for optimizing energy use without compromising thermal comfort (Ahn and Cho, 2017).

During five periods, in addition to affecting inlet water temperature, the algorithms also controlled supply air temperature for AHUs. The influence on supply air temperature, in terms of deviations from the standard control profiles, was not as stark as for the inlet water temperature and the deviations were similar across all five periods.

A major drawback of the current work may be pointed out as the lack of data on heating energy usage or heating power. For the studied wing, this was not possible due to certain technical barriers. To gain a holistic understanding of the DR scenarios' impact, future works will be undertaking comprehensive heating energy and power monitoring as well. But, even when such monitoring is possible, the comparison of the energy or monetary cost results of different periods may not be able to identify relatively small effect of demand response control because of the confounding contributions from user profiles changing loads, changes in outdoor conditions, and changes to operation hours. In particular, for this case, since the building was a university campus building, its usage varies a lot due to, for example, different schedules of the courses.

Future challenges of DR relate to improved control strategies and markets that can support the DR economically (Pinson et al., 2014). Fixed energy price remains an archaic concept that may hinder the progress of modern DHNs. Fixed pricing does not conform to the principles of modern market prices and precludes any consumer contribution and responsibility in improving the system efficiency (Gelazanskas and Gamage, 2014; Syri et al., 2015; Wernstedt et al., 2007). Without variable pricing, customers may lose a major incentive for saving energy. The non-tangible incentive, in the form of helping the planet and the environment, may gain only limited success (Wernstedt et al., 2007). With variable energy prices, an engaged and active user stands to benefit the most.

In practical terms, variable pricing schemes for electric grid are already used quite widely across the US and Europe with programs such as critical peak pricing, peak time rebated, and time of use (Hu et al., 2015; Pallonetto et al., 2016). Hence, it is expected that energy prices conforming to the actual generation costs, as used in the current work, would be a reality sooner than later. As it cannot be expected that occupants constantly monitor price changes and make manual changes to usage, this role would be taken up by the building management system, and this makes an eventual business case for the energy service companies (ESCo) (Reynolds et al., 2017).

For future studies, another interesting aspect to include would be extending the DR measures to the whole building and even possibly multiple buildings. While occupant behaviour and interaction with the heating system can lead to diverse energy use profiles, system level variations go down as more consumers are included (Xu et al., 2009). Aggregation of buildings, adds diversity of usage and can help demand side management (Aduda et al., 2016; Amaral et al., 2018).

5. Conclusion

The current work started out with a unique perspective of field testing demand response in the context of DHNs and successfully achieved the desired implementations. Eleven variants of DR algorithms that influenced the space heating water inlet temperature and the supply air temperature to certain rooms, were tested in a university building. One of the most conclusive results obtained was that occupant perception of the indoor thermal environments did not deteriorate during the DR implementations. Certain DR implementation periods even seemed to improve occupant perception over the reference periods. This was while wide changes were noted for the maximum and minimum room air temperatures. This wide fluctuation suggests that a decentralized strategy could be more successful in limiting the highs and lows of air temperature in certain rooms, ensuring needs of occupant comfort. In a supplementary study, it was also found that changes made to water temperature at the substation level reflected in the rooms' radiators with minimal time delay.

The different implementations were able to achieve lowered inlet water temperature to different degrees of success. Irrespective of how the price signal was being assessed to determine periods of conservation vs loading, the achieved lowering with respect to standard algorithms, depended on the allowed temperature deviations. For the last two periods, even while keeping to the predefined comfort constraints, temperature deviations of ∼20 ℃ were achieved, compared to the default control algorithms. The measured temperatures in most of the rooms of the Wing only infrequently ventured out of the defined comfort limits. This would imply that the building's thermal mass, along with the price based implementation of the algorithms, present significant avenues of energy flexibility.

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References

Abdurafikov, R., Grahn, E., Kannari, L., Ypyä, J., Kaukonen, S., Heimonen, I., and Paiho, S. (2017). An analysis of heating energy scenarios of a Finnish case district. *Sustainable Cities and Society*, 32:56–66.

Aduda, K., Labeodan, T., Zeiler, W., and Boxem, G. (2017). Demand side flexibility coordination in office buildings: A framework and case study application. *Sustainable Cities and Society*, 29:139–158.

Aduda, K., Labeodan, T., Zeiler, W., Boxem, G., and Zhao, Y. (2016). Demand side flexibility: Potentials and building performance implications. *Sustainable Cities and Society*, 22:146–163.

Aghniaey, S., Lawrence, T. M., Mohammadpour, J., Song, W., Watson, R. T., and Boudreau, M. C. (2018). Optimizing thermal comfort considerations with electrical demand response program implementation. *Building Services Engineering Research and Technology*, 39(2):219–231.

Aghniaey, S., Lawrence, T. M., Sharpton, T. N., Douglass, S. P., Oliver, T., and Sutter, M. (2019). Thermal comfort evaluation in campus classrooms during room temperature adjustment corresponding to demand response. *Building and Environment*, 148:488–497.

Ahn, J. and Cho, S. (2017). Development of an intelligent building controller to mitigate indoor thermal dissatisfaction and peak energy demands in a district heating system. *Building and Environment*, 124:57–68.

Alimohammadisagvand, B., Alam, S., Ali, M., Degefa, M., Jokisalo, J., and Sirén, K. (2017). Influence of energy demand response actions on thermal comfort and energy cost in electrically heated residential houses. *Indoor and Built Environment*, 26(3):298–316.

Alimohammadisagvand, B., Jokisalo, J., and Sirén, K. (2018). Comparison of four rule-based demand response control algorithms in an electrically and heat pump-heated residential building. *Applied Energy*, 209:167–179.

Amaral, A. R., Rodrigues, E., Gaspar, A. R., and Gomes, Á. (2018). Review on performance aspects of nearly zero-energy districts. *Sustainable Cities and Society*. doi:10.1016/j.scs.2018.08.039.

Aslani, A., Naaranoja, M., Helo, P., Antila, E., and Hiltunen, E. (2013). Energy diversification in Finland: Achievements and potential of renewable energy development. *International Journal of Sustainable Energy*, 32(5):504–514.

Aste, N., Buzzetti, M., and Caputo, P. (2015). District heating in Lombardy region (Italy): Effects of supporting mechanisms. *Sustainable Cities and Society*, 14:43–55.

Bojic, M. and Trifunovic, N. (2000). Linear programming optimization of heat distribution in a district-heating system by valve adjustments and substation retrofit. *Building and Environment*, 35(2):151–159.

Comite'Europe'en de Normalisation, C. (2007). Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics. *EN 15251*.

Gelazanskas, L. and Gamage, K. A. (2014). Demand side management in smart grid: A review and proposals for future direction. *Sustainable Cities and Society*, 11:22–30.

Gils, H. C. (2014). Assessment of the theoretical demand response potential in Europe. *Energy*, 67:1–18.

Good, N., Cesena, E. A. M., and Mancarella, P. (2017). Ten questions concerning smart districts. *Building and Environment*, 118:362–376.

Gu, W., Wang, J., Lu, S., Luo, Z., and Wu, C. (2017). Optimal operation for integrated energy system considering thermal inertia of district heating network and buildings. *Applied Energy*, 199:234–246.

Harb, H., Paprott, J.-N., Matthes, P., Schütz, T., Streblow, R., and Müller, D. (2015). Decentralized scheduling strategy of heating systems for balancing the residual load. *Building and Environment*, 86:132–140.

Hasan, A., Kurnitski, J., and Jokiranta, K. (2009). A combined low temperature water heating system consisting of radiators and floor heating. *Energy and Buildings*, 41(5):470–479.

Hu, Z., Kim, J.-h., Wang, J., and Byrne, J. (2015). Review of dynamic pricing programs in the US and Europe: Status quo and policy recommendations. *Renewable and Sustainable Energy Reviews*, 42:743–751.

Kalamees, T., Jylhä, K., Tietäväinen, H., Jokisalo, J., Ilomets, S., Hyvönen, R., and Saku, S. (2012). Development of weighting factors for climate variables for selecting the energy reference year according to the EN ISO 15927-4 standard. *Energy and Buildings*, 47:53–60.

Kensby, J., Trüschel, A., and Dalenbäck, J.-O. (2015). Potential of residential buildings as thermal energy storage in district heating systems — Results from a pilot test. *Applied Energy*, 137:773–781.

Khabdullin, A., Khabdullina, Z., Khabdullina, G., Lauka, D., and Blumberga, D. (2017). Demand response analysis methodology in district heating system. *Energy Procedia*, 128:539–543.

Knudsen, M. D. and Petersen, S. (2017). Model predictive control for demand response of domestic hot water preparation in ultra-low temperature district heating systems. *Energy and Buildings*, 146:55–64.

Koutra, S., Ioakimidis, C. S., Gallas, M.-A., and Becue, V. (2018). Towards the development of a net-zero energy district evaluation approach: A review of sustainable approaches and assessment tools. *Sustainable Cities and Society*, 39:784–800.

Kreuder, L. and Spataru, C. (2015). Assessing demand response with heat pumps for efficient grid operation in smart grids. *Sustainable Cities and Society*, 19:136–143.

Le Dreau, J. and Heiselberg, P. (2016). Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy*, 111:991–1002.

Lund, H., Østergaard, P. A., Chang, M., Werner, S., Svendsen, S., Sorknæs, P., Thorsen, J. E., Hvelplund, F., Mortensen, B. O. G., Mathiesen, B. V., et al. (2018). The status of 4th generation district heating: Research and results. *Energy*, 164:147–159.

Lund, H., Østergaard, P. A., Connolly, D., Ridjan, I., Mathiesen, B. V., Hvelplund, F., Thellufsen, J. Z., and Sorknæs, P. (2016). Energy storage and smart energy systems. *International Journal of Sustainable Energy Planning and Management*, 11:3–14.

Lund, H., Werner, S., Wiltshire, R., Svendsen, S., Thorsen, J. E., Hvelplund, F., and Mathiesen, B. V. (2014). 4th generation district heating (4GDH): Integrating smart thermal grids into future sustainable energy systems. *Energy*, 68:1–11.

Marantos, C., Lamprakos, C., Siozios, K., and Soudris, D. (2019). Towards plug&play smart thermostats for building's heating/cooling control. In *IoT for Smart Grids*, pages 183–207. Springer.

Martin, K. (2017). Demand response of heating and ventilation within educational office buildings. `https://aaltodoc.aalto.fi/handle/123456789/29149`.

Motegi, N., Piette, M. A., Watson, D. S., Kiliccote, S., and Xu, P. (2007). Introduction to commercial building control strategies and techniques for demand response. *Lawrence Berkeley National Laboratory LBNL-59975*.

Müller, D., Monti, A., Stinner, S., Schlösser, T., Schütz, T., Matthes, P., Wolisz, H., Molitor, C., Harb, H., and Streblow, R. (2015). Demand side management for city districts. *Building and Environment*, 91:283–293.

Nyholm, E., Puranik, S., Mata, É., Odenberger, M., and Johnsson, F. (2016). Demand response potential of electrical space heating in Swedish single-family dwellings. *Building and Environment*, 96:270–282.

Ogunjuyigbe, A., Monyei, C., and Ayodele, T. (2015). Price based demand side management: a persuasive smart energy management system for low/medium income earners. *Sustainable Cities and Society*, 17:80–94.

Ovchinnikov, P., Borodiņecs, A., and Strelets, K. (2017). Utilization potential of low temperature hydronic space heating systems: A comparative review. *Building and Environment*, 112:88–98.

Paiho, S., Saastamoinen, H., Hakkarainen, E., Similä, L., Pasonen, R., Ikäheimo, J., Rämä, M., Tuovinen, M., and Horsmanheimo, S. (2018). Increasing flexibility of Finnish energy systems — A review of potential technologies and means. *Sustainable Cities and Society*. `https://doi.org/10.1016/j.scs.2018.09.015`.

Pallonetto, F., Oxizidis, S., Milano, F., and Finn, D. (2016). The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling. *Energy and Buildings*, 128:56–67.

Pedersen, T. H., Hedegaard, R. E., and Petersen, S. (2017). Space heating demand response potential of retrofitted residential apartment blocks. *Energy and Buildings*, 141:158–166.

Pinson, P., Madsen, H., et al. (2014). Benefits and challenges of electrical demand response: A critical review. *Renewable and Sustainable Energy Reviews*, 39:686–699.

R Core Team (2016). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Reynders, G., Lopes, R. A., Marszal-Pomianowska, A., Aelenei, D., Martins, J., and Saelens, D. (2018). Energy flexible buildings: An evaluation of definitions and quantification methodologies applied to thermal storage. *Energy and Buildings*, 166:372–390.

Reynolds, J., Rezgui, Y., and Hippolyte, J.-L. (2017). Upscaling energy control from building to districts: Current limitations and future perspectives. *Sustainable Cities and Society*, 35:816–829.

Robert, F. C., Sisodia, G. S., and Gopalan, S. (2018). A critical review on the utilization of storage and demand response for the implementation of renewable energy microgrids. *Sustainable Cities and Society*, 40:734–745.

Siano, P. (2014). Demand response and smart grids — A survey. *Renewable and Sustainable Energy Reviews*, 30:461–478.

Sweetnam, T., Spataru, C., Barrett, M., and Carter, E. (2018). Domestic demand-side response on district heating networks. *Building Research & Information*, pages 1–14.

Syri, S., Mäkelä, H., Rinne, S., and Wirgentius, N. (2015). Open district heating for Espoo city with marginal cost based pricing. In *European Energy Market (EEM), 2015 12th International Conference on the*, pages 1–5. IEEE.

Talebi, B., Haghighat, F., and Mirzaei, P. A. (2017). Simplified model to predict the thermal demand profile of districts. *Energy and Buildings*, 145:213–225.

Talebi, B., Haghighat, F., Tuohy, P., and Mirzaei, P. A. (2018). Validation of a community district energy system model using field measured data. *Energy*, 144:694–706.

Tereshchenko, T. and Nord, N. (2018). Future trends in district heating development. *Current Sustainable/Renewable Energy Reports*, pages 1–9.

Verda, V. and Colella, F. (2011). Primary energy savings through thermal storage in district heating networks. *Energy*, 36(7):4278–4286.

Wernstedt, F., Davidsson, P., and Johansson, C. (2007). Demand side management in district heating systems. In *Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems*, page 272. ACM.

Xu, B., Fu, L., and Di, H. (2009). Field investigation on consumer behavior and hydraulic performance of a district heating system in Tianjin, China. *Building and Environment*, 44(2):249–259.