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Individual Temperature Control on Demand Response in a District Heated Office Building in Finland

Sonja Salo^{a,b,*}, Juha Jokisalo^b, Sanna Syri^b, Risto Kosonen^b

^aFourdeg Ltd, Kalevankatu 13a 5th floor, 00100 Helsinki, Finland

^bAalto University, School of Engineering, Department of Mechanical Engineering, P.O. Box 14100, FIN-00076, Aalto, Finland

ABSTRACT

Keywords:

District heating;
Demand Response;
Cloud control;
User-centric design

The Internet of Things can be an effective way to manage the demand side and perform demand response in thermal grids. The concept provides new models for predicting demand and gathering data in a smart and inexpensive fashion. This research investigates the deployment of room-specific demand response in a district-heated office building in Southern Finland. It is fulfilled by controlling set-point temperatures on thermostatic radiator valves. By developing a predictive algorithm on a cloud platform and gathering feedback from the environment and the users, the paper presents findings about load shifting on room level and about local discomfort. The results indicate that heating power can be increased and decreased at the thermostat, even by 104% and 47% respectively. On average this accounts for 40 W/m². However, the larger the set-point temperature variation is, the larger local discomfort grows. Indoor air temperature readings do not give enough evidence of thermal comfort. Hence, demand response with room-level accuracy should be deployed in areas of the building in which flexibility is least noticed.

1. Introduction

1.1. Intelligent Buildings and Renewable District Heating

Urban energy systems are undergoing a digital transition as inexpensive data are increasingly available [1]. The management of buildings is leading towards fact-based decision-making and continuous assessment in cloud servers. The digital transition is tightly related to the building management system, concentrating especially on customer engagement, and contemporary automation [1]. Similarly to renewable energy technologies, smart buildings are rolling into the market at a fast pace. However, the technology readiness level is not similar at all hierarchy levels. Zhang et al. [1] denoted that the technology readiness level of digital transition at city level is still below technology development compared to the digital transition at building level. In particular, the district heating (DH) sector still lacks intelligence technology [2]. Integrating smart-electricity, smart-thermal and smart-gas grids to enable 100% renewable energy sources which is the goal of the smart energy system's concept [3], and would lead to the target of climate neutrality [4] at a low cost. In this study, integrating energy systems means to make use of the thermal demand, or thermal load, of the buildings more flexible for the energy system.

Using the thermal load in buildings as an additional degree of freedom is not a new idea but an affordable global communication infrastructure, and embedded systems, such as the Internet of Things (IoT), make it relatively easy to add intelligence to the control of the loads [5]. By increasing flexibility in buildings, enough energy can be distributed to end-users with maximised efficiency, and minimal cost and emissions [6]. This enhanced flexibility enables us to distribute

sufficient energy to end-users with maximised efficiency, and minimal cost and emissions while staying within the smart energy framework. Smart load control is a cost-effective alternative for the building owner [7] and influencing the load from the production side can be less expensive than building new power plants and additional grid capacity or investing in hot-water storage tanks [8]. Building-based energy control is generally referred to as *demand-side management*, whereas the momentary shift of loads is referred to as *demand response (DR)* [9].

In the DH context, DR is a term used for programs designed to make short-term modifications to the building's energy use from one hour to another in response to triggers initiated by the DH operator [10, 11]. The energy consumption during the times when there is a high price can be decreased, and heating power can be modulated in hours when there is a medium and low price by storing heat in the thermal mass. Dréau et al. [6] noted that the additional energy consumption is limited to only a few per cent, which is counterbalanced by an increase in the flexibility of the building. In a recent field study in England [12] DR was deployed on residential buildings connected to a DH system. By using the buildings' thermal inertia during times of hot water usage and space heating, led together with outdoor weather compensation to peak demand reduction.

As mentioned in Ref. [9, 13, 14], a mutual understanding with the stakeholders needs to be maintained, and hence, the indoor comfort must not be sacrificed. To succeed in user acceptability, room-specific control is enabled in this research, and rooms are divided into flexibility zones for DR. Research by the International Energy Agency observed that the technocratic method that is currently used to bring energy efficiency technologies to the market is confronted by an

acceptability problem on the demand side (i.e. it is a problem for the end-user) [15]. When implementing DR algorithms correctly, it can receive a high acceptance among participants [16]. In Ref. [12], the majority of participants would be willing to participate in a commercial scheme for a small financial reward. Hence, DR actions might require financial reward to gain support from the end-users.

Many studies have utilised building simulation tools to investigate the flexibility potential of buildings and their suitability for DR with advanced building simulation tools [7, 13, 17, 18]. In Ref. [17] a qualitative tool is described for investigating the relative importance of the thermal properties of materials in thermally heavy buildings. Dréau [19] argued that the level of insulation in buildings implies differences in control strategies. Dominković et al. [20] modelled different archetypes of single-family houses and their potential preheating and subsequent heat supply cut-off periods. The results showed that a longer preheating time increased the possible duration of cut-off events. Hence, more detailed, building-specific, control algorithms appear to bring comprehensive results.

1.2. The Research Objective

A simulated and measured environment does not necessarily give adequate data about the perceived thermal comfort. Therefore, an important factor is to distinguish if temperature measurements correlate to the local temperature perception. The user-centric approach can be validated on the monetary side as well as literature shows that work performance declines when employees are exposed to a non-optimal thermal environment [21]. Using the IoT and cloud computing, the objective of this study is to validate room-specific DR in DH-connected buildings. The paper presents novel data acquisition, rule-based categorisation of rooms and control algorithms for optimising DR while sustaining a good indoor climate.

Furthermore, buildings are more and more imbalanced, which means they have large differences in indoor air temperature between each zone. DR would increase the temperature difference. Adjusting DR with room-level accuracy is novel to the field. Martin [18] simulated that controlling rooms separately could be economic for the building owner and the approach has been tested in a previous study [14]. In residential buildings, Kensby et al. [22] have found that in the given buildings, the amount of stored heat in the building mass has an almost linear relation to the magnitude of the control signal (CS) given. Now, room-based DR control is developed further for more individual control, giving more attention to end-user preferences.

Based on these findings, the research questions are as follows: How is DR triggered in a district-heated office building? Is a good indoor climate maintained during room-level temperature control? How much heating power can be shifted with room-level accuracy? How do users perceive the local thermal comfort?

This paper is divided into five sections. Section 1 consists of this introduction. In Section 2, methods utilised to assess DR at the test site are described and a description of the test site is

given. In Section 3, the case under study and the numerical results are presented. Section 4 provides discussions on the attained results. Finally, Section 5 concludes this paper.

2. Methodology

This chapter presents the test site of the study and describes the IoT control devices, the cloud server, the DR signal and room-based categorisation.

2.1. The Office Building as DR Test Site

The test site selected is one floor in a district-heated office building in Espoo, Southern Finland. The floor plan is illustrated in Fig. 1. The brick building was constructed in 1966 and renovated in the 2000s. It is used by the students and staff of Aalto University [23].

Fig. 1. The test bed for the research. The red dots denote thermostatic radiator valves and the blue dots denote indoor air temperature measurement devices.

The radiators are placed under the windows and indoor measurement devices are located on walls in the middle of the room. The test area is an upper floor with a heated net floor area of 586 m², and a constant air volume (CAV) air handling unit. The area's envelope is 947 m² with a modelled radiator dimensioning power of ~1000 W/room [24]. The energy consumption of the radiators can either be controlled with inlet water temperature adjustment in the radiator network or with water flow adjustment in each radiator. This study focuses on the room air-temperature control though the latter approach, in other words, there is decentralised control though smart thermostatic radiator valves (TRVs). The designed outdoor temperature in Southern Finland is -26°C and the radiator network's design temperatures are 70/40°C. In Fig. 2, the building's outside temperature-compensated radiator flow temperature curve is shown.

Fig. 2. The building's radiator network control characteristic.

The actual heating power demand and mass flow rate according to the design documents are 760 kW and 2.6 l/s of the whole building, accounting for a specific consumption of 125kWh/m². The U-values of external walls, the roof and windows are 0.38, 0.3 and 1 W/(m²K) respectively. It can be noted that the U-values are decent, and the draught caused by cold windows can be neglected [22]. The supply air temperature is set as 20°C, in other words, the CAV should not heat the room air temperature.

2.2. System Architecture

The control strategy is calculated in the backend server (see Fig. 3) [25]. Collecting data from outdoor weather forecasts [26], DR price signals (discussed in Section 2.3), user settings (discussed in Section 2.4) and TRV data from the previous hour, the server computes set-point temperatures for each next hour. The TRV's valve operates based on a proportional integral derivative (PID) controller, which principally operates on a CS, depending on the temperature difference of the set-point temperature and the feedback temperature (i.e. the room's air temperature at the radiator level).

Fig. 3. The conceptual system's architecture.

The functions of the TRVs become extendable through the computing capacity provided by the cloud platform [27]. The

electronic TRVs receive and send data every 15 minutes to the cloud, such as the temperature reading at the radiator level (accuracy ± 0.5 K) and valve position (range 0–100%). The valve position indicates the operations of the motorised thermostat.

2.3. The DR Signal

The price signal from the local energy company is retrieved via FTP [28] to the cloud server. The predictive signal can reach up to 48 hours in one-hour intervals, of which the algorithm uses the nearest six hours from the future and the past. Production profiles of the local DH network have been simulated, for example in Ref. [29, 30]. However, the price signal does not directly indicate the marginal cost of each hour but indicates demand-shifting requests (i.e. it is designed for DR in the local grid).

Based on the moving 12-hour price signal, lower and upper price thresholds are calculated. The hourly low and high price limits were defined as follows:

- Low price < 1st quartile of the moving 12-hour price signals.
- High price > 3rd quartile of the moving 12-hour price signals.

Though these thresholds, a CS is calculated for each price p on the hour t as follows:

$$CS_t = \begin{cases} +1 & \text{if } p_t < \text{Low price} \\ -1 & \text{if } p_t > \text{High price} \\ 0 & \text{if } p_t = \text{Medium price} \end{cases} \quad (1)$$

This signal indicates if the set-point temperature should be changed. The methodology for determining temperature change amplitude ΔT is described in the following chapter.

2.4. Rule-based Categorisation

Martin [18] modelled DR for both centralised control (i.e. control at the building's substation level by adjusting water radiator inlet temperatures) and decentralised control (i.e. the water amount is controlled via TRVs). The simulation with the decentralised control was based on the test site of this research, but a different control strategy was utilised. Cost savings were estimated with a dynamic price for DH. The centralised strategy had relatively low success as energy costs only declined by 1.6% compared to the reference case. The main restriction in the centralised control was the coldest zone which directed the control. The decentralised control, on the other hand, has more potential for DR, with a 5–6% cost saving.

Mishra et al. [16] studied different variants of DR through centralised control in a district heating office building in Finland. It was found that changes to circulating water temperature at the substation level were measured in the rooms' radiators with minimal time delay. It was noted that wide changes in maximum and minimum room air temperatures were measured with centralised DR. These can lead to a decrease in thermal satisfaction although the study did not indicate that.

Decentralised DR has been previously studied in the obtained test bed in Ref. [14]. The literature claimed that set-

point temperature can be switched in a moderate manner as the building structure stores heat with a high thermal inertia, preserving a steady indoor air temperature [9, 17]. However, in Ref. [14] the users were asked about the perceived indoor air temperature during days of DR actions and on placebo days, and the satisfaction was generally lower on DR days.

Therefore, the test site's rooms were divided into flexibility zones. The flexibility zones determined the amplitude of the set-point temperature change, which is based on each room's ability for temperature change. This was defined by the usage type of the room (office room, meeting room, corridor, kitchen) and by the velocity of indoor temperature change (i.e. its ability to store heat).

The rooms in the test site were divided into three categories:

- Category I: high flexibility (i.e. $\Delta T = \pm 2$ K)
- Category II: moderate flexibility (i.e. $\Delta T = \pm 1$ K)
- Category III: poor flexibility (i.e. $\Delta T = \pm 0.5$ K).

The amplitude of the CS is retrieved from these categories. Corridors and the kitchen have fair flexibility as the temperature variation does not affect working performance. The meeting room and the office rooms can be in all categories if the temperature change is slower than 2 K/h according to the ISO 7730 standard [31]. The rooms have been categorised based on previous measurements [14].

The test site is usually occupied during 07-17.00 on working days. While adapting DR in the building, it is assumed that good lighting, noise level and airflow are provided. The set-point temperature was set to 22.5°C during office hours. This temperature was set for the radiator level and so the air temperature in the middle of the room can be lower. To get high user acceptability, the users could adjust the set-point temperature from the TRV.

Outside office hours, the room air temperature was decreased for energy saving purposes, although it is not a form of DR. The recovery of the minimum indoor temperature is calculated by rise-time velocities and outdoor weather forecasts from the Finnish Meteorological Institute's open data portal [26] so that it is achieved before the occupants arrive in the morning [25]. The rise-time velocity is determined by the predicted outdoor temperatures.

2.5. Measurement

The measurement period was conducted in spring 2018, of which one week is represented. During the period, each room was equipped with indoor air temperature and relative humidity measurement loggers (accuracy ± 0.3 K; $\pm 3\%$ when temperature = 25°C; 15 min time intervals) [32]. As plotted in Fig. 1, the loggers are mounted on a wall, and they did not face direct solar radiation. Weather data was retrieved from Ref. [26] and an additional outdoor weather logger [32] was mounted onto the adjacent building.

Because the test site only comprises 7% of the total heated floor area of the building, it is very unlikely to measure the

impact of DR on the DH demand of the whole building. Hence, the heat output of the hydronic panel radiators was calculated by using a simple steady-state model. The radiator's heat output depends on the heat balance between the heat injected into the panel, the heat emitted towards the indoor environment and the heat stored into the thermal unit. For the calculation, the following assumptions were made:

- the surface temperature of the panel radiator is equal to the flow temperature for each element
- the heat capacity of the radiator and water are not considered
- the radiator can only heat the room – the cooling process is not considered.

The equation for heating power output P [W] is based on the manufacturer's experimental values [33] and on the general heat emission equation:

$$P = P_n * \left(\frac{\ln \left(\frac{T_{in} - T_{air}}{T_{out} - T_{air}} \right)}{\Delta T_n} \right)^n * w, \quad (2)$$

where:

P_n	heat output according to standard EN 442-2:2014 in Ref. [34], depending on radiator model, radiator height and heat output in W/m
T_{in}	the radiator's inlet water temperature in °C
T_{out}	the radiator's outlet water temperature in °C
T_{air}	room air temperature in °C
ΔT_n	the standard excess temperature between the water and the air (49.8°C; defined by the manufacturer)
n	the radiator-specific exponent
w	the radiator's width in m.

The heat output can be calculated by entering the inlet and outlet water temperatures and the room air temperature. The rooms in each category were equipped with radiator surface temperature devices. As the radiator exponents are known [33], the heat output can be calculated by installing thermoelements on the inlet and outlet pipes of the radiators. These were measured at 15-minute time intervals. The thermoelements installed on the pipes were covered by thermal insulation material.

2.6. Questionnaire

A questionnaire was designed for retrieving information on thermal comfort. Thermal comfort expresses satisfaction with the thermal environment and is linked to a person's heat loss [35]. To this end, the measurements provide information on the room air temperature but not on the local thermal comfort. Local thermal comfort depends, amongst other things, on asymmetrical thermal radiation, drafts and vertical air temperature difference [35].

The test site comprises workstations for 31 office workers. The workstations are next to the radiators, and hence, a change in the heating should be noted rapidly. If the workstations were in the middle of the rooms, the changes would not necessarily be noted as the primary air mixes with the room air. Two persons occupied one room on average.

A daily questionnaire was sent to the office workers during the test period. The users were asked to insert their room number and note how satisfied they were with the indoor temperature. The used range was from -3 (“very dissatisfied”) to +3 (“very satisfied”) based on Ref. [36]. Comments on perceived indoor temperature and indoor air quality were also collected. Additionally, users could specify if they perceived indoor temperature variations during the day. If the occupants registered changes in the room air temperature, they could specify the time of the day in terms of *morning*, *noon*, *afternoon* or *evening*.

Careful consideration must be performed to the quality of the information provided to the users [12]. Therefore, the participants were informed that DR is not necessarily deployed every day and they did not know on which days it was deployed. Also, a post-experiment questionnaire was conducted which attempted to recognise the users’ understanding of thermal comfort both during and after the study period.

3. Results

This chapter presents the performance of the CS, indoor air temperature measures, heat power output and the questionnaire results on the local thermal perception.

3.1. CS Performance

Based on the predictive price signal received from the local energy company, the lower and upper price thresholds are calculated with a 12-hour moving average (Fig. 4).

Fig. 4. The control signal based on the DH price signal.

The price signal can change rapidly, giving a decent amount of DR actions. These might cause large thermal variation as the set-point temperature can change, even by 4 K. The DH operator might be inclined to load the buildings so that the heat is stored

in the building structure and then released. During the daytime in the selected week (i.e. five working days), 27% of the events were CS = -1, 22% were CS = +1 events and 51% were CS = 0 events.

3.2. The Heating Power of Radiators

Fig. 5 presents the radiator measures of a room in Category II (i.e. with a DR amplitude of ± 1 K). The valve reacts similarly to a PID controller in order to change night-time mode to daytime mode. When a considerable change in the set-point occurs, the integral term causes an overshooting error during the rise. It can be noted that the calculated power consumption lags a little bit behind the measured valve position and that the power consumption is not always as high in the morning as could be expected from the valve position. This might be due to the inertia of the radiator. After an event CS = -1, the specific power consumption increases slightly as the PID controller opens the valve.

Johansson et al. [13] argued that energy savings in relation to heat load reductions can be achieved if the control system is able to smoothly handle the transition from reduction to normal operation. Also, when comparing P controller types and on-off controller types in DR measures, the range of acceptable indoor temperature set points is wider in the P controller than that of the on-off controller type [37].

Fig. 5. The specific power consumption and valve position of a selected radiator.

The average heat output shown in Fig. 5 was around 10 W/m². During the event CS = +1, the load increased to 33 W/m² alongside the valve position change. In the event CS = -1, the heat output declined momentarily to 0 W/m² but shortly after increased to 3–9 W/m². In longer periods, the load might be almost at the same level as it would be without DR. Hence, DR works best if the CSs are short. After the event CS = -1, the set-point increased, causing a short incline in power output.

The radiator power output for the selected time period is pictured in Fig. 5. The week starts on Thursday, it is followed by the unoccupied office days on the weekend and ends on Wednesday. Four out of five weekdays had DR actions, and one

was kept free from actions for use as a reference. The Fig. presents the data of one radiator.

As seen in Fig. 6, the heating power output equalled zero during nights and the weekend. The largest peak occurs during mornings. Throughout the DR measures, the valve position reacted to the changing set-point temperature, thus changing radiator output linearly.

The error of the calculation in Equation 2 is not large when the circulating radiator water temperature difference $T_{in}-T_{out}$ is small but rises when the temperature difference increases as T_{out} approaches room temperatures (i.e. when the amount of circulating water is small) [38]. Hence, the calculation shows errors during the night-time as the valve is opened but the heat output is zero.

The change of power output and valve position during DR events is presented in Table 1. The heating power is calculated with Equation 2. The specific heating power is based on each room's floor area; the valve opening is the current value of each measurement event.

The values have been calculated based on each data point's DR event value. Notably, the intermediate rises when the event changes (e.g. from CS=-1 to CS=0) have been numbered. The operative temperature changes relatively fast with a radiator due to the thermal inertia [38]. Consequently, the amount of energy stored depends on the heating capacity for brief charges and on the comfort limits for extended charges [6].

The night drop is presented as a reference for the DR actions. The power output is considerably lower during the day, which is also seen in the total heat consumption of the building during nights.

Even so, the relative error increases with high temperature differences. The findings display that DR has no effect in the office building as the night-time drop is activated.

Table 1

The load shift in different categories.

Category	DR event	Radiator Power		Valve	
		[W]	[W/m ²]	Change	Opening Change
Cat. I ±2K	CS = +1	332	80	204%	24
	CS = 0	162	39	100%	15
	CS = -1	86	21	53%	0
Cat. II ±1K	CS = +1	280	67	127%	24
	CS = 0	221	53	100%	19
	CS = -1	161	39	73%	13
Cat. III ±0.5K	CS = +1	186	41	99%	19
	CS = 0	189	42	100%	17
	CS = -1	158	35	84%	16

Fig. 7 presents temperature measures during the selected

Fig. 6. Radiator performance during the selected week.

3.3. Indoor Air Temperature

The chosen algorithm targets sustaining comfortable room temperatures, including during DR actions. Keeping users satisfied is at the core of deploying DR on a wider scale.

week. During nights and weekends, the set-point temperature might vary, but it does not affect the indoor air temperature as the difference between the set-point and measured temperature is comparably large.

Fig. 7 shows one office room. In general, the measured indoor temperature is around 22°C when the normal target set-point is 23°C. As mentioned in Section 2.4, the initial indoor set-point was 22.5°C but the user increased the set-point temperature by 0.5°C. All in all, 83% of the rooms had different set-point temperatures as designed. The figure is slightly higher than anticipated, but the users were encouraged to adjust their

In Category III, almost no dip in indoor air temperature can be noticed while in Category I and Category II, the difference between maximum and minimum temperature (i.e. between the CS = +1 and the CS = -1 event) is 0.7°C in 110 minutes. This fits with the temperature change velocity requirements [31].

Table 2 summarises the temperature measures in the categories. The values represent measurements taken during working days. DR increases the deviation of indoor air

Fig. 7. The temperature curves for the selected week.

temperature to their optimal comfort temperature.

The measured temperature at radiator level is very close to the set-point temperature, and indoor air temperature follows with a 1.2–2.7K difference. During the day with no DR (“Wed.”, pictured in Fig. 7), the indoor air temperature rose during the day, probably due to external heat sources. In the

temperature readings. The smallest deviation between DR days and days of no DR is found in Category III, which is reasonable. As seen from the table, initially the rooms in Category III have large variations in indoor temperatures. Hence, they were categorised in the *poor flexibility* category. On the other hand, the deviation in Category I is smaller than in Category II. This

Fig. 8. The effect of DR on room air temperature.

measured rooms, the temperature increased by an average of 1.9K during the day if no DR actions were implemented. During DR days, the maximum and minimum temperature difference was 2.2K. During CS = -1 events, the indoor air temperature can possibly momentarily fall, as pictured in . It is apparent, that when the higher amplitudes are utilised, the more the indoor temperature rises or falls.

shows that rooms with high flexibility can be used for DR without varying the room temperature considerably. This shows that rooms with high flexibility can be used for DR without varying the room temperature considerably. Category I involves corridors with a large air mass. Nevertheless, these do not affect the results significantly.

Table 2

The temperature measures in the categories.

	Cat. I		Cat. II		Cat. III	
	DR	No DR	DR	No DR	DR	No DR
Maximum [°C]	22.4	22.3	22.2	22.2	23.1	21.7
Minimum [°C]	20.5	20.5	20.0	20.3	19.7	19.8
Average difference [°C]	1.3	0.7	1.6	1.1	1.9	1.4
Average [°C]	21.7	21.6	21.3	21.3	21.2	21.2
Deviation	0.4	0.2	0.5	0.3	0.6	0.4

The indoor air temperature can be observed to be slightly high, but this is seen as appropriate since the users could set the temperatures. In winter, the operative temperature is set for the standard EN15251:2006 for office buildings, having a minimum heating of 20°C [39]. The relative humidity is very low in Finnish office buildings, and it was measured in the studied site as 20.3% on average. The indoor air temperature duration curve of the selected week is plotted in Fig. 9.

Fig. 9. The indoor air temperature duration curve during the daytime.

Fig. 9 shows that the room air temperature falls within acceptable ranges. Some measurement points fall below 20°C in the figure, which is not necessarily the result of DR. In some cases, the algorithm might fail to retain sufficient indoor temperatures in the morning. In fact, all the rooms which have measurements below 20°C in Fig. 9 are either in Categories II or III (i.e. they have moderate or low flexibility). On the other hand, temperatures exceeding 23°C are found in rooms of all the categories. However, summarising temperatures only gives a hint of the thermal comfort in the room as each room was individually controlled.

Table 3 shows that the numbers for the mean responses lie quite far from thermal neutrality, and these averages were mainly derived from DR days.

Table 3

The thermal perception results during DR days and no DR days.

	Cat. I		Cat. II		Cat. III	
	DR	No DR	DR	No DR	DR	No DR
Average	0.4	1.4	0.2	0.7	-0.7	1.3
Minimum	-2	-2	-1	-2	-1	0
Maximum	3	3	3	3	0	3

It can be clearly perceived that DR has lowered the perceived thermal comfort of the occupants. As in Ref. [14], the occupants gave lower ratings for thermal comfort during DR days. The lowest average satisfaction rates were perceived in Category III during DR and the highest rates were in Category I when there was no DR. This poor performance was not unexpected as the users were situated next to the radiators and perceived the unequally distributed air mixture first hand. Therefore, local thermal discomfort should be one of the major concerns in decentralised DR. Looking at Table 2, the measured temperature change does not directly indicate the amount of dissatisfaction. This is in line with previous research that thermal perception consists of multiple factors (i.e. Fanger's model on thermal comfort [40]).

In the post questionnaire, no real difference between the study period and the week after the study period was found. Some claimed that the temperature changed often. Additionally, some claimed that the temperature was too high, others claimed it was too low. Although the results in Table 3 indicate a general dissatisfaction in the thermal environment, it did not come up in the post-experiment questionnaire. Therefore,

4. Discussion and Further Research

The study presents a test site designed to prove that heating DR with room-level accuracy can sustain acceptable indoor conditions and thus consumer comfort. The validation of the radiators' heat emission model would require the measurement of inlet and outlet water temperatures inside the pipes. However, the research shows that the steady-state heat emission model,

3.4. Questionnaire Results

During the research period, the users were asked whether they were satisfied with the indoor environment. The office workers were on average 46 years old and 78% were women. On average, 10 answers were given each day, equalling a response rate of 32%. The users did not know on which days DR was performed.

which is initially utilised for radiator dimensioning, can be utilised for calculating dynamic heat outputs in a test environment.

Martin's [18] simulations showed that charging the space (i.e. CS = +1) led to an annual DH energy cost increase so it might not be a financially viable case from the building owner's point of view. Similar results cannot be drawn from this research, but the influence of a short charging time needs to be considered. Dréau et al. [6] assumed that the increased energy consumption through DR is compensated for by the additional flexibility of the building.

The price signal from the local DH operator is not directly comparable to the actual marginal cost for each hour. It rather indicates whether DH is expensive or not. By having the price signal, the research is brought into a real-world context. Nevertheless, it emphasises that market initiatives are not yet defined and depend heavily on the local DH producer. Also, the development of optimal control strategies and DR applications depend on the business model of the local energy provider. The optimisation includes a strategy for mitigating the rebound, in other words, stacking new peaks onto another hour [13]. Changes to the value proposition were often made in order to incorporate user requirements and they were repeatedly changes with non-financial values, such as changes for safety, social cohesion and comfort [15].

As two persons occupied one room on average, a compromise in the target air temperature might be difficult to find. The users claimed that the temperature varied sometimes and opinions on it being both too hot and too cold were represented, with a tendency towards considering it too cold. There is evidence that the occupants changed their target temperature, and hence, each room could provide the desired indoor temperature. In Ref. [12], despite the inconveniences identified in previous responses, most respondents would participate for a financial reward.

As the test site has been profoundly modelled in Ref. [18], further research could be accomplished by comparing real-world measurement results with the simulation results. This would give new aspects to measurement errors and, on the other hand, improve simulation accuracy. New control strategies could be agilely tested and hence mitigate excessive set-point variations (see Section 3.1).

During the study period, night-time set-backs were deployed into the control strategy. Noussan et al. [41] argued that set-back settings cause problems on the energy system-level because of the high morning peaks that were seen here as well. Yet again, as the study concentrates on user benefits, energy savings during the night-time are an important monetary factor in smart devices' business models. One can argue as well that the morning peak of an individual building does not necessary occur at the system peak time, as discussed in Section 3.2. Additionally, increased morning peak loads are potentially reflected in the dynamic price for DH.

Although there is a large potential for DR, as identified in the literature, there are still several obstacles to overcome before a large-scale rollout can take place. Not least, studies on

quantifying the benefits at the system level have not revealed satisfying outcomes as the most expensive hours of the year cannot be reduced [6, 22]. Moreover, research needs to be conducted that will fully describe the interactions between the supply and demand side in order to deploy novel business models which benefit the distributor, aggregator, building owner and end-user. Building energy-demand flexibility can potentially play an important role in the utilisation of renewable energy sources. One must look at the right balance between the renewable energy cost and the energy efficiency measures' cost. However, energy efficiency improvements are constantly taking place, and thereby, the deployment of smart control systems is inevitable.

5. Conclusion

The paper introduced a novel method of conducting DR in DH-connected buildings with electronic thermostat valves. External data were processed on a cloud server which controlled the thermostats in a district-heated office building in Southern Finland. Real price signals of DH, as well as weather forecasts, were used to calculate room-level temperature set-points. Temperature readings and an individual questionnaire were deployed to measure the effect of the room-specific control on thermal comfort. Additionally, radiator-specific measurement was deployed to measure heat output.

The temperature was sustained at a good indoor environment status, which is defined by the national indoor climate classification. However, individual thermal comfort was measured to be lower during DR days than during days of no DR.

By changing set-point temperatures, the thermostat's valve follows (and thus increases or decreases) heating power at the thermostat (by 104% and 47% respectively). It shows that DR can be accurately deployed on a decentralised level. If thermal comfort is prioritised, the set-point temperature amplitudes can be lowered. The effect of DR is short as the heating power returns almost back to its initial level. Hence, DR works best if the CSs are short.

The research suggests dividing rooms into flexibility zones in order to fully utilise the DR potential of the building by individually adjusting the set-point temperature change amplitude during DR measures. Through this, indoor air temperatures can be adjusted based on the users' individual heat perception. Additionally, each room's ability to store and release heat can be utilised to its full potential. Although satisfaction rates slightly decreased in cases with DR, they can be generally be kept at a satisfactory level.

Although the study had multiple angles, three aspects when considering advanced building flexibility can be observed: (i) the low cost of external, room-specific predictive control, (ii) accurate temperature adjustment with individual set-point modulation amplitude and (iii) the difference in measured temperature variation and perceived thermal comfort. By applying these aspects properly, an investment in IoT devices can both enhance the indoor climate and add flexibility to the

local thermal network, which supports the shift to a 100% renewable energy system.

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