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Exploring the impacts of consumer reaction to dynamic heat prices in district heating☆

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ABSTRACT

Dynamic price is considered a key demand response (DR) strategy that could be essential in solving demand and supply mismatch issues in the energy sector. As a dominant heating solution in northern Europe, district heating has a huge potential to support large-scale demand response. While the end-user consumption fee is currently flat for most district heating systems, a dynamic heat price can reflect the heat network's production costs and carbon emission intensity, encouraging consumers to change their heat demand behavior. Still, the transition to dynamic price has not happened, mainly due to unknown impacts on consumers and operators. This study aims to reveal the impacts of dynamic heat prices on households with different reaction types and unveils potential savings compared to flat prices. We model a neighborhood consisting of consumers with no reaction, manual reaction, and automatic reaction to price. We then characterize the relationship between price and heat demand for different scenarios. It is shown that frequent thermostat adjustments are required to comply with prices, which can be overwhelming for consumers. Accordingly, occupants who only reduce their thermostat setting during expensive hours could reduce their heat costs by 34%. Automatic controllers can resolve this and can be designed to seamlessly react to price changes and save up to 46% of the heat costs. The study suggests that dynamic pricing can be leveraged to motivate consumers for load shifting, leading to decreased heating costs and decarbonization.

1. Introduction

Demand response (DR) is recognized as an effective strategy for decarbonizing energy systems by managing the time of use of energy to promote the integration of renewable energy sources [1,2]. In district heating, DR enables better management of heat demand by unlocking the flexibility of heat consumers, helping to reduce peak loads, and improving the overall efficiency of the heating network [3,4]. DR is mentioned to provide significant economic opportunities to facilitate decarbonization [5]. Occupants play a crucial role in achieving DR by adjusting their energy consumption behaviors. District heating operators and policymakers recognize the pivotal role of residents in achieving future flexible district heating systems, but their understanding of how residents can contribute is often limited [6]. Findings from a survey study on the heating behavior of consumers in 5 countries suggest that heating-related actions of consumers are not always rational and are affected by factors other than economic interest, logic, and rationality (i.e., demographical attributes and myopic preferences) [7]. For instance, non-rational behaviors, such as adjusting heating for luxury, highlight the complexity of occupant heat behavior [8]. According to the final report of Annex 53 by the International Energy Agency [9], the driving forces of occupant's energy-related behavior are:

1) internal: Biological, psychological, socio-economic, socio-demographic, and contextual factors.

2) external: Physical environment, building characteristics, government regulations, and time.

The report shows that psychological driving forces are more significant than other internal driving forces, and heating and cooling thermostat set points are highly correlated with age. There are some studies dedicated to analyzing these effects on building energy consumption across different countries [10,11]. They report that while some social factors, such as the positive relationship between household income and electricity consumption, are consistent across many countries, the other social factors, including family composition, age of the household

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Nomenclature

u	*Consumer heat price*(DKK)
T	*End time*(*hour*)
D	*Expected demand* (kW)
B	*Baseline demand* (kW)
Y	*Measured demand* (kW)
C_{prod}	*Heat production cost*(DKK)
P_{target}	*Target demand* (kW)
k	*Price ratio*
t	*Time* (*hour*)
μ	*Average value*
γ	*Heat production price* (DKK/KWh)
θ	*Flexibility function parameters*

Abbreviations

DR	Demand Response
RBC	Rule-base Control
FF	Flexibility Function
KPI	Key Performance Indicator
DKK	Danish Krone

responsible, and education level, vary significantly by country. These studies suggest that energy consumption habits are deeply embedded in social, economic, and cultural conditions, requiring context-specific analysis. For example, a study in Denmark realized that a higher education level is correlated with decreased electricity consumption, but conversely, another study in China found the opposite [12]. A global study on building energy consumption and future trends revealed significantly different energy consumption patterns, growth trends, and future projections between developed and developing countries [13]. They stated policy maturity as one of the main reasons for this significant difference. According to [14], the building energy consumption patterns of South and Southeast Asia are likely to be very different from North America and Europe. One main factor is air conditioning technology, which is decentralized in hot and humid countries but centralized in northern Europe. Other factors are Economic development and household income, cultural norms, urbanization, and building characteristics.

Many studies identified energy price as one of the most dominant factors in determining the energy consumption of buildings [15,16]. A field study on 72 single-family houses connected to district heating in southern Denmark [17], focusing on DR using night setbacks in two consecutive heating periods (i.e. January 2014 – April 2014 and November 2014 – April 2015), revealed that although participants reacted quite differently to price changes, they all continued to use night setbacks during the second heating season deliberately. Accordingly, buildings could reduce their heating demand by 4–10 %. A survey study in Quebec, Canada [18], on the participation of people in DR programs, revealed that 84 % of the people agreed on the role of smart thermostats in facilitating participation in DR programs. One finding was that low-income families expressed high interest in participating in DR programs but faced barriers such as limited smart technology. Eventually, they reported age, education, and frequency of working from home as the most significant variables in DR during peak winter periods. Stelmatch et al. [19] conducted a study surveying 337 households in a Northern California city, investigating social aspects and household willingness for DR and peak load shifting. The study reported that households frequently adopt rules (e.g., keeping doors and windows closed) based on prices. They mention that homes with smarter technology, more household members, and smaller floor areas usually have more willingness for DR. Li et al. [20] examined the readiness of building users for energy-flexible buildings in the Netherlands based on a survey of 785 respondents. According to their findings, financial incentives are the most compelling motivator for respondents, and 11 % of respondents showed a positive willingness to change their energy use behavior. The authors concluded that widespread adoption hinges on raising awareness, providing incentives, and offering user-friendly control options that align with individual needs and preferences. According to another field-level study on household heating preferences and thermostat control, people reacted quite differently when allowed to control their thermostats [21]. Some never changed their thermostats during winter, while others had up to seven different setpoint settings, highlighting the diversity in DR participation.

District heating is widely recognized as a reliable and cost-effective heating solution and serves as the primary heating method in many Northern European countries [22]. Its popularity is attributed to its ability to integrate diverse energy sources, including waste heat from industries and data centers, waste incineration, and renewable energy [23]. Furthermore, district heating systems can be operated with varying configurations, such as different supply temperatures, to adapt to diverse geographical and climatic conditions [24]. District heating can benefit DR for improved efficiency, reduced costs, lower carbon emissions, etc. According to a survey on DR in district heating, experimental studies reported a 35 % peak shaving [25], a reduction of primary energy by up to 4 % [26], and cost and emission reduction of up to 10 % [27]. DR in district heating can be triggered by implementing dynamic pricing, offering time-based incentives, or sending control signals to consumers. DR can therefore be achieved by consumers responding to these price signals through changing thermostat settings manually or by advanced controllers. For example, Mokhtari et al. [28] designed a deep reinforcement learning controller that reacts to dynamic heat price information and conducted a field test in a living lab. They reported a 79 % heat cost reduction compared to the default rule-based controller, only by intelligently shifting heat demand to cheap hours. Another way to activate DR in district heating is the control of forward water temperature to the building space heating based on the price signals, which is not within the focus of this paper. Dynamic price plays a crucial role in DR since it can better reflect true production costs while addressing demand fluctuations. If designed correctly, a dynamic price signal can incentivize heat consumers to change their energy use behavior, helping to balance demand in the network [29,30]. Behavioral studies indicate that while economic theory predicts rational responses to price signals, real-world behavior often deviates due to biases like loss aversion and reference pricing. According to neoclassical economic theory, consumers make logical decisions to simply maximize their utility, reducing consumption as prices rise and adhering to the law of demand [31,32]. However, real-world behavior often deviates from this ideal assumption, particularly in situations like district heating, where different perceptions of thermal comfort exist among heat consumers and understanding of dynamic pricing schemes might be limited. Several behavioral economics concepts can shed light on these deviations. In behavioral economics, prospect theory explains that human decision-making is often irrational and influenced by psychological biases [33]. For example, prospect theory explains that consumers are usually more sensitive to losses (price increases) than gains (price decreases), implying that heat customers might react more intensely to price hikes during peak demand than price drops. Additionally, consumers often rely on their own reference prices, forming expectations about fair prices based on past experiences and perceived norms [34].

Consumers often react to price changes in ways that economists consider irrational, meaning that factors other than price play roles in that response [34]. For example, Brewer [35] analyzed occupants' heating behavior under dynamic prices in the US and concluded that more than half of all individuals are completely ignorant of price changes. While Hansen [36] analyzed the impact of district heating prices on the heating consumption of Danish households in single-family detached houses, found that occupants had significant DR participation with district heating prices. Accordingly, when supplied with expensive heating, households compensated with lower setpoint by wearing warmer clothes, heating only some parts of the house, and lowering comfort expectations. A study using data collected from Norwegian building stock during the 2021/22 energy crisis analyzed residential demand response during extreme electricity prices [37]. They realized that an energy saving of 11.4 % and a peak reduction of 10.4 % were achieved during this period and concluded that dynamic prices could potentially activate demand response in residential households. Although DR is widely recognized as an effective strategy for decarbonization, real-world DR programs often show lower consumer participation than predicted due to factors like limited awareness, inadequate incentives, and behavioral biases affecting willingness to engage [38,39]. It is realized that residents would not be willing to comply with DR strategies unless the benefits are clear and worthy [40]. Therefore, barriers to the widespread application of DR in district heating are not technology-related but rather due to social, economic, and regulatory aspects [41]. Additionally, it is also argued that new tariffs and business models are required for district heating and cooling operators to incentivize consumers for DR purposes. [42] mentions that as the price profile determines the demand profile and vice versa, the operator must consider consumer behavior when computing the price values.

Even though dynamic pricing has been recognized as an effective approach for both suppliers and consumers for a long time, it has not yet been implemented for district heating. This is mainly due to its unknown impact on consumers and district heating companies. There is a clear research gap in understanding different consumer types and the effectiveness of dynamic pricing for DR in district heating, and to understand to what extent different reactions impact consumer's energy costs. This paper aims to fill this gap by conducting a comparative and scenario-based analysis. We use a virtual testbed of a neighborhood consisting of nine building blocks and use a novel method to design a dynamic price for activating DR. The purpose is to test dynamic pricing in district heating and reveal the impacts of dynamic pricing on different consumers. We do this by designing nine controllers, including fixed controllers, manual controllers, and automatic controllers. The controllers aim to represent different consumers. We then test the dynamic price on these consumers and assess the economic impacts. We then conduct a

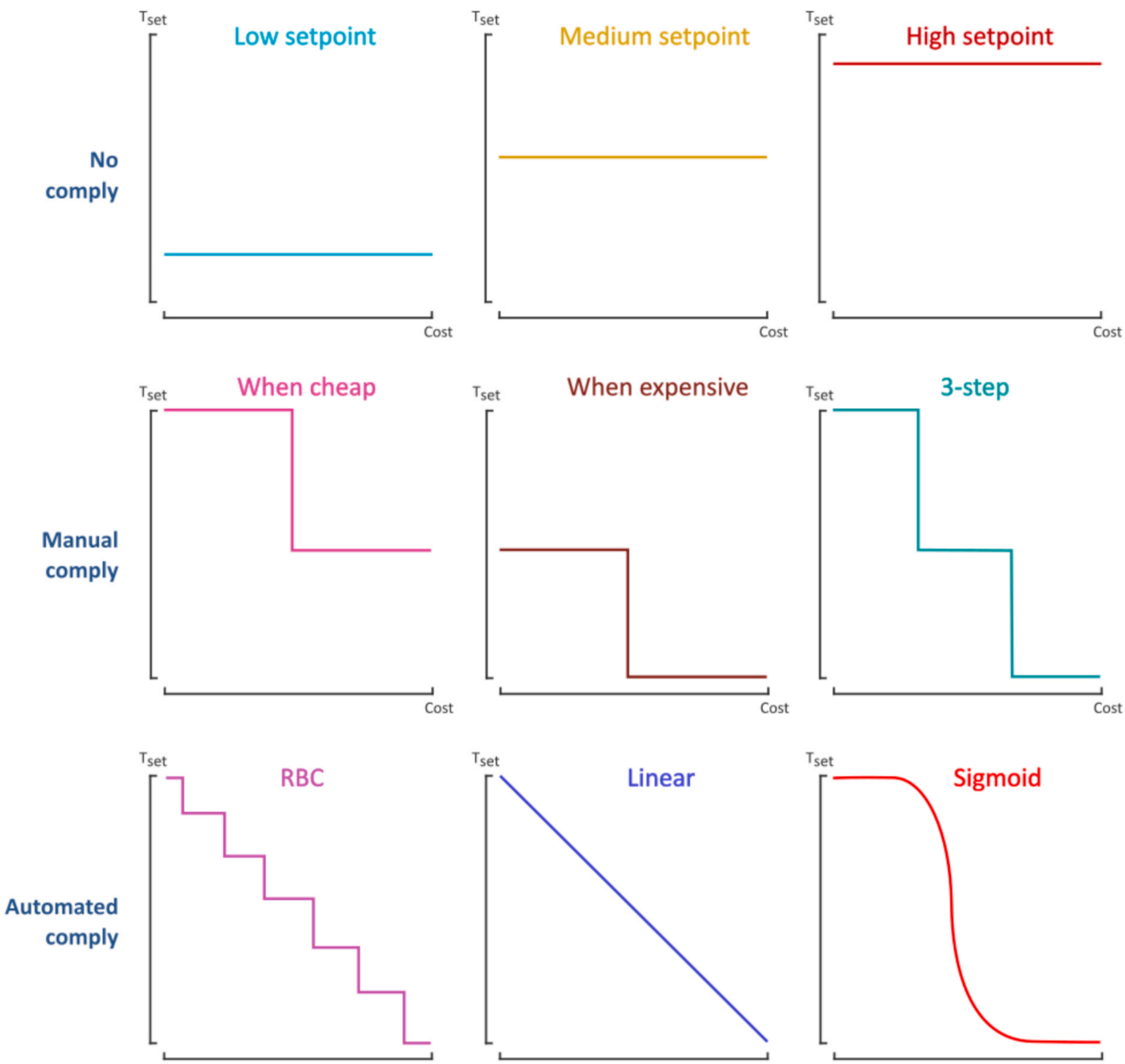

Fig. 1. Reference consumer reactions to dynamic price (by thermostat setpoints), categorized into 3 main groups: Manual-comply, Automated-comply, and No-comply.

scenario-based analysis to understand the overall impacts of different DR participation rates and potential risks and benefits. In fact, the solutions can help decarbonize the electricity sector as well, since DH can provide flexibility on the scales needed to integrate renewables [43].

The paper is organized into seven sections. In Section 1, an introduction to the topic is given, and essential terms are described. Section 2 is devoted to describing the considered consumer reaction categories. Section 3 is mainly about designing the study frameworks which includes the virtual testbed, dynamic price specifications, and scenarios considered. Section 4 is for the findings of the study, including the reaction of the consumers and scenario-based analysis. Key points are discussed in Section 5, mentioning essential elements, limitations, and future studies. Eventually, Section 6 concludes the paper, with the main findings, limitations and recommendations for future research.

2. Consumer reaction to price

In theory, consumers can respond to price changes in various ways. Their reactions largely depend on the building application, social influences, household economic status, available control systems, and personal preferences [18,44]. While capturing every possible reaction type of each heat consumer is impossible, we can identify key categories based on representative responses, which can be seen in Fig. 1. The categories are designed to span the space of a significant amount of possible real-life reactions.

The No-Comply category includes consumers who do not adjust their thermostat settings in response to price changes, keeping them fixed. This group is divided into three subcategories—Low Setpoint, Medium Setpoint, and High Setpoint, each representing a consumer profile who keep their temperature setpoint fixed at 20 °C or 22 °C or 24 °C. Many buildings fall in this group due to lack of motivation, lack of information or lack of equipment. This segment is critical for district heating companies shifting to using dynamic pricing.

The Manual-Comply category consists of consumers who respond to price changes by manually adjusting their thermostat settings. While this method allows for immediate response, it is subject to high variability and uncertainty, as it relies on user behavior. Understanding the range of manual reactions and the influence of social, economic, and psychological factors require in-depth research beyond the scope of this paper. A study on price-responsiveness of 3746 Norwegian households in the presence of dynamic electricity prices revealed the potential of users who manually complied with dynamic prices in peak reduction and suggested that manual compliance can be relied upon in power system planning and operation [45]. According to [34], consumers typically hold a pre-established notion of a reference price (often based on previous experience), and deviations significantly higher from this reference price influence their consumption patterns. Based on this principle, we designed the Manual-comply consumers and considered consumer reaction only in cheap and expensive hours. The first reaction, “When-cheap,” is for consumers who comply with the dynamic price when heat prices are lower than usual. Some consumers would use low-price periods for extra heating of rooms or heating of some specific areas such as pools, but increased prices might not affect their reference heating behavior. The other consumer, “When-expensive,” is for consumers who only change their consumption patterns when the heat prices are high. This group responds to high prices and decreases consumption to prevent overconsumption. But in low-cost periods, they do not change their consumption levels. According to findings of a field test study in Norway [45], this reaction type includes the majority of consumers who react to prices. Another consumer is the “3-step” which combines previous reactions and contains consumers who change their heat behaviors under both conditions: when heat prices are cheap or expensive. The last group is called Automated-comply and is representing consumers equipped with price-responsive controllers. By automating the control process, uncertain reactions would be reduced. Many types of controllers can be designed for this purpose with different characteristics and preferences. In this study, three main consumers are considered. A rule-based controller (RBC) assigns an indoor temperature setting based on the current heat price. The steps for indoor setpoints can vary between 2 to an infinite number based on user preferences. Here, five control levels are considered. The next consumer is for controllers that linearly change thermostat settings based on heat price, providing continuous compliance with price changes. The last type is a sigmoid-type controller represents nonlinear compliance with heat prices. This controller shows the fastest changes in thermostat settings in mid-price periods and slower changes in low and high-extreme price periods.

3. Methodology

The method for designing and conducting the simulations are described here. Accordingly, the virtual testbed specifications, the dynamic price specifications, scenarios and assumptions are described in this section. However, for more detailed description about the methods, please refer to [46].

3.1. Virtual testbed

Since the real implementation of the analysis was impossible due to the need for different controller implementation and the current fixed heat price market, a virtual testbed was used here. Modelica (in Dymola interface) is used to model the building and neighborhood for the virtual testbed, a suitable option for creating dynamic district heating models. Different controllers and consumer reaction types are implemented in Simulink, which receive heat price and set the indoor setpoint. To connect the two models, Functional Mock-Up interface is used. Hereby, the reaction to different prices would be calculated as the measured demand. The integration process is illustrated in Fig. 2.

3.2. Designing the price signal

To design a price signal that effectively triggers DR in buildings, a dynamic model is needed to predict building reactions to different prices at different times. For this purpose, the stochastic nonlinear flexibility function, developed by Junker et al. [43] is used. The predicted demand profile of the building, called expected demand (D), in response to a dynamic heat price is calculated by:

$$D = FF(u, B, \theta) \tag{1}$$

In this equation, FF is the flexibility function, u is the heating price, is the baseline demand and θ is the parameters of the flexibility function. D, B and u are time series data for a period, e.g., 24-hour-long profiles. The parameters of the FF (θ) are estimated using a set of historical data containing measured time series demand and prices. Measured demand is different from the expected demand (D) since the expected demand (D) corresponds to the demand estimated by the FF as a result of the given dynamic heat price. In contrast, measured demand (Y) is the actual demand of the neighborhood after sending the dynamic heat price to the virtual testbed and measuring the exact reaction of the buildings. Baseline demand (B) is determined using the Modelica model with a fixed pricing structure. A baseline scenario is defined to compare the impacts of dynamic heat price on each building, as having a flat price of 591.88 DKK/MWh, the average heat price of a local district heating company in Denmark [43]. For further reading about FF, readers can refer to [43]. The process for designing dynamic price is shown in Fig. 3.

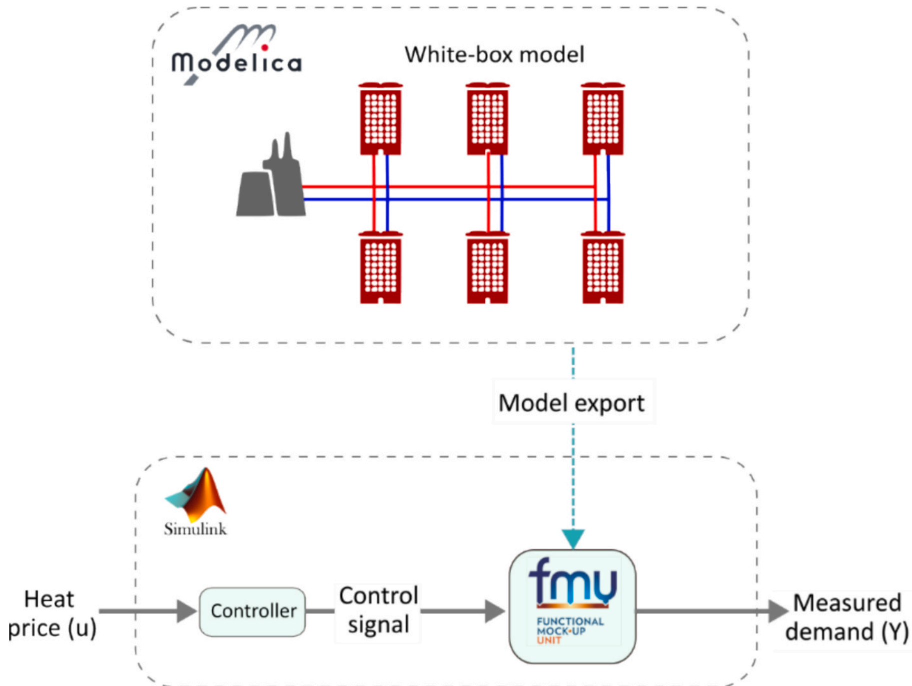

Fig. 2. Workflow for integration of controller and district heating model.

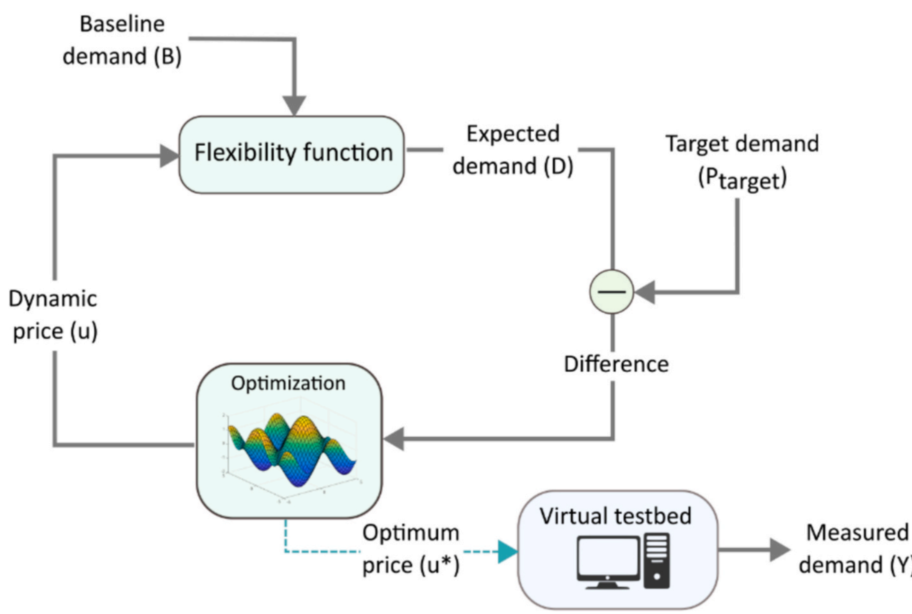

Fig. 3. Workflow for designing dynamic price.

The trained FF is coupled with an optimization algorithm to obtain the optimum price signal for reshaping the heat demand profile to a desired profile. The procedure is suggested and described in more detail in [43,47]. The desired profile is called target demand (P_{target}), usually given by the district's heating operator for economic or environmental optimization. A more detailed explanation of the process is described in [46]. When designing a dynamic heat price based on the target demand (P_{target}) and the district's flexibility, the resulting profile might have a higher or lower shift than the baseline flat profile. The resulting dynamic price is shifted to an equal average price to the baseline to prevent complaints and make a fair comparison with the baseline. When the optimum price is achieved by the algorithm, it is then sent to the simulation model and the measured demand is calculated. In an ideal case, target demand, expected demand, and measured demand should be the same, but in reality, there are differences. The difference between the target demand and the expected demand comes from the inverse optimization non-convergence, leading to suboptimal price profiles. The difference between the expected demand and the measured demand, however, comes from the stochastic behavior of the consumers. Considering a highly accurate model for baseline demand prediction, the difference between the measured demand and baseline demand are solely the result of dynamic price. In another word, expected demand, measured demand and baseline demand are correlated variables. The flexibility function model was validated using data from the virtual testbed. The data included timeseries of baseline demand, price and measured demand. Then, the expected demand was compared with the measured demand from the testbed in response to a random price. The model could match the measured demand 6.6 % Mean Absolute Percentage Error (MAPE). Further details can be found in [46].

3.3. Price ratio

When demand response (DR) is focused on peak shaving, systems with lower energy flexibility need more dramatic price adjustments to incentivize consumer reactions. However, extremely high prices during peak hours may be unfair to consumers and lead to complaints, while very low prices could expose district heating operators to increased economic risk. Therefore, even after determining an optimal dynamic heat price, it may be necessary to adjust prices by rescaling them—-specifically by modifying the standard deviation while keeping the mean value constant. This adjustment is applied using the following equation:

$$u_{new} = \mu(u) + k(u - \mu(u)) \tag{2}$$

where u_{new} and u are the new and old prices, μ is the average value function, and k is a scaling parameter. Low values of k result in more flat profiles, and higher k values provide sharper peaks and valleys. A price-ratio (k) value of 1.0 returns the original optimum price. A k value of 0.0 results in a flat price, representing the baseline demand profile.

3.4. Scenarios of DR

Knowing how consumers react to different prices is essential to understanding the potential impacts of dynamic heat pricing on a larger scale. While some consumer response categories were defined in Fig. 1, neighborhoods and cities contain a blend of these behaviors, making overall responses difficult to predict. Without historical data on price reactions, it's challenging to characterize these behaviors accurately. In addition, no relevant information regarding this could be found in the literature. Therefore, we considered various scenarios featuring different combinations of consumers and conducted analyses on each scenario to gain insight into potential outcomes. Since this study aims to analyze the impacts of the response level of consumers to price, these scenarios are designed to cover various responsiveness levels to dynamic prices and represent different situations. The scenarios are described in Table 1.

Scenario 1 represents an ideal case in which all buildings are equipped with automatic controllers that adjust to price changes seamlessly. In contrast, Scenario 5 represents the opposite extreme, where no buildings respond to price changes. The remaining scenarios illustrate varying mixes of controllers, capturing a range of possible consumer responses to dynamic pricing.

3.5. Case study

The case study is a residential multi-family building with 45 flats in Sønderborg, Denmark. The building was constructed in 1971 and is heated by radiators. To have a controlled study on consumers' reactions to price changes, 9 identical buildings are considered. A detailed description of the building and network models can be found in [46]. The "MixedAir" component from Modelica Buildings Library is used to create the building thermal models. Further information about the building can be found in Appendix. A photo of the building and an illustration of the neighborhood model are shown in Fig. 4.

Simulink Matlab is used to model the nine reference consumers described in Fig. 1 and is coupled with the neighborhood model using Functional Mock-up Interface [48]. For validation of the neighborhood model, we used daily historical measured data from substations for 30 days in January. The MAPE of 4.8 %–8.9 % was achieved for the substations. Details about the validations can be found in [46].

3.6. Dynamic price evaluation

A baseline case is defined for each controller to assess the effectiveness of dynamic heat price for each building and the total neighborhood, where the heat cost and average indoor temperature are calculated at a flat price. The baseline is different for each controller since controllers react differently to a given fixed cost. Then, the dynamic price impacts are compared with the baselines. The simulations for analyzing dynamic heat price's effect are conducted on 1st February 2022. The target demand is considered as having lower morning (6–9) and evening (16–20) peak demands but higher consumption around noon (11–14). Dynamic heat price is then designed accordingly, and the impacts on the buildings and the neighborhood are analyzed. For the economic analysis of each consumer, a one-week simulation is conducted in February 2022.

3.7. Production costs

From the district heating operator's point of view, an economically effective DR would eventually lead to lower production costs. This can be achieved by setting the target demand based on production costs. Production costs can vary based on the availability of heat sources, carbon emission taxes, the need for peak boilers, fuel prices, etc. Therefore, a production price (γ) can be defined to be the basis for finding target demand. This way, the production cost at the time t can be defined as:

$$C_{prod,t} = \gamma_t Y_t \tag{3}$$

A certain production price profile is considered to find the target demand. Accordingly, the target demand is assumed to have an inverse production cost profile. Then, the optimum heat price is calculated. This

Table 1
Considered scenarios of DR for reaction to prices in a neighborhood.

Scenario	Description	Corresponding to
1	All consumers using automated controllers	100 % Automated
2	The majority of consumers react to the prices automatically or manually	50 % Automated 33 % Manual 17 % No-comply
3	There is an even mixture of all types of controllers	33.33 % Automated 33.33 % Manual 33.33 % No-comply
4	Half of the consumers have a No-comply strategy	17 % Automated 33 % Manual 50 % No-comply
5	No user complies with the dynamic price	100 % No-comply

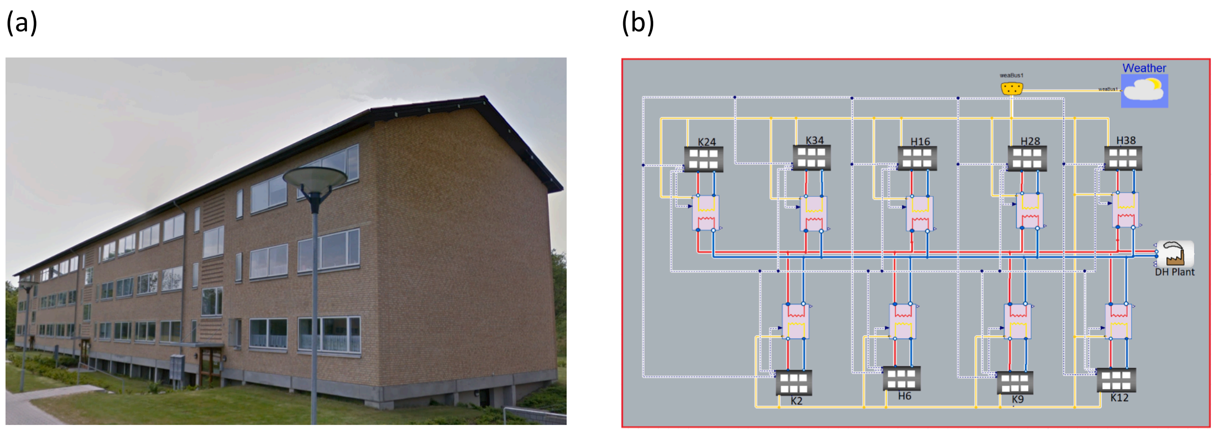

Fig. 4. Photo taken outside one of the buildings, (b) white-box model of the neighborhood created using Dymola.

setup could also be used to study more realistic variations in production prices e.g., a very low price in periods with high availability of industrial waste heat.

3.8. Assumptions

This study requires many assumptions and sets boundaries. The setpoint curves are considered solely based on cost, and we ignore the building characteristics, stochastic behavior of occupants, heating system efficiency, etc. It is also considered that the heating systems are sized perfectly to reach the setpoints, and there is no window opening or other unusual behavior to disrupt the heating. As [41] showed in his study on measured data, the reaction of occupants to dynamic prices is extremely stochastic. However, we considered the occupants to always have a fixed behavior and always have access to react to prices. The flexibility function that is used to characterize the flexibility of consumers considers the behavior to be the same throughout time. It does not take into account the external factors, behavioral aspects or dynamic behaviors. The virtual testbed does not include influencing factors such as window opening, shading and stochastic behaviors. Although these assumptions deviate from the real-world conditions, they enable a focused study on the behavior of consumers and controllers to dynamic price.

4. Results

This section is dedicated to present the findings of the analyses. We start by presenting the reaction of the whole neighborhood and individual buildings to dynamic price, proceed with testing price ratio, and then we focus on economic impacts on each consumer, and the total district.

4.1. Reaction of controllers to dynamic price

This section analyzes the impacts of a given dynamic price on the neighborhood and each building's demand profile. An artificial target demand is considered with the purpose of reducing consumption during mornings and evenings. The dynamic price is designed accordingly, and the measured demand of the neighborhood is calculated. Results can be seen in Fig. 5.

It can be seen at the bottom of the figure. The measured demand is following the target demand in most hours, but is accompanied by some deviations. An upward shift of the measured demand (Y) compared to target demand (P_{target}) can be seen between hours 0–4 and 20–24, which

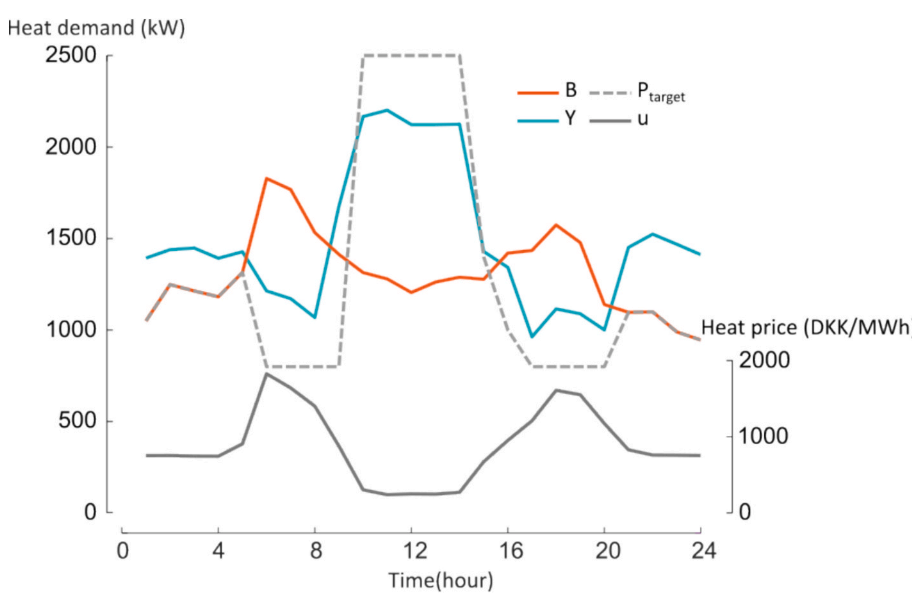

Fig. 5. Obtained measured demand (Y), baseline demand (B), and target demand (Ptarget) followed by the optimum heat price (u) at the bottom.

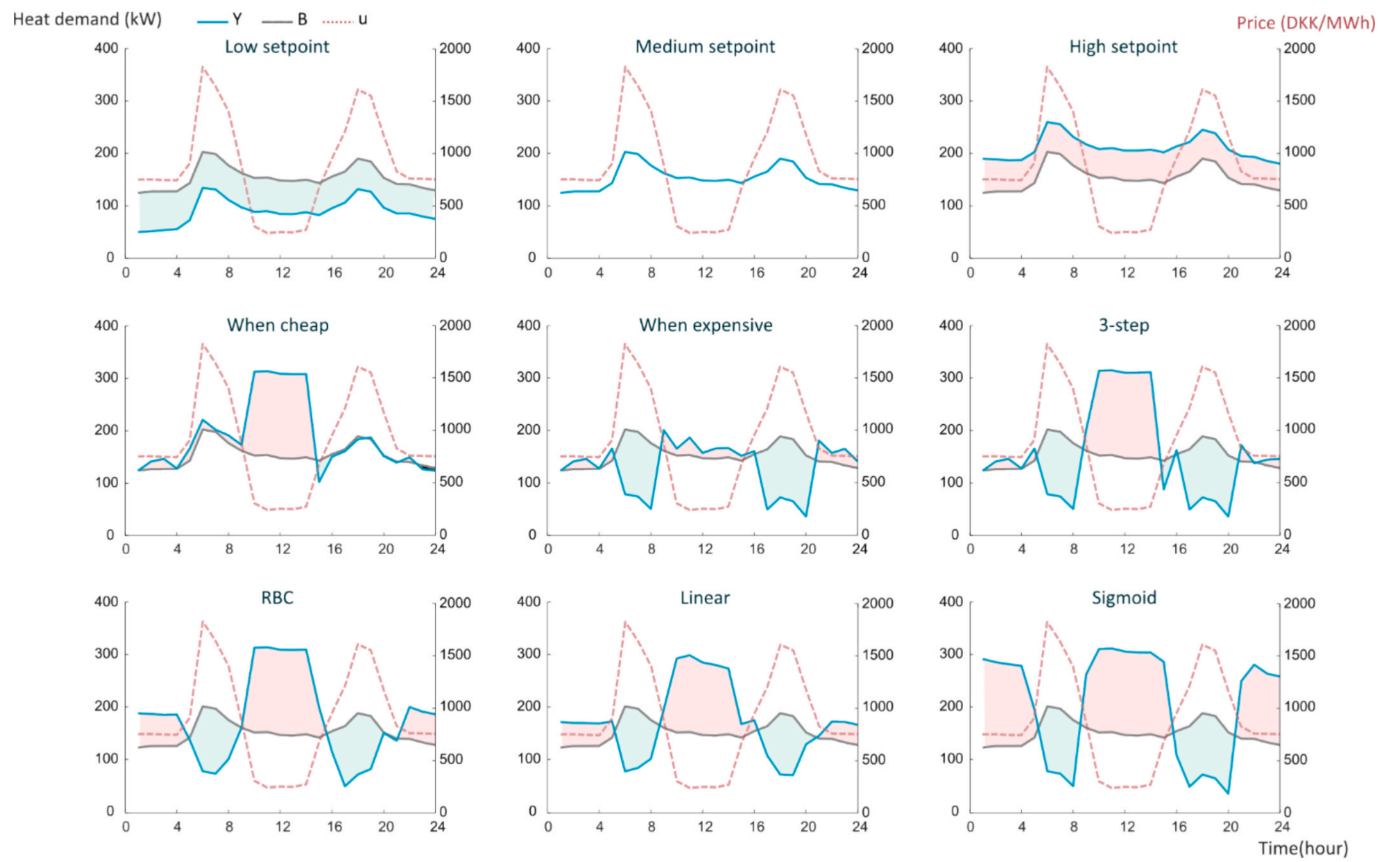

Fig. 6. Reaction of each reference consumer to dynamic price. The area in cyan represents times when consumption is lower than baseline, and red represents times when consumption is higher than baseline. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is probably due to the sudden behavior of the Sigmoid controller in this period, according to Fig. 1. At 6, when the baseline peaks at 1800 kW, the target demand is 55 % lower than the baseline, and a relatively expensive heat price of 1930 DKK/MWh is suggested. This has reduced the demand by 33 %, which is not enough to reach the target demand. Between 10 and 14, the target demand is 52 % higher than the baseline demand, so the price gets as low as 235 DKK/MWh. This price could shift the baseline demand upwards by 44 %, which is only 8 % lower than target demand. This suggests that buildings of this neighborhood are responding better to price peaks than price valleys. The individual reaction of each of the nine reference consumers to the dynamic price is shown in Fig. 6.

The first row depicts buildings with the reaction category of "No-comply", described in Fig. 1. Building demand follows the baseline profiles in all three buildings of this category and only differs in the offset, where the Low setpoint has the lowest demand, and the High setpoint has the highest demand. The three buildings represent the inflexible part of the neighborhood and limit the activated DR. Second row is for buildings with "Manual-comply". The building with When-cheap consumers is responding to prices during cheap hours (between 10 and 14) when the prices are lower than 400 DKK/MWh. When-expensive controller responds during peak hours when prices are

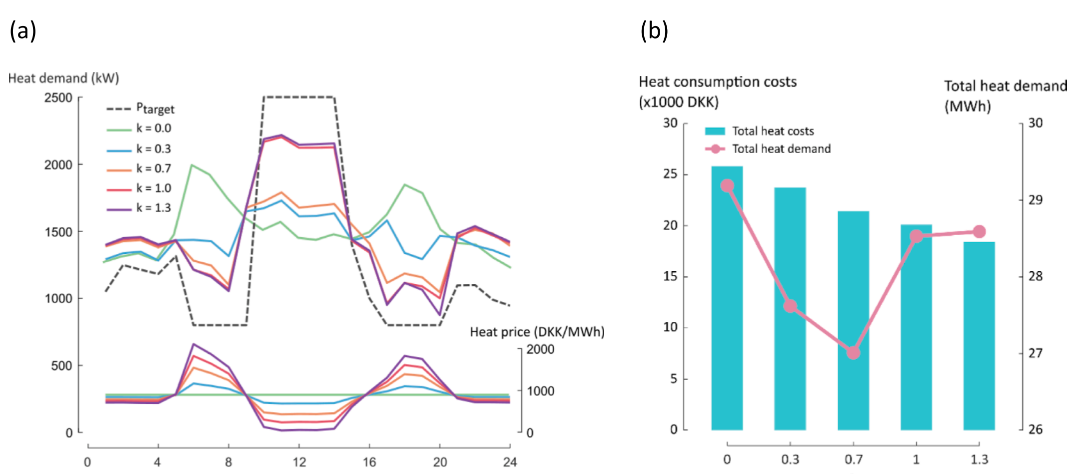

Fig. 7. (a) Neighborhood measured demand (Y) profiles and (b) heat consumption costs and heat demand of the neighborhood given different price ratio values.

higher than 1000 DKK/MWh, and normal operation in other periods. The 3-step controller type combines previous controllers and activates in cheap and expensive periods by maximizing and minimizing the thermostat settings. The bottom row is for buildings that are controlled using smart price-responsive controllers. For the RBC controller, the thermostat setting changes step by step as the price increases or decreases. Linear controller has a similar heat consumption to RBC controller. However, the Sigmoid controller represents sudden changes in heat consumption in mid-price periods, which can be recognized from the figure. The indoor temperatures for each controller are illustrated in Appendix. Due to this controller behavior, heat consumption in the start and ending hours are quite different than the baseline, which might be the reason for the upward shift in measured demand compared to target demand at the start and end of Fig. 6.

4.2. Impacts of price ratio on DR

The impacts of the price ratio on the total demand of the neighborhood are depicted in Fig. 7.

As described in Section 3.3, $k = 0.0$ results in a flat profile and is the baseline demand. It can be seen that even with small changes in heat prices ($k = 0.3$), heat demand is reduced notably compared to the baseline due to the aggregated effect in large-scale DR. By increasing the number of buildings that react to price changes, the flexibility of the neighborhood will grow and even small changes could achieve a high DR. Accordingly, total heat demand and heat consumption costs were reduced by 5.4 % and 8.8 % respectively, by shifting from a flat price ($k = 0$) to a slightly dynamic price ($k = 0.3$). The demand profiles of $k = 1.3$ and $k = 1.0$ are quite similar because, in extreme periods, only the Automated-comply controllers are still reacting to price changes. Manual-comply controllers could not further comply with prices when prices pass a certain threshold. This is in line with findings of a field test study on price-responsiveness of residential buildings in Norway in response to dynamic prices [49]. This shows that maximum flexibility potential is leveraged and further increase of the scaling factor would not change the demand profiles much. The heat demand costs were reduced by 28.7 % for $k = 1.3$, which has the highest peaks and valleys (Fig. 8).

Fig. 7.b shows that heat consumption costs reduce seamlessly as the price ratio increases. However, heat demand decreases until $k = 0.7$ and then increases. The sudden jump in the total heat consumption from$k = 0.7$ to $k = 1$ is mainly due to the response of manual controllers that have been activated after prices reached low enough values. Accordingly, heat demand has increased during cheap hours, but the costs are still reduced. When k is increased from 1 to 1.2, heat demand is only increased by 2 %, but the heat cost is reduced by 10 %.

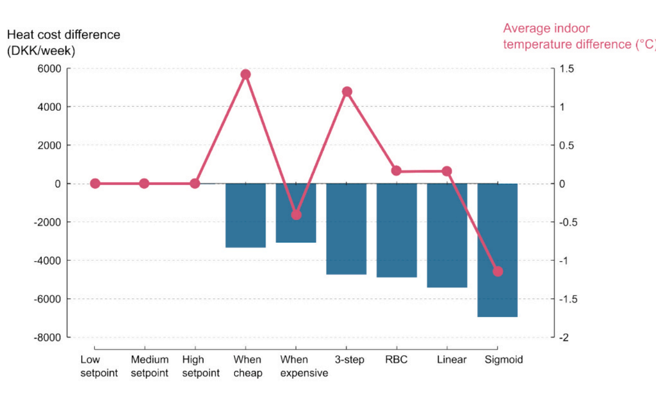

Fig. 8. Differences in heat costs (bars) and average indoor temperature (line) compared with baseline for each reference consumer. Baseline is defined as having a flat heat price during the same period.

4.3. Dynamic heat price evaluation

The results of assessing the impacts of dynamic heat price on each controller are shown in 8.

The heat cost of consumers with No-comply consumers is similar to that of a flat price because the mean value of the dynamic heat price is fixed to the flat price. This shows that dynamic heat prices would have a minor economic impact on inflexible consumers. All remaining reactions led to savings regardless of the reaction type. According to the figures, When-cheap consumers saved slightly more (2.2 % more) in costs than when-expensive consumers. This is because consumers who only increase their thermostat during cheap hours store heat in building elements. During the following expensive hours, the heating system can be turned off. The indoor temperature graph shows that this building also has a higher average indoor temperature than the When-expensive consumer due to frequent increases in indoor setpoint. The 3-step controller has an even higher saving potential with a relatively higher indoor temperature than the baseline. The automated controllers provide higher savings potential, while Sigmoid delivers the highest potential but at the expense of lower indoor temperature. Linear controllers and RBC have slightly higher indoor temperatures than baseline while providing significant savings. The Sigmoid controller reduced the heat costs by 46.5 % but at the expense of 1.2 °C lower average indoor temperature. At the same time, the linear controller reduced heat costs by 46.0 % while the average indoor temperature was 0.16 °C higher than the baseline. Eventually, the controllers of Manual-comply indicate that a 3-step control can reduce the costs by 41.0 % while keeping the indoor average temperature 1.2 °C higher than the baseline. This means that with almost no capital costs or instruments, users can significantly benefit from dynamic heat prices. These findings show that the controllers could achieve cost saving by shifting loads from expensive to cheap hours. In some cases, the indoor temperature is increased by 4 °C, but still, cost saving is achieved, showing the effective potential of load shifting for cost saving.

4.4. Scenario-based analysis

This section is dedicated to results obtained from analyzing the five scenarios introduced in Section 3.4. Fig. 9 illustrates the impact of each scenario given the dynamic heat price on consumer reaction and heat costs.

Target demand is shown by the dashed line, and the corresponding optimum heat price is depicted by the gray line in the background. The total demand of the neighborhood in each scenario is plotted. All Scenarios showcase notable peak load potential during morning and evening peaks. Peak loads have reduced by 65 %, 55 %, 44 %, and 34 % by Scenarios 1–4, respectively. Relevant experimental studies show up to 30 % peak reduction due to small scale experiment, using fixed heat price or tight comfort bounds [25,50].

Accordingly, Scenario 1 has the closest match with the target demand while Scenario 5 (i.e. corresponding to the baseline demand) has the lowest compliance. The figure shows that despite all consumers complying automatically with prices (Scenario 1), the target demand still could not be reached. This indicates the flexibility limit of the neighborhood, which in this case is driven by the indoor setpoints. In the right figure, the total heat consumption cost of each scenario for the district is illustrated. Accordingly, Scenario 5 has the highest heat consumption cost, which is the baseline scenario. Scenario 4 has 15 % less consumption cost than Scenario 5, due to a small number of consumers complying with prices. Scenarios 3 and 2 have respectively reduced consumption costs by 17 % and 19 % compared to Scenario 5, due to lower consumption during peak hours and higher consumption in cheap hours. However, Scenario 1 shows higher consumption costs. This is due to higher consumption during cheap hours than in other scenarios, leading to higher total consumption costs. This highly depends on the controller type; in this case, the automatic controllers have a major role

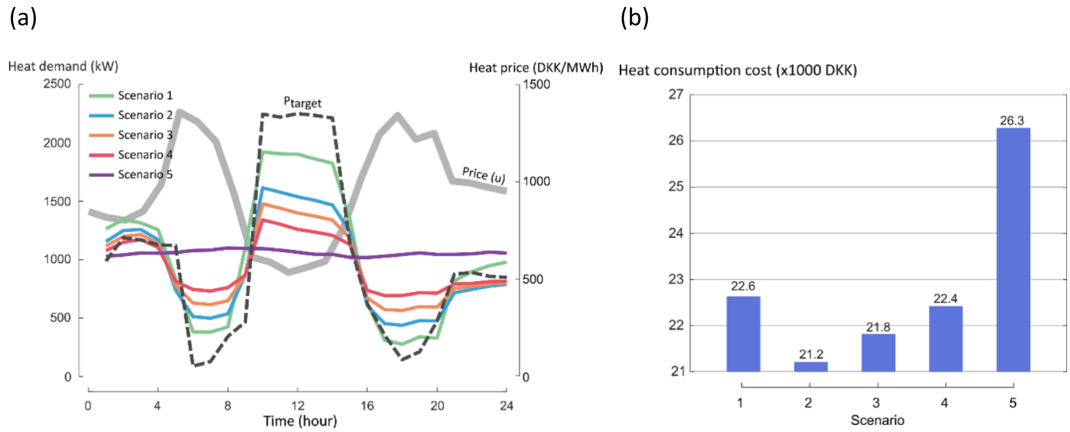

Fig. 9. (a) Total neighborhood demand (Y) of each scenario, target power (Ptarget), and the given heat price signal (u). (b) Total daily heat consumption cost for each scenario.

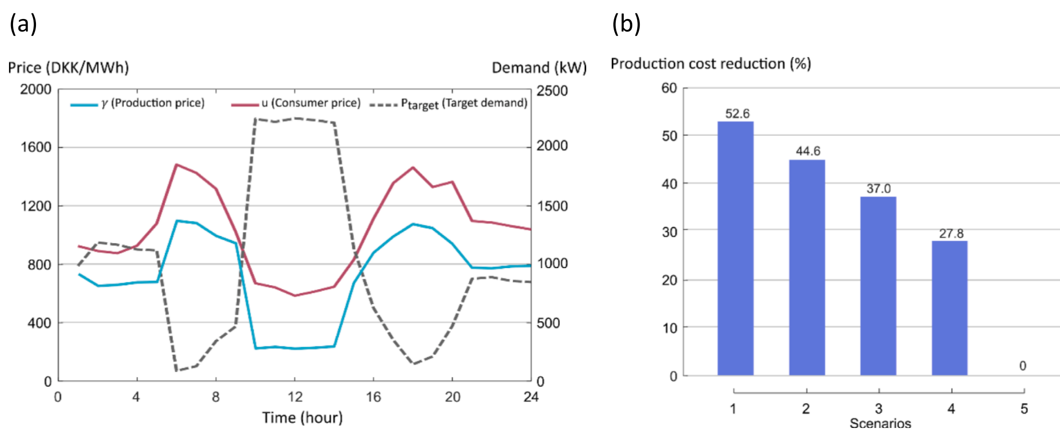

Fig. 10. (a) Heat production and consumption prices along with target demand.

in causing higher consumption costs. Fig. 10 shows the effects of dynamic price for each scenario from the production cost perspective.

Fig. 10.a shows the production cost and target demand profiles, as described in Section 3.7. The dynamic heat price is calculated accordingly, and it can be noted that it follows the same pattern as the production cost profile. Fig. 10.b shows the production cost reduction of each scenario compared to the baseline. Accordingly, Scenario 4 (composed of 17 % Automated-comply and 33 % Manual-comply consumers) could reduce costs by 27.8 %. Comparing scenarios C and D, it could be realized that only by increasing the share of heat consumers with Automated-comply by 16 % could the cost reductions increase by 9.2 %. In the same manner, Scenario 2, with 33 % more consumers with Automated-comply, has a 44.6 % reduction in production costs. Comparing this figure with Fig. 9.b shows that although Scenario 1′s heat consumption costs are lower than Scenario 5′s, the production costs are reduced significantly. Eventually, it can be concluded that even consumers who comply manually can provide a notable demand response to reduce production costs in district heating. However, these reductions can be further increased by installing automated consumers and attracting more consumers to comply with dynamic prices.

We realized that production costs can be reduced notably by applying dynamic prices for district heating. The level of reduction depends on the scale and intensity of compliance with prices. Therefore, it is important to know the factors affecting consumer's willingness to accept dynamic prices [30]. However, our findings suggest that even with modest demand response scale, peak consumptions can be reduced, leading to notable cost saving.

5. Discussion

Social acceptance is crucial in a changing paradigm, as it fosters public support, eases the adoption of new solutions, and ensures that innovations are embraced rather than resisted. When shifting from the prevailing flat heating prices to a dynamic heat price, consumer acceptance should be considered one of the most influential factors in successful demand response participation. In a qualitative interview study by [51] when describing the benefits of load shifting using smart dishwashers and washing machines, one of the interviewees commented, “I could postpone washing my clothes if I was informed how much euros I was saving by doing this.” This highlights the importance of clarity in people's attitudes towards load shifting. People understand that load shifting is not a free lunch and must sense how much they are paid in exchange for extra effort or sacrificing comfort. People usually prefer simple flat prices due to their simplicity. People will only embrace dynamic pricing when the advantages are clear and encouraging enough. Moreover, dynamic pricing will not be accepted if people perceive it as unnecessary complexity or adding additional costs to their bills. According to [34], some people strongly resist price discrimination, perceived as unfair or arbitrary. Therefore, to ensure people's positive attitude towards dynamic prices, it should be the same for all consumers. The way price information is shared is also crucial in determining the level of compliance with dynamic prices [49]. A complex and unclear approach to sharing price information would hinder the participation of most households. In contrast, a simple and easy platform, e.g., applications on phones, SMS messages when prices are low or high, or an integrated API interface, would encourage more people to comply with prices.

There is an argument that low-income households would have high economic motivation to comply with dynamic prices, which are great assets for peak shaving. However, Hansen [36] argues that low-income households with inefficient buildings already use their maximum heating capacity to maintain thermal comfort, leaving no room for further response to prices. Conversely, high-income households with more efficient buildings and heating systems would have more potential to comply with dynamic prices. Still, on the other hand, economic motives might not be encouraging enough for these households. Therefore, other advantages of dynamic prices, e.g., environmental and societal benefits together with financial benefits, should also be clearly stated to promote both parties.

Results of this study and another relevant study [49] showed that users who manually comply with dynamic prices can provide flexibility for load shifting to some extent. The advantage of this method is that it requires no upfront costs for consumers, and users take full control of the systems. However, this type of control is prone to significant uncertainties and does not usually extract the full flexibility potential of the buildings. More importantly, manual control requires frequent adjustments, leading to response fatigue, where consumers get tired of adjusting thermostat settings repeatedly and lose motivation to act over time []. This issue is resolved in automated controllers, where the response is automatic, while consumers can override the actions [52]. This is important information for energy policy to encourage sector development in this direction. Even though this study shows significant cost savings, savings might be limited in practice. The preset high indoor comfort range might not be desired by residents, or the designed dynamic prices might have a low peak-to-valley, limiting the savings and peak reductions.

This study showed that automatic control solutions for heating systems provide the highest economic benefit compared to manual occupant-based control. However, automatic control requires occupant acceptance and trust. As mentioned in [53], building trust in society is one of the most critical factors in accepting automation in control. Karjalainen [51] conducted a study based on qualitative interviews to reveal occupants' attitudes toward levels of automation in building energy systems. The interviews revealed a large amount of mistrust towards automation. Based on the feedback from interviewees, most people did not accept full automation in control due to mistrust, low savings, discomfort concerns, personal preferences, etc. However, they neither preferred zero automation at all. Most people preferred a compromise between automation and manual control, where occupants had the full authority to override the settings and have the final control. This should be considered when designing the automatic controllers for this purpose.

While this study focused on analyzing various thermostat controller types, it did not include more advanced controllers, such as Model Predictive Controllers and Reinforcement Learning controllers, which employ intelligent decision-making. This omission is primarily due to their limited adoption in the current heat control market, largely resulting from their complex modeling requirements. Nonetheless, these advanced controllers are an active area of research and hold significant promises for broader implementation soon. In particular, when real-life data with dynamic pricing becomes available such that the parameters describing the observed flexibility function can be estimated/calibrated. Consequently, future real-life dynamic pricing studies should incorporate these controllers' analyses to ensure comprehensive design considerations.

6. Conclusion

This study used a scenario-based approach based on a virtual testbed with nine identical buildings to examine the impacts of dynamic heat price as a DR strategy in district heating. The buildings were acquainted with a unique DR behavior, and the impacts of dynamic price were analyzed for each consumer. Afterward, to reveal the probable outcomes of shifting from flat to dynamic price, five possible scenarios for DR participation were analyzed. Dynamic price was designed using an inverse-optimization method based on energy flexibility of the consumers to activate DR. Results show that shifting from a flat price to a dynamic price can significantly reduce heat consumption costs and reshape the heat demand to match with a target demand profile set by district heating operators. The target demand can be set for peak load shifting, cost minimization, efficiency improvement, etc.

Dynamic heat prices can encourage consumers to shift their heat load to off-peak hours, leading to a more balanced energy system and facilitating the integration of renewable energy sources. While consumers using automated controllers showed the highest economic benefit, even manual adjustments in response to price signals can result in significant cost savings. Accordingly, the analysis results indicated that any compliance with price changes would benefit both consumers and operators economically. While the results show that occupants can save energy by only reducing their thermostat during expensive hours, in the real world, this can be an overwhelming task. Automatic controllers can resolve this issue but require upfront costs for implementation. Automatic controllers showed the highest saving potential, whereas a linear controller could save up to 46 % of heat costs while maintaining indoor thermal comfort. Consumers who manually comply with price changes could save up to 41 % of their heating costs, showing that notable savings could be obtained with almost no upfront costs. Results of analyzing possible scenarios for demand response indicated that dynamic heat price could lead to notable savings in production costs by shifting production to cheap hours and avoiding expensive productions. Accordingly, Scenario 1, which represents an ideal district with automated controllers, could save 52.6 % of production costs compared to the flat price. Scenario 4, representing a district with 17 % of consumers having Automated-comply and 33 % Manual-comply consumers, could reduce production costs by 27.8 %. This study demonstrates that production costs and consumer heating bills could be reduced even with consumers with no smart controllers and only manually complying with dynamic prices. In countries where district heating companies are non-profitable, such as Denmark, lower production costs would lead to cheaper district heating for consumers. In addition to economic benefits, peak fossil-fuel boilers can be limited by sending the right price signal to consumers and encouraging consumers to comply with prices in any form.

6.1. Limitations

Due to the current district heating market with fixed price and the level of complexity, it was not possible to conduct a real experiment. Therefore, many assumptions had to be used to conduct this study. We used a virtual testbed instead of real buildings to conduct the analysis. The model we used for the virtual testbed does not cover these stochastic behaviors. We considered nine different reaction types to price. While the assumed consumer types mimic specific groups of buildings, many buildings and consumer behaviors are left out of the study. The introduced consumers in the study are considered to have a fixed behavior, meaning that a consumer's thermostat level is only a function of price. Moreover, consumers might change their heating behavior from one consumer to another. For example, a household that does not comply with price changes during weekdays due to working hours can manually comply with prices on weekends. Another example is a building equipped with a price-responsive thermostat, where consumers override the settings under special circumstances, e.g., having guests. In addition, certain consumers might not fit into the introduced categories. For example, some users might value heat during expensive hours more than cheap hours and think that availability might be limited. This behavior results from the scarcity effect, a form of irrational behavior by consumers when reacting to prices [54]. In practice, the long transmission pipes from the district heating plant to consumers would introduce thermal delays and long response times. This can impact the design and implementation of dynamic prices, but it was not considered in this study.

6.2. Recommendations and future research

The methods and findings of this study can be used as a guideline for operators and heat consumers to consider dynamic prices as an effective approach to reducing costs. Dynamic heat prices showed promising potential for consumer cost savings, increased operational efficiency for district heating operators, and reduced carbon emissions. There are mainly two pathways to investigate dynamic pricing in heating. First is to find ways to increase acceptance and willingness to comply with dynamic pricing. This includes testing the long-term impacts of dynamic pricing on consumer behavior, considering factors like changing weather patterns and evolving consumer preferences. The other aspect to study is the technical side of dynamic pricing. Topics such as designing dynamic price, testing different controllers, leveraging dynamic price to integrate waste heat from industries, data centers, etc., into district heating networks are important to reveal their potential and challenges. Sector coupling and integration of renewable heat in district heating is reported to be easier with dynamic heat price. Dynamic heat prices are also reported to be a proven solution to solve common issues in district heating, such as network congestion, demand and supply mismatches, dependency on peak backup boilers, overpriced heating, etc. These topics are crucial for the decarbonization of the district heating sector and require a series of studies.

CRediT authorship contribution statement

Reza Mokhtari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Henrik Madsen:** Writing – review & editing, Supervision, Resources, Project administration, Formal analysis. **Rongling Li:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Flexibility function parameters of the different scenarios of DR are shown in the following Table A1.

Table A1
Flexibility function parameters for each scenario.

Parameter	Scenarios A	B	C	D
Δ	1	1	0.90	0.67
C	131.686	62.39	54.97	45.36
k	3.31	2.44	2.55	3.24
ε	0.25	0.13	0.12	0.11
α_1	−0.5	−0.5	−0.5	−0.5
α_2	1	0.66	0.60	0.53
α_3	−1	−0.66	−0.6	−0.53
α_4	1	1	1	1
β_1	0.04	0	0	0
β_2	0.02	0	0	0
β_3	0.16	0.40	0.43	0.49
β_4	0.21	0.15	0.13	0.07
β_5	0.1	0.10	0.09	0.07
β_6	0.47	0.35	0.32	0.24
β_7	0	0	0.04	0.14

Parameter shows the total capacity of the consumer's flexible energy, which depends on the thermal properties of the building, controller type, and indoor setpoint limits. A higher setpoint limit range will result in a higher flexible energy (C). Δ is the proportion of flexible demand indicating the relative available flexible demand to the baseline demand. ε is a tuning parameter that shows how the building would move toward the baseline over time. k is called energy flexibility eagerness, indicating the speed of demand changes and are tuning parameters of the FF. More descriptions of the parameters can be found in [47]. It should be noted that FF could not fit Scenario 5 due to its inflexibility.

The indoor temperatures associated with the response of each controller is shown in Fig. A1.

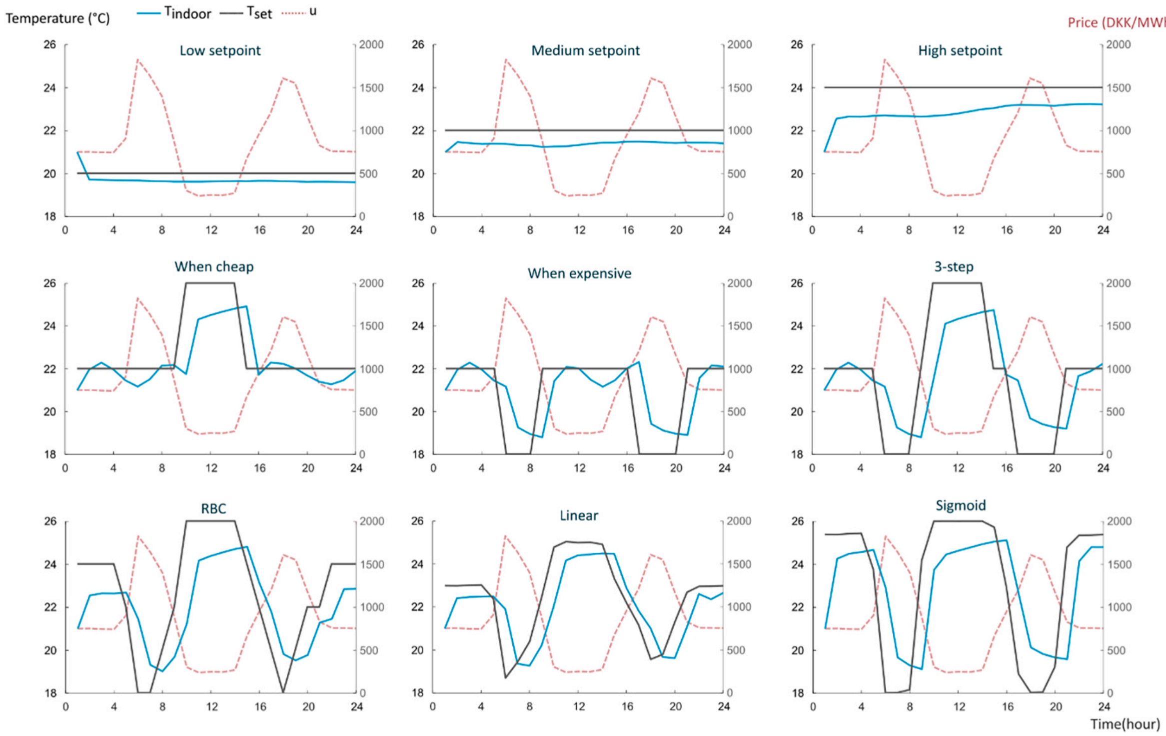

Fig. A1. Indoor temperatures of each reference consumer, responding to the dynamic price.

The initial indoor condition was set to 21 °C. The first row presents controllers with fixed thermostats and ignoring the dynamic price. The indoor temperatures try to follow the setpoint, except for the High setpoint, where the heating systems struggle to reach the setpoint quickly. The indoor temperature for When cheap controller jumps from 9 to 15, where it is cheap. The indoor temperature for all controllers is within the defined comfort bounds (i.e., 18 °C–26 °C). A response delay of around one hour can be realized for all controllers due to the thermal inertia of the building.

Since the exact information on the most building construction elements were not available, databases such as Danish Building and Housing Register (BBR), the Danish Building Standard (DS/EN 15251) [55] and the TABULA project [56] were used to create building models. The components used for modelling are listed in Table A2.

Table A2
Components used in creating building models.

Component	Materials (thickness)
Roof	Roof tiles (59 mm)
	Insulation (300 mm)
	Hollow core concrete (270 mm)
Exterior wall	Brick (108 mm)
	Insulation (375 mm)
	Aerated concrete (100 mm)
Floor/ceiling	Concrete (220 mm)
	Insulation (93 mm)
	Concrete (80 mm)
	Oak planks (14 mm)
Ground floor	Insulation (350 mm)
	Concrete (120 mm)
Windows	Clear double glazing with air
Internal wall	Concrete (200 mm)

Data availability

Data will be made available on request.

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