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Review article

Managing residential demand response in district heating systems: A review of coordination strategies

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ABSTRACT

Residential district heating demand response offers significant potential for enhancing system flexibility and supporting decarbonization, yet widespread implementation remains limited. While technical feasibility has been demonstrated in numerous studies, a systematic understanding of how different demand response approaches shape utility-customer interactions and implementation requirements remains fragmented. Through a systematic review of 26 studies, we analyze utility-customer interactions across five key dimensions: goals, thermal comfort, intelligence mechanisms, coordination strategies, and incentive structures and identify three distinct interaction patterns that emerge from different coordination approaches: direct utility control, dynamic price signals, and static price incentives. Our synthesis of quantitative evidence from field studies and simulations reveals characteristic performance outcomes and implementation requirements for each pattern. Direct utility control demonstrates reliable peak management capabilities of 5%–35% maximum power reduction, but requires substantial infrastructure investment and faces unresolved challenges in incentive design. Dynamic price signals enable customer systems to respond to variable production costs, with reported outcomes ranging from 4%–65% peak load reduction and 1%–53% cost savings depending on price elasticity and coordination approach, though purely decentralized implementations face risks of synchronized responses that can amplify rather than reduce peaks. Static price incentives achieve moderate, sustained peak reductions (10%–20%) with minimal infrastructure requirements but lack short-term flexibility. This systematic analysis provides utilities with evidence-based understanding of the operational implications, performance characteristics, and implementation challenges associated with each coordination approach.

Contents

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1. Introduction

Space heating and Domestic Hot Water (DHW) account for 78% of residential energy consumption in the EU, constituting approximately one-third of the EU's total final energy consumption (Eurostat, 2024; European Commission and Directorate-General for Energy, 2022). Fossil fuels supplied nearly three-quarters of European heat demand in 2022, both directly and through electricity and DH systems (International Energy Agency, 2023a; European Environment Agency, 2024). This substantial fossil fuel dependency has made residential heating a primary target for the European Green Deal's 2050 climate neutrality goal and the Fit for 55 package's 2030 emissions reduction targets (European Commission, 2021; European Commission and Directorate-General for Communication, 2021; European Parliament and Council of the European Union, 2023), highlighting its critical role in Europe's decarbonization strategy.

DH offers significant advantages for decarbonizing the heating sector, particularly in densely populated urban areas (Sayegh et al., 2017; Rezaie and Rosen, 2012). These systems can integrate waste heat from industrial processes (Torío and Schmidt, 2010) and serve as platforms for renewable energy integration. However, modern DH networks are undergoing significant transformation, characterized by lower network temperatures, reduced pipe diameters, and stronger interconnections with electricity markets through Combined Heat and Power (CHP) plants and heat pumps (Lund et al., 2014; Schmidt et al., 2017). While these developments improve overall system efficiency, they also increase the need for flexibility and effective peak load reduction strategies. Besides supply-side measures such as thermal storage (Guelpa and Verda, 2019), demand-side approaches have emerged as particularly promising for enhancing system flexibility without extensive additional infrastructure (Guelpa and Verda, 2021).

Demand response has gained particular attention as a cost-effective demand-side strategy to address flexibility needs in evolving DH systems (Vandermeulen et al., 2018). It represents a strategy where consumption patterns are adjusted to better match supply conditions (International Energy Agency, 2023b), enabling utilities to optimize system operation while potentially reducing costs for both providers and consumers. Despite successful demonstrations in research environments, including field trials showing significant peak reductions and cost savings across various coordination approaches, demand response in DH systems has seen limited deployment in practice (Marszal-Pomianowska et al., 2024). Some static price incentives with peak-based tariff components have been implemented in European networks (Song et al., 2017; Ala-Kotila et al., 2020), but insights into their practical effectiveness and customer awareness of potential savings remain limited. Implementing more sophisticated coordination approaches, such as direct control or dynamic pricing, faces additional barriers, including the need for smart meters, controllable heating devices, and communication infrastructure, which are costly and intrusive to install in existing buildings. Beyond these deployment challenges, systematic understanding of how different coordination approaches shape implementation requirements, stakeholder relationships, and performance outcomes remains fragmented (Marszal-Pomianowska et al., 2024). Approaches range from direct control to various price-based mechanisms, each with distinct implementation requirements and operational characteristics, yet existing research has not systematically synthesized what each approach requires in practice and what outcomes can be expected based on real-world experience.

Understanding these coordination challenges requires recognizing that demand response in DH can be implemented at various infrastructure levels. At the household level, thermostats or radiator valves adjust individual consumption while building thermal mass temporarily maintains indoor temperatures (Christensen et al., 2022, 2020; Beltram et al., 2019). At the building level, substations modulate heat transfer to entire buildings, affecting all connected dwellings simultaneously (Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Wernstedt and Johansson, 2008). This distinction fundamentally shapes utility-customer relationships: household-level control involves direct resident participation, while building-level control, at least in the case of multi-family homes, would involve utilities negotiating with building owners or property managers on behalf of multiple residents.

Within DH systems, the residential sector represents an especially important customer segment that requires specific consideration when implementing demand response strategies. Unlike industrial or public sector consumers connected to DH networks, residential customers are typically non-experts who directly adjust their heating preferences based on personal comfort rather than technical or economic optimization. Their consumption patterns are influenced by diverse factors, including DHW usage and individual occupancy patterns (Idowu et al., 2016), creating significant variability in heat demand. Unlike electricity customers who can often switch suppliers in liberalized markets, residential DH customers typically also face supplier monopolies (Egüez, 2021), which has implications for demand response program design. While residential DH users offer substantial potential for demand response due to their scale, the social acceptance and technology adoption challenges also tend to be more complex, requiring specific consideration of utility-customer interactions. By utility-customer interaction, we refer to how utilities and residential customers work together to implement demand response: who makes decisions about heating adjustments, what information flows between parties, how customers are motivated to participate, and how thermal comfort is maintained.

Despite technological readiness and proven benefits in pilot projects, a critical gap exists in understanding how utilities and residential customers should interact in demand response programs in DH (Marszal-Pomianowska et al., 2024). Existing research has focused predominantly on technical optimization and system modeling, while analyzing the patterns of effective utility-customer coordination across different studies remains largely unexplored. This knowledge gap hampers real-world implementation as utilities lack frameworks to design programs that balance technical performance with customer acceptance and engagement. The absence of a systematic classification of different coordination approaches might prevent utilities from selecting strategies appropriate for their specific contexts, thereby potentially limiting the practical adoption of demand response in DH systems. Without addressing these interaction patterns, the potential for demand response to contribute significantly to DH flexibility and decarbonization will remain unrealized.

Abbreviations

ADMM	Alternating Direction Method of Multipliers
CHP	Combined Heat and Power
CTSM	Continuous-Time Stochastic Model
DHW	Domestic Hot Water
DH	District Heating
EMS	Energy Management System
HEMS	Home Energy Management System
MPC	Model Predictive Control
RC	Resistance-Capacitance

To address this critical knowledge gap, this paper makes three significant contributions to advancing residential demand response in DH systems: First, we synthesize the fragmented body of literature through a systematic review, providing the first comprehensive analysis of utility-customer interaction patterns in residential DH demand response, an aspect notably absent in existing reviews. Second, we introduce a novel classification framework with five key dimensions: goals, thermal comfort, intelligence mechanisms, coordination approaches, and incentives. That enables a systematic evaluation of demand response strategies, revealing how fundamental differences in coordination mechanisms shape the overall system design. Finally, we identify three fundamental utility-customer interaction patterns: direct utility control, dynamic price signals, and static price incentives and analyze their operational characteristics based on evidence from field studies and simulations, including quantitative performance metrics for peak reduction and cost savings. This analysis provides utilities with realistic expectations regarding implementation requirements, technological prerequisites, expected performance outcomes, and available evidence on customer attitudes for each coordination approach, synthesizing both demonstrated capabilities and critical evidence gaps that currently limit comprehensive evaluation.

To achieve these contributions, the remainder of this work is structured as follows: First, Section 2 examines prior literature reviews and identifies their limitations regarding utility-customer interaction patterns. Section 3 presents the systematic review methodology used to identify and analyze relevant literature. Section 4 thoroughly discusses the five key dimensions of utility-customer interaction identified in residential demand response studies in DH. Section 5 presents the three fundamentally different interaction patterns between utilities and customers, analyzing their operational characteristics and strategic implications for various stakeholders. Section 6 presents identified research gaps and opportunities for future work. Finally, concluding remarks are presented in Section 7, along with recommendations for future research directions.

2. Existing literature reviews

Our study identifies and classifies the fundamental patterns of utility-customer interactions in residential demand response for DH systems. This section motivates our research by examining and distinguishing it from existing literature reviews focusing on related topics. More specifically, we identify four groups of existing literature reviews, highlight their limitations, and present the research gap addressed with this study.

The first identified group comprises reviews that focus on the technical optimization of DH systems. These reviews provide overviews of demand-side management techniques for DH (Guelpa and Verda, 2021) and distinguish different control approaches (Vandermeulen et al., 2018). However, they primarily address the technical challenges related to the respective control strategies, rather than fully exploring the consumer dynamics and incentives critical for effective demand response implementation.

Considering the flexibility aspects, the second identified group comprises literature reviews that focus on energy flexibility in buildings and DH systems. These reviews examine energy demand flexibility, focusing on the integration of electrical and thermal systems (Luc et al., 2019), and explore low-temperature DH concepts in relation to system flexibility (Schmidt et al., 2017). In this group, however, the focus is clearly on technical definitions and quantification methods for energy flexibility rather than on the patterns that characterize operator-customer interactions in residential demand response programs.

The third identified group consists of reviews that consider the economic dimensions of demand response. These works conduct comprehensive analyses of demand-side energy management, including monetary incentives (Meng et al., 2024) and examine stakeholder expectations from flexibility initiatives (Ma et al., 2020). Whilst these reviews explore certain economic aspects, they consider only specific evaluation criteria and thus fail to consider the utility-customer interaction patterns specifically relevant to residential demand response in DH.

The fourth identified group of related reviews focuses on implementation barriers. These reviews identify the absence of effective collaboration models between utilities and customers as a critical barrier to widespread adoption of demand response in DH systems (Marszal-Pomianowska et al., 2024).

To the best of our knowledge, no comprehensive review analyzing operator-customer interactions in residential DH demand response exists. While previous research has thoroughly examined technical aspects, it has neglected the systematic analysis of interaction patterns crucial for implementation success. Evidence from electricity markets reveals that program effectiveness depends on well-designed utility-customer communication approaches (Sloot et al., 2022; Srivastava et al., 2018). Implementation requires coordinated efforts across multiple stakeholders, as no single entity can manage this process in isolation (Greening, 2010). Consumer participation is significantly influenced by regulatory frameworks, relationship structures, and communication strategies (Hampton et al., 2022; Skoczkowski et al., 2024). Despite technical readiness, residential DH demand response faces adoption barriers, due to the absence of effective collaborative frameworks between utilities and customers (Marszal-Pomianowska et al., 2024). This study addresses this gap by developing a systematic classification framework for understanding utility-customer interactions in residential demand response.

3. Methodology

This section outlines the methodological framework applied in this structured review, based on the structured approach proposed by Webster and Watson (2002) and vom Brocke et al. (2009). We present the systematic search strategy and the subsequent extraction of key aspects from the identified literature.

The systematic search process consists of four stages, ensuring a comprehensive and rigorous identification of relevant literature. This process is illustrated in Fig. 1.

The first stage of the process involves identifying an initial corpus of relevant literature. For this, we chose *Scopus*, *Web of Science*, and *IEEE XPLORE* as relevant databases to be queried with our search string. The search string adapts Guelpa and Verda's (2021) methodology to identify research specifically addressing demand response among residential customers in DH systems. It is defined as follows:

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"demand response"
AND ("district heating" OR "thermal network" OR
"thermal load")
AND "residential"
AND heat*
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This formulation ensures that the identified studies focus on the intersection of demand response, DH, and residential applications. The additional inclusion of the term *heat** avoids works solely focused on district cooling. We queried the title, abstract, and keyword fields in

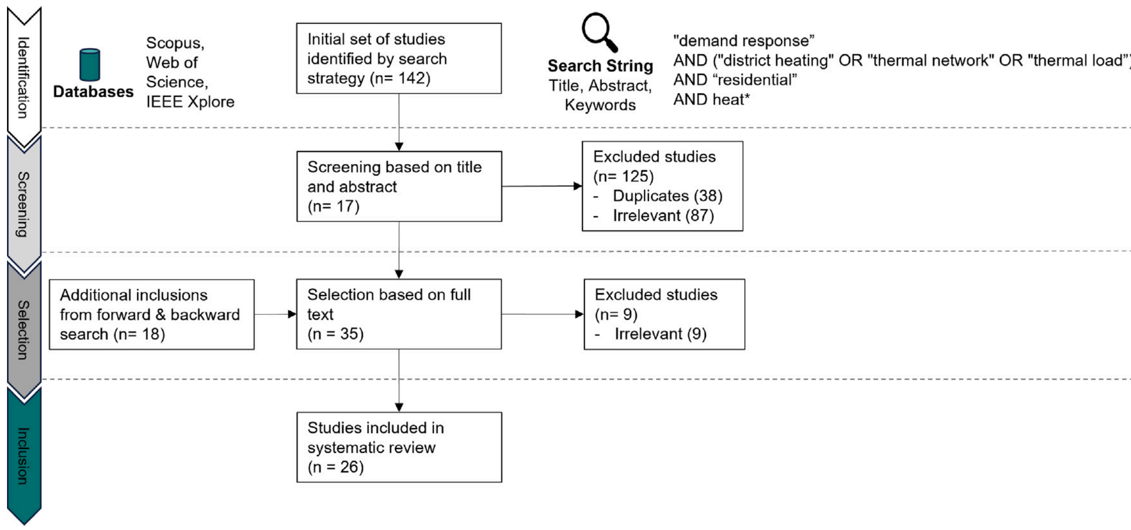


Fig. 1. Search strategy.

the databases mentioned above using the aforementioned search string. The initial search, conducted in September 2025, yielded 142 studies.

In the second stage, we screened the titles and abstracts of all studies from the first search stage and excluded duplicates and irrelevant studies. To ensure relevance to our systematic review, we applied methodological inclusion criteria that are independent of the search string: studies must consider (i) residential customers, (ii) district heating systems, and (iii) a thermal demand response mechanism. In detail, this means that, first, the work must test a demand response approach through either simulation or real-world implementation. We thus exclude literature reviews, pure surveys, and study designs without results. Second, the heat provisioning system must be DH as this defines the scope of our investigation into thermal demand response mechanisms. The study must consider residential dwellings because our research specifically examines utility-customer interactions in the residential sector. Third, the study must encompass some form of thermal demand response, i.e., deliberate modulation of thermal demand at the customer site in response to a supplier-side stimulus. This stimulus may be explicit, such as direct control commands or dynamic price signals, or implicit, such as tariff structures that discourage individual demand peaks through additional price components. This is the fundamental process we aim to characterize through our analysis of the five dimensions of utility-customer interaction. In contrast to other reviews in this field, which consider monetary incentives a critical criterion for demand response (Meng et al., 2024), we include studies addressing thermal demand modulation even when they do not explicitly discuss incentives. This inclusive approach allows us to identify potential implementation gaps between technical capabilities and market-ready solutions, providing a more comprehensive understanding of the current state of residential demand response in DH.

We include both simulation studies and real-world experiments to capture the full development trajectory of demand response approaches. Real-world experiments validate performance with actual participants under operating conditions. Simulation studies, while conducted in a controlled environment, allow systematic evaluation of approaches across diverse scenarios and parameter settings that would be impractical, costly, or impossible to test in the field. Importantly, analyzing both types together enables identification of implementation gaps – approaches that are feasible in simulation but not yet validated in practice – which is critical for understanding barriers to adoption.

During this second stage, 125 studies were excluded. Of these, 38 were duplicates, likely due to the query being executed across multiple databases. The remaining 87 were excluded for irrelevance, primarily because they focused on demand response in the electricity domain by leveraging flexible thermal loads without meeting the criterion that the heat provisioning must come from DH. After this step, 17 studies were retained.

In the third stage, we performed a forward and backward search of the reference lists of the 17 included studies and related literature reviews, based on title and abstract screening. Since forward/backward searching complements database queries, it can identify relevant studies that do not match the original search string but still meet the methodological inclusion criteria. This complementary approach identified 18 additional records that the initial search string had not captured. Together with the 17 studies from the initial screening, this resulted in 35 articles that underwent full-text screening. While the methodological inclusion criteria were initially assessed at the title and abstract stage, studies with unclear relevance or ambiguous descriptions of their methodology, system type, or customer segment were included in the full-text screening to ensure comprehensive coverage. Of these 35 articles assessed at full-text, 9 were excluded for not meeting the inclusion criteria, leaving 26 studies in the final dataset. Several projects were reported in multiple publications; these were consolidated into single study entries to avoid double-counting.

The analyzed studies were both simulation studies and real-world experiments. They were relatively evenly distributed between these two types with 13 studies being experimental tests (Ala-Kotila et al., 2020; Christensen et al., 2022, 2020; Beltram et al., 2019; Van Oevelen et al., 2020, 2023; Wernstedt and Johansson, 2008; Sweetnam et al., 2018; Suhonen et al., 2020; Eguiarte et al., 2022; Kontu et al., 2019; Amato et al., 2023; Langner et al., 2025; Knudsen et al., 2021), 11 studies being simulation studies (Hedegaard et al., 2019; Golmohamadi and Larsen, 2022; Håkansson et al., 2024; Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021; Li and Wang, 2015; Knudsen et al., 2025; Mokhtari et al., 2025) and two studies combining a simulation study with experimental tests (Guelpa et al., 2019; Cai et al., 2020). Geographically, all studies are based in Europe, predominantly in Finland, Sweden, and Denmark, as illustrated in Fig. 2. This geographical concentration reflects a focus on regions with extensive existing DH networks (Werner, 2017).

Through a comprehensive screening of the reviewed papers, we identified five key aspects that shape the utility-customer interaction in residential demand response: goals, thermal comfort, mechanisms for intelligent control, coordination, and incentives. We analyzed how each study addressed these aspects and grouped similar approaches into categories, allowing for multiple categorizations per study where appropriate. The resulting categorization framework, which identified between three and seven categories per key aspect, serves as the basis for our subsequent analysis, which is presented in the following section.

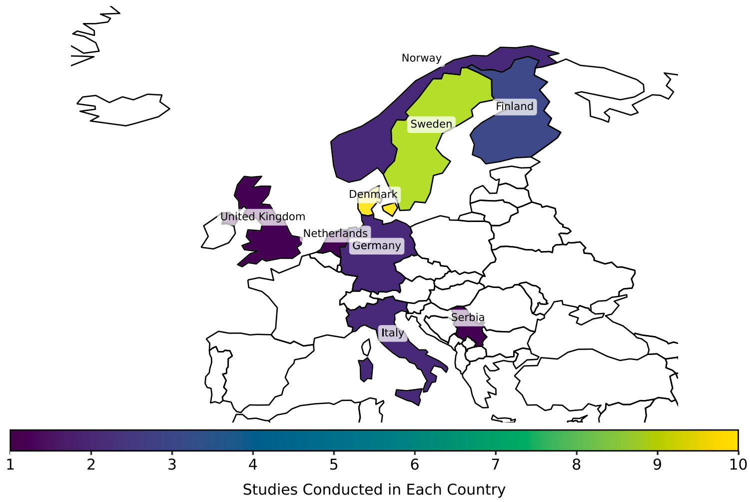


Fig. 2. Geographic distribution of studies on residential demand response in DH.

4. Dimensions of utility-customer interaction in residential demand response

Residential demand response in DH systems operates at the intersection of technical capabilities and human preferences, requiring structured frameworks to understand the complex interactions between utilities and customers. In the body of reviewed literature, five patterns were mainly characterizing these interactions: goals, thermal comfort considerations, mechanisms for intelligent control, coordination approaches, and incentive structures. Fig. 3 provides an overview of the reviewed dimensions and their possible manifestations.

The dimensions identified in our framework represent the critical decision points that shape the implementation of residential demand response. Each dimension encompasses multiple approaches observed in the literature, with significant variation in how studies address these aspects. A detailed mapping of how each study in our corpus approaches these dimensions is provided in Table A.1 in Appendix, and displays both patterns and gaps in current research.

In the following subsections, we analyze each dimension independently, examining the various approaches researchers have employed and their implications in the implementation of residential demand response schemes in DH systems. This structured analysis lays the groundwork for identifying cohesive interaction patterns that emerge when these dimensions – goals, thermal comfort, mechanisms for intelligent control, coordination, and incentives – are considered holistically.

4.1. Goal

This section analyzes the different goals that residential demand response in DH served in the analyzed studies. Two crucial, overarching goals can be identified: managing thermal peak loads and responding to price fluctuations, both of which are ultimately tied to reducing cost. This is also reflected in the analyzed corpus:

The majority of studies focus primarily on reducing thermal peak loads (Ala-Kotila et al., 2020; Christensen et al., 2022, 2020; Beltram et al., 2019; Guelpa et al., 2019; Sweetnam et al., 2018; Hedegaard et al., 2019; Kontu et al., 2019; Van Oevelen et al., 2020, 2023; Wernstedt and Johansson, 2008; Håkansson et al., 2024; Romanchenko et al., 2019; Mokhtari et al., 2025; Li and Wen, 2014). Thermal demand in DH system varies over time and is typically met by a combination of efficient base-load generators and less efficient peak-load units. The latter are often fossil-fuel powered heat-only boilers that are typically less efficient and expensive to operate and only activated to meet demand peaks (Christensen et al., 2022; Ala-Kotila et al., 2020; Beltram et al., 2019; Håkansson et al., 2024). By reducing thermal peak loads, utilities can avoid the significantly higher marginal costs associated with these peak-load units. Peak reduction offers additional benefits beyond lowering fossil fuel consumption. Several studies indicate that effective demand response can reduce the need for centralized thermal storage systems that are traditionally used for peak management, thereby lowering initial infrastructure investment costs (Christensen et al., 2020; Romanchenko et al., 2019). Furthermore, when peak demands are reduced, the entire distribution network can be designed with smaller capacity requirements, resulting in substantial reductions in upfront construction costs (Sweetnam et al., 2018). Lower peak flow rates can also reduce pumping energy requirements (Sweetnam et al., 2018). Additionally, reduced network temperatures can decrease pipework heat losses (Van Oevelen et al., 2023; Sweetnam et al., 2018), although this benefit is discussed primarily as motivation rather than being quantitatively evaluated in the demand response experiments themselves. Similarly, capital cost benefits through infrastructure optimization remain largely theoretical: even studies addressing new building areas during planning (Knudsen et al., 2025) focus on operational rather than infrastructure design optimization. One reason for this might be that most studies are conducted in existing networks or testbed environments. This gap suggests unrealized potential for incorporating demand response into network planning to enable more efficient infrastructure dimensioning.

The second key objective is to reduce operational costs by aligning heat consumption with short-term fluctuations in marginal production costs, which are not directly tied to heat demand levels (Suhonen et al., 2020; Golmohamadi and Larsen, 2022; Eguiarte et al., 2022; Cai et al., 2020; Romanchenko et al., 2021; Knudsen et al., 2021; Mokhtari et al., 2025; Knudsen et al., 2025; Langner et al., 2025). Such cost fluctuations arise in various modern configurations of district heating systems. For example, in CHPs, heat and electricity are produced simultaneously. When electricity prices are high, the revenue from selling the electricity offsets part of the heat production costs, effectively lowering the net cost of heat. As a result, the cost of heat generation is inversely related to the market price of electricity (Suhonen et al., 2020). In contrast, heat pumps consume electricity to generate heat. Their operational costs therefore rise and fall with electricity prices, meaning they can produce heat particularly cheaply during periods of low electricity prices (Golmohamadi and Larsen, 2022; Langner et al., 2025). A third reason for the fluctuation of heat provisioning cost can be a fluctuating supply of waste heat Knudsen et al. (2025).

Three studies do not explicitly state the goal of employing demand response but focus on proving the concept of achieving flexibility on the customer side (Hamp and Levihn, 2022; Amato et al., 2023) or promoting the equitable distribution of thermal discomfort across

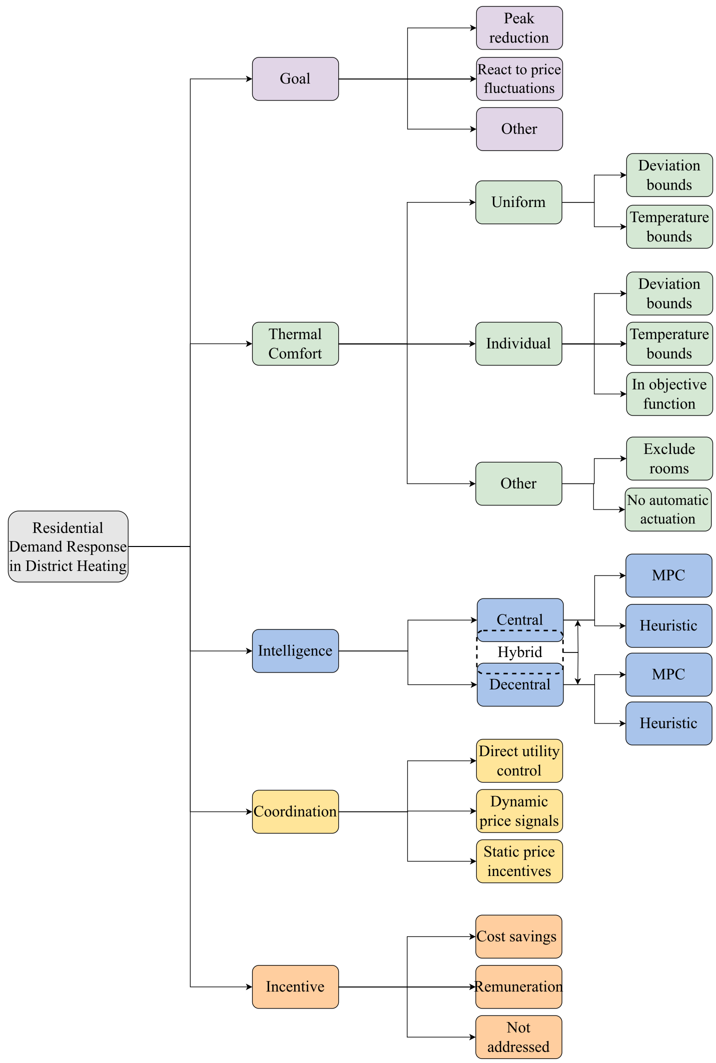


Fig. 3. The five key dimensions of supplier–customer interaction in residential demand response in district heating.

participating households in residential demand response (Bhattacharya et al., 2016).

Across the reviewed studies, demand response in DH systems is primarily motivated by economic optimization, encompassing both operational and capital cost dimensions. The stated goals focus predominantly on peak reduction and responding to price fluctuations. The underlying economic rationale includes operational savings by avoiding expensive peak-load units and aligning consumption with favorable production periods and capital cost reductions through decreased infrastructure requirements, including smaller network capacity and reduced need for centralized thermal storage. While both cost dimensions are recognized in the literature, the quantitative evaluation focuses predominantly on operational metrics such as peak reduction percentages and cost savings, with capital benefits typically assessed qualitatively as secondary implications. The specific objectives pursued depend on the characteristics of the heat supply system. In systems where heat generation costs fluctuate in the short term (such as those influenced by electricity price variations), demand response strategies typically focus on shifting consumption to lower-cost periods. In contrast, systems with especially high marginal costs during peak demand periods tend to prioritize reducing peak loads to avoid the significant costs associated with meeting these demands.

The goals identified in the reviewed studies align well with the broader expectations documented in literature, where DH suppliers generally expect demand response to reduce overall heating costs, alleviate peak load-related expenses, and minimize the need for large infrastructure investments (Ma et al., 2020).

4.2. Thermal comfort

A central challenge in residential demand response is balancing thermal comfort for space heating with reliable DHW supply. These constraints differ in flexibility: space heating can leverage building thermal inertia for load shifting, whereas DHW often requires immediate delivery. In this section, we first examine how thermal comfort is modeled in the literature and then discuss approaches to managing DHW demand.

Accurately modeling and prioritizing thermal comfort needs is crucial for ensuring residential customer satisfaction and participation in demand response programs (Bhattacharya et al., 2016). However, Christensen et al. (2022) found that although DH customers are sensitive to temperature fluctuations caused by demand response, they are willing to tolerate some variation when offered monetary incentives and explained environmental benefits. The reviewed literature presents various approaches to modeling and maintaining the thermal comfort of the participating residents. Most studies rely on establishing boundary conditions that must be respected (Suhonen et al., 2020; Wernstedt and Johansson, 2008; Knudsen et al., 2021; Langner et al., 2025; Mokhtari et al., 2025; Van Oevelen et al., 2020, 2023; Christensen et al., 2022; Hedegaard et al., 2019; Ala-Kotila et al., 2020; Christensen et al., 2020; Beltram et al., 2019; Sweetnam et al., 2018; Romanchenko et al., 2019, 2021; Håkansson et al., 2024; Hamp and Levihn, 2022). These bounds can be categorized into individual and uniform limits. Individual bounds are tailored to accommodate the personal preferences of each customer, which requires actively gathering this information. In contrast, the uniform approach applies the same limits across all customers, offering a simpler but less personalized approach. The least individual approach is uniform temperature bounds. In this approach, the same lower and upper absolute temperature limits are applied to all participants (Suhonen et al., 2020; Wernstedt and Johansson, 2008; Knudsen et al., 2021; Langner et al., 2025; Mokhtari et al., 2025; Van Oevelen et al., 2020, 2023).

In contrast, instead of the fixed absolute temperatures, uniform set point deviation bounds allow some degree of individualization by establishing maximum allowed variations from each customer's chosen set point. This approach was the most used in the considered literature (Christensen et al., 2022; Hedegaard et al., 2019; Ala-Kotila et al., 2020; Christensen et al., 2020; Beltram et al., 2019; Sweetnam et al., 2018; Romanchenko et al., 2019, 2021). Within the context of individual temperature bounds and individual setpoint deviation bounds, each participant can choose their temperature bounds (Håkansson et al., 2024) or maximum deviation from setpoint (Hamp and Levihn, 2022) individually.

An alternative approach for thermal comfort involves modeling the loss of utility due to reduced thermal comfort and incorporating it as a penalty into the objective function of the underlying cost-optimization problem (Golmohamadi and Larsen, 2022; Bhattacharya et al., 2016; Cai et al., 2020). This method offers greater flexibility than bounds. However, it poses the significant challenge of accurately estimating individual utility functions. The approach has been examined primarily in simulation studies (Golmohamadi and Larsen, 2022; Bhattacharya et al., 2016), and even when implemented in field deployments, has relied on comfort parameters assumed in prior simulation work rather than values empirically derived from preferences of actual occupants (Cai et al., 2020). This reflects the difficulty of parametrizing comfort utility functions in field application scenarios.

In addition to ensuring thermal comfort through constraining the indoor temperature, alternative approaches exist. For example, three studies excluded certain rooms, such as bathrooms, from the demand response scheme, citing user feedback (Christensen et al., 2020; Beltram et al., 2019; Amato et al., 2023). This was typically done in addition to one of the other thermal comfort strategies mentioned above. Lastly, one approach provided recommendations to users instead of automatically controlling heat loads, thus eliminating the need for explicit thermal comfort modeling (Eguiarte et al., 2022). However, the affected customers stated that they would prefer automatic actuation.

In studies that explicitly address DHW, DHW demand is treated as a priority constraint: space heating is reduced during DHW peaks (Ala-Kotila et al., 2020), or dynamic pricing is applied specifically to mitigate DHW-induced peak loads (Hedegaard et al., 2019). In these approaches, DHW loads are considered non-flexible and are not directly curtailed. However, it should be noted that in many cases DHW systems have storage buffers that could be used to provide additional demand response potential by charging or discharging these buffers.

In conclusion, thermal comfort strategies in residential demand response range from simple uniform bounds to more sophisticated individualized approaches and utility-based penalties. In contrast, DHW availability is treated as non-negotiable. While individualized methods offer greater flexibility, they require additional data and complexity. Although the DH demand response literature shows variation in thermal comfort approaches, research in related domains such as heat pump demand response suggests convergence towards individual temperature bound setting as an effective practice. Further research into translating these insights to district heating contexts would support more standardized implementation guidance.

4.3. Mechanisms for intelligent control

Due to the complexity of managing variable demand patterns, integrating fluctuating renewable energy sources, and implementing effective load management while maintaining residential comfort, intelligent control mechanisms in DH networks have become essential for coordinating heating operations while balancing multiple objectives (Lund et al., 2010; Carpaneto et al., 2015). In the context of residential demand response in DH networks, three main paradigms of intelligent control can be identified: central intelligence, decentralized intelligence, and hybrid intelligence. These paradigms differ in terms of how control decisions are made and how information flows within the system, with each offering distinct approaches to managing heating loads and optimizing energy consumption.

Central intelligence is characterized by its reliance on a central decision-making unit that governs the demand response schedules of all participating households. In the reviewed literature, there are two variations of central intelligence. The first variation is central Model Predictive Control (MPC) (Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021; Van Oevelen et al., 2020, 2023), where schedules are optimized to respect each household's thermal comfort limits by modeling the impact of setpoint changes through thermal building models. The primary advantage of this approach is its ability to optimize the system comprehensively, but it is also highly computationally demanding when modeling a large number of households or a long timeframe (Mayne et al., 2000). Notably, while centralized MPC dominates simulation studies (Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021), experimental implementations (Van Oevelen et al., 2020, 2023) operate at aggregated infrastructure levels, such as mixing stations serving multiple buildings or building-level substations rather than controlling individual household heating systems. This aggregation substantially reduces computational complexity by limiting the number of thermal models and control variables that must be optimized simultaneously, addressing the scalability challenges inherent in centralized optimization (Mayne et al., 2000). The second form of central intelligence is the central heuristic, where one central authority governs the pre-heating and load shedding of all participating households. In the considered studies, the heuristic is time-based (Christensen et al., 2022, 2020; Beltram et al., 2019; Guelpa et al., 2019; Wernstedt and Johansson, 2008; Li and Wang, 2015). Unlike MPC, this approach does not explicitly model the effects of these changes on the system's behavior, thereby eliminating the need for a building model and reducing computational requirements. However, this computational simplicity comes at the cost of reduced precision and adaptability, as the heuristic cannot predict or respond to the actual thermal dynamics of individual buildings or anticipate system-wide effects of its control actions (Yao and Shekhar, 2021).

Decentral intelligence, on the other hand, allows each household to optimize its heat load independently. As with central control, decentralized strategies can be either MPC- or heuristic-based. Most studies focusing on decentralized intelligence utilize MPC (Suhonen et al., 2020; Golmohamadi and Larsen, 2022; Håkansson et al., 2024; Kontu et al., 2019; Langner et al., 2025; Knudsen et al., 2021). In these studies, the underlying optimization problem typically aims to minimize a cost-related utility function. Since only a single building is modeled, the problem is less computationally expensive than in the central case, though a building model remains a necessary prerequisite. Three of the reviewed studies use decentralized heuristics. In addition to time-based heuristics (Amato et al., 2023), rule-based approaches aim either to reduce individual peak loads, for example, by avoiding the simultaneous use of DHW and space heating (Ala-Kotila et al., 2020) - or to respond to energy price signals (Eguiarte et al., 2022). While these decentralized approaches align with household-level objectives, they typically do not consider system-wide constraints or objectives. This limits their effectiveness, especially in settings where network-wide peaks incur high costs.

Hybrid intelligence emerges by combining central and decentralized approaches. One example of hybrid intelligence is the combination of local MPC with central heuristic control, where local units perform MPC for individual households while a central authority applies a heuristic to coordinate these local decisions, ensuring system-wide efficiency (Sweetnam et al., 2018; Knudsen et al., 2025; Hedegaard et al., 2019). In one instance, a dynamic heat price is calculated using inverse optimization on a central level, serving as the basis of heuristic cost optimization on a household level (Mokhtari et al., 2025). Another approach is Alternating Direction Method of Multipliers (ADMM). In ADMM, central and decentralized intelligence is integrated by iteratively coordinating local optimizations with central directives (Cai et al., 2020). This can effectively balance computational efficiency with system-wide optimization and additionally respect system-wide limitations such as network constraints.

The intelligence mechanisms described above vary significantly in their field validation maturity, with important implications for utilities considering demand response deployment. Central heuristic approaches have been successfully tested at the household level in multiple field studies (Christensen et al., 2022, 2020; Beltram et al., 2019; Guelpa et al., 2019; Wernstedt and Johansson, 2008), demonstrating that simple time-based control can achieve significant peak reductions without sophisticated building models. Decentralized approaches-both heuristic (Ala-Kotila et al., 2020; Eguiarte et al., 2022; Amato et al., 2023) and MPC-based (Langner et al., 2025; Knudsen et al., 2021)-have also been validated in residential settings, with the key practical finding that building-level optimization becomes computationally tractable when only individual buildings are modeled. In contrast, centralized MPC for household-level control remains predominantly simulation-based (Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021), with field implementations limited to aggregated building-level control (Van Oevelen et al., 2020, 2023), and hybrid approaches remain at pilot scale (Sweetnam et al., 2018; Cai et al., 2020). This difference in maturity suggests that utilities seeking low-risk implementation pathways may benefit from starting with field-proven central or decentralized heuristic approaches, while those with greater risk tolerance and technical capability might pursue decentralized MPC. The prominence of centralized household-level MPC in academic literature should be weighed against its absence from field validation when making implementation decisions.

The reviewed literature reveals a spectrum of intelligent control mechanisms for residential demand response in DH, each with distinct trade-offs. Central intelligence approaches offer comprehensive system-wide optimization, but face significant computational and scalability challenges (Mayne et al., 2000). Decentralized approaches reduce computational burden and preserve household autonomy, yet may sacrifice system-wide efficiency. Hybrid approaches such as ADMM (Cai et al., 2020) attempt to balance these considerations by combining central coordination with distributed decision making. A critical insight from the literature is the strong reliance of MPC-based strategies on thermal building models. These models simulate how indoor temperatures evolve in response to external conditions and heating input, which is essential for forecasting heat demand and optimizing control actions in DH networks (Li and Wen, 2014). The most prevalent type is the Resistance-Capacitance (RC) model, a simplified representation of building thermal dynamics using electrical analogies to describe heat transfer and thermal storage (Drgoňa et al., 2020). RC models are favored due to their low computational requirements and their compatibility with control algorithms (Prívara et al., 2013). Many studies align their modeling with standards like ISO 13790 (International Organization for Standardization, 2008), which provides a standardized method for calculating the thermal performance of buildings. However, implementations vary widely in complexity, reflecting different trade-offs between accuracy and tractability. Some researchers explore alternatives such as commercial building energy simulation tools (Suhonen et al., 2020; Sweetnam et al., 2018), while others adopt heuristic approaches (Christensen et al., 2022, 2020) that entirely bypass the need for explicit modeling, relying instead on rule-based or data-driven control.

4.4. Coordination of demand response

The coordination of demand response refers to the mechanisms by which consumption is influenced to achieve system-level goals such as peak reduction or cost efficiency. In DH networks, coordination strategies vary in their degree of centralization, reliability, and the role of customer agency. They shape how suppliers and consumers interact, thus fundamentally affecting both technical implementation and user participation. We identified three different approaches of coordinating demand response in DH networks. The first approach is direct utility control (Christensen et al., 2022, 2020; Beltram et al., 2019; Sweetnam et al., 2018; Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021; Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Wernstedt and Johansson, 2008; Li and Wang, 2015). In the context of this approach, the DH supplier remotely controls either the valves or the setpoints at the dwellings of participating customers. This method is typically integrated with centralized intelligence that determines the optimal dispatch strategy for demand response measures. The primary advantage of this approach is its high reliability, as it involves sending direct control signals that ensure immediate and predictable responses. A potential drawback is that it gives the supplier a high level of control and potential privacy concerns. Direct utility control can be considered a direct or explicit demand response (International Energy Agency, 2023b).

In contrast, the other two approaches fall under indirect or implicit demand response, where coordination is achieved through economic incentives (International Energy Agency, 2023b). The first indirect approach is dynamic prices, where the heat price is dependent on the cost of heat procurement, which fluctuates over time (Hedegaard et al., 2019; Suhonen et al., 2020; Golmohamadi and Larsen, 2022; Eguiarte et al., 2022; Amato et al., 2023; Cai et al., 2020; Knudsen et al., 2021, 2025; Langner et al., 2025; Mokhtari et al., 2025). Dynamic price signals offer a key advantage: they enable flexible responses to varying heat provisioning costs. In modern district heating systems, these costs can fluctuate for several reasons. Electricity prices may change, affecting the operational costs of combined heat and power plants (Suhonen et al., 2020) or heat pumps (Langner et al., 2025). Waste heat availability may vary over time (Knudsen et al., 2025). During periods of anticipated high demand, expensive peak units may need to be activated (Hedegaard et al., 2019). Dynamic pricing accommodates all these scenarios by reflecting the actual cost of heat production at any given time. However, depending on its implementation, this approach can also lead to avalanche effects in cases of high participation rates among flexible customers, potentially overwhelming network constraints, or just shifting the dispatch of peak units in time if too many customers respond simultaneously (Hedegaard et al., 2019). One way to address this effect is the application of a hybrid intelligence that also involves a central step to counter such overloads. Additionally, the method of dynamic prices for coordination is less reliable than direct utility control because there is no guarantee of how many customers will respond to the price signals.

The second indirect approach employs static price incentives for behavioral shifts by incorporating peak-based components in the cost structure (Ala-Kotila et al., 2020; Håkansson et al., 2024; Kontu et al., 2019). In these systems, the maximum load during a specified billing period significantly impacts the total heat cost, thereby encouraging customers to flatten their consumption profiles and avoid demand peaks that strain network capacity. However, while these policies effectively reduce individual peaks, peak demand charges might not always sufficiently address aggregated peak demand across the network (El Gohary et al., 2023). Additionally, because these policies are usually set for long intervals, they lack the flexibility to respond to short-term price fluctuations, resulting in a method with high inertia. Peak pricing policies are already implemented in different Northern European countries (Kontu et al., 2019; Håkansson et al., 2024). However, further investigation is needed to assess customer awareness of the potential savings they could achieve by modifying their behavior in response to these pricing signals.

In summary, direct utility control offers high reliability and immediate control but requires a central decision unit. This might limit computational feasibility and raise privacy concerns. Dynamic prices still offer a high degree of flexibility while allowing localized decisions, although they are less immediate and thus less reliable than direct utility control. Lastly, pricing policies like peak pricing are highly indirect, with adjustments typically made over longer time frames, limiting their responsiveness to short-term fluctuations. However, they might still be feasible for reducing peak loads.

The selection of a coordination strategy extends beyond mere operational goals, fundamentally dictating the mechanisms of intelligent control. Central intelligence paradigms inherently depend on reliable, immediate dispatch, necessitating direct utility control, while decentralized approaches rely on economic signals as prerequisite coordination mechanisms. Critically, the chosen coordination strategy not only determines technical implementation but also profoundly shapes the motivations for customer participation.

4.5. Incentives

An integral aspect of establishing demand response programs in DH is the consideration of the incentive structure that motivates customers to participate in them. The most prominent incentives are monetary incentives, which play a crucial role in encouraging residential customers to participate in demand response programs (Christensen et al., 2022). A comprehensive analysis of the reviewed studies reveals several types of incentive structures. These depend on the specific coordination strategy employed.

In studies focusing on indirect demand response mechanisms, specifically dynamic price signals and pricing policies, incentives emerge as a central component of the coordination strategy, acting as the primary catalyst for customer engagement (Hedegaard et al., 2019; Suhonen et al., 2020; Golmohamadi and Larsen, 2022; Eguiarte et al., 2022; Amato et al., 2023; Cai et al., 2020; Ala-Kotila et al., 2020; Håkansson et al., 2024; Kontu et al., 2019; Knudsen et al., 2021, 2025; Langner et al., 2025; Mokhtari et al., 2025). These strategies explicitly leverage economic signals to encourage flexible energy consumption or flat load profiles, respectively, creating a direct financial motivation for customers to alter their heating patterns.

Conversely, in the case of direct utility control, incentives are not as prominently featured in the reviewed studies. Three direct utility control studies acknowledge the need for some form of monetary incentive (Christensen et al., 2022; Sweetnam et al., 2018; Bhattacharya et al., 2016), with two of these studies drawing on direct feedback from participating users. Nevertheless, the ten remaining studies examining direct utility control do not discuss incentives at all (Romanchenko et al., 2021; Hamp and Levihn, 2022; Romanchenko et al., 2019; Beltram et al., 2019; Christensen et al., 2020; Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Li and Wang, 2015; Wernstedt and Johansson, 2008). This suggests that developing effective incentive mechanisms for direct utility control may be particularly challenging, potentially due to the more intrusive nature of direct control strategies and the lack of a natural incentive contained in the coordination mechanism itself. This limited attention to incentives in direct utility control studies raises a more fundamental question specific to DH systems: given that residential DH customers typically face supplier monopolies (Egüez, 2021) and cannot switch providers, are economic incentives truly necessary for demand response participation? The monopolistic market structure might suggest that utilities possess sufficient leverage to implement direct control programs without explicit compensation. However, available evidence from household-level implementations, though limited, suggests that incentives remain important for securing participation. In these implementations, although customers cannot exit the system, they can refuse program participation or resist equipment installation in their homes. The few household-level field studies that engaged directly with residents found that customers expect tangible benefits, typically financial compensation, in exchange for accepting automated control (Christensen et al., 2022; Sweetnam et al., 2018). Paradoxically, the fact that DH customers are subject to supplier monopolies may actually increase the importance of fair treatment: In many jurisdictions, regulatory frameworks impose equity obligations on monopolistic providers (Joskow, 2007), because customers cannot discipline utilities through market exit. For this reason utilities must instead rely on voluntary cooperation, making perceived fairness a key condition for program acceptance.

At the building level, however, the situation is fundamentally different and remains largely undocumented. In these implementations (Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Wernstedt et al., 2007), utilities negotiate with building owners or property managers in multi-family settings. In at least one documented case, residents were not informed that demand response was being implemented (Wernstedt et al., 2007), indicating that building-level control can proceed without individual resident consent or participation decisions. Yet the literature provides no information about how incentives are structured in these arrangements or whether and how benefits reach residents experiencing comfort impacts. This absence of information about stakeholder arrangements and benefit distribution raises important questions about fairness and acceptance that are particularly acute given customers' inability to switch suppliers.

In summary, while indirect strategies integrate incentives explicitly, direct control studies largely omit them. Household-level evidence indicates participants expect compensation despite monopolistic market structures. At the building level, the literature provides no information on incentive structures or benefit distribution to residents. This knowledge gap extends to comparative research, as no study examines different incentive approaches or compares acceptance across implementation levels.

4.6. Quantitative results across coordination approaches

The previous sections analyzed residential demand response in DH across five key dimensions. This subsection examines quantitative performance outcomes, comparing what peak reduction and cost savings the three coordination approaches achieve in practice.

Table 1 synthesizes reported outcomes from field tests and simulations. We only include studies in this table that report on at least one of the considered metrics.

Alongside cost savings, studies report three peak reduction metrics: maximum instantaneous power reduction, intervention-period reduction, and threshold energy reduction. Maximum power reduction reflects the system's ability to lower peak capacity requirements, which is particularly relevant for infrastructure planning and addressing network stress. Intervention-period reduction measures temporary demand reduction during specific, constrained hours (e.g., morning peaks), capturing how well a coordination approach can manage acute demand spikes. Threshold energy reduction quantifies the decrease in energy supplied above a critical power level across the full considered period, indicating the extent to which costly peak-unit operation can be avoided. Cost savings, by contrast, reflect the financial benefit achieved for customers or utilities. Different coordination approaches tend to emphasize different operational objectives, which explains why some metrics appear only for certain strategies.

Direct utility control achieves its strongest results in intervention-period reductions, ranging from 25%–85%, reflecting centralized temporary demand reduction during targeted hours. Maximum power reductions are more moderate (5%–35%), while threshold reductions vary widely depending on participation rates and intervention duration

Table 1
Peak load reduction and cost savings across demand response strategies for district heating systems, rounded to full percentages.

Study	Intelligence	Peak reduction			Cost reduction	Type
		Max power[a]	In interv. period[b]	Load above threshold[c]		
Direct utility control						
Christensen et al. (2020)	Central	–	**85%**	–	–	Field test
Beltram et al. (2019)	Central	–	**68%**	–	–	Field test
Romanchenko et al. (2019)	Central	–	**25%**	–	–	Simulation
Guelpa et al. (2019)	Central	**5–35%**[d]	–	–	–	Field test
Van Oevelen et al. (2023)	Central	–	–	**60–70%**	–	Field test
Van Oevelen et al. (2020)	Central	–	–	**3–13%**[e]	–	Field test
Romanchenko et al. (2021)	Central	–	–	–	**9%**	Simulation
Wernstedt and Johansson (2008)	Central	–	–	–	**4–10%**	Field test
Dynamic price signals						
Hedegaard et al. (2019)	Hybrid	**4–5%**	–	–	–	Simulation
Suhonen et al. (2020)	Decentral	–	–	–	**1–8%**	Simulation
Cai et al. (2020)	Hybrid	–	–	–	**2%**	Simulation
Knudsen et al. (2025)	Hybrid	–	–	–	**13%**	Simulation
Mokhtari et al. (2025)	Hybrid	**34–65%**	–	–	**28–53%**	Simulation
Langner et al. (2025)	Decentral	–	–	–	**8–33%**	Field Test
Knudsen et al. (2021)	Decentral	–	–	–	**23%**	Field Test
Static price incentives						
Ala-Kotila et al. (2020)	Decentral	**14–15%**	–	–	–	Field Test
Håkansson et al. (2024)	Decentral	**10–20%**	–	–	–	Simulation

[a] Maximum Power Reduction: Reduction in maximum instantaneous system demand.
[b] Intervention Period: Peak load reduction during active demand response intervention window (e.g., 06:00–12:00).
[c] Threshold Energy: Reduction in energy supplied above the defined power threshold.
[d] 5% field test (30% of buildings participate, 20 min intervention), 35% simulation (100% of buildings participate, 90 min intervention).
[e] Buildings representing 34% of heat load participated. 3.1% including all months; 12.7% excluding January 2019 when new, uncontrolled building connected to grid. Dash (-) indicates metric not reported in study.

(3%–70%). Reported cost savings are limited but range from 4%–10%, consistent with the approach's focus on operational flexibility rather than direct financial optimization. Field tests provide the majority of evidence, lending greater confidence to these findings under real-world conditions.

Dynamic price signals show the widest variation in performance. Maximum power reductions range from 4%–65%, and reported cost savings span 1%–53%, depending on customer responsiveness and whether hybrid intelligence coordinates the response. High-performing simulations typically employ hybrid approaches, hinting that some level of centralized coordination could potentially enhance both peak management and cost optimization. Purely decentralized implementations achieve more variable outcomes, reflecting heterogeneity in individual customer response and more limited direct control over loads.

Static price incentives yield moderate and relatively consistent maximum power reductions (10%–20%), though evidence is limited to a small number of studies. Cost savings are not reported, reflecting the approach's long-term behavioral focus rather than short-term operational or financial objectives.

Overall, these results indicate that coordination strategy fundamentally shapes achievable outcomes. Direct control is most effective at targeted peak management, dynamic pricing produces variable performance depending on intelligence and customer response, and static incentives deliver modest but stable reductions. Observed outcomes also depend on participation rates, intervention duration, building characteristics, and whether evidence comes from field tests or simulations, which rely on behavioral assumptions. These quantitative findings provide a basis for evaluating trade-offs between peak reduction, cost savings, and operational complexity in residential demand response schemes for district heating networks.

4.7. Summary

Our analysis of the five key dimensions – goals, thermal comfort, intelligence, coordination, and incentive – determine how residential demand response is implemented in DH systems. Coordination methods emerge as particularly influential, with direct utility control, dynamic price signals, and static price incentives each creating distinct system architectures. This coordination choice significantly affects other dimensions, especially intelligence mechanisms and incentive structures, as well as achievable outcomes. Meanwhile, the goals of residential demand response in DH consistently focus on economic optimization, either through peak reduction or cost minimization-while approaches to thermal comfort show considerable variation across studies.

5. Fundamental interaction patterns

Section 4 identified five key dimensions shaping utility-customer interactions: goals, thermal comfort, intelligence, coordination, and incentives. While utility goals and operational constraints influence which coordination approaches are feasible, our analysis reveals that each approach can address multiple objectives with different capabilities and tradeoffs. Critically, once a coordination approach is adopted, it strongly shapes intelligence mechanisms, incentive structures, technological requirements, and risk distribution. Organizing our synthesis around coordination patterns, therefore, enables systematic comparison of what each approach requires and delivers in practice. This helps utilities understand the full implications of their coordination strategy and evaluate which approach best fits their specific context.

Fig. 4 illustrates the relationships between coordination styles and the remaining dimensions observed in the considered literature, distinguishing between strong and weak associations. Strong associations indicate dimensions that appear in over 30% of studies employing a given coordination approach; weak associations appear in less than 30% of the respective studies, but at least once. Direct utility control shows strong associations with peak reduction goals and centralized intelligence, with weaker links to accommodating price fluctuations. Dynamic pricing is strongly associated with price fluctuation response and hybrid or decentralized intelligence, while also enabling peak reduction in some configurations. Static incentives primarily connect to peak reduction goals through decentralized approaches. There appears to be no relation between the choice of coordination strategy and the chosen approach for ensuring thermal comfort. However, it is important to note that only in the case of direct utility control, the utility is concerned with the conflict between load shifting and thermal comfort, as in indirect approaches, the customer is responsible for controlling their load changes and thus also for thermal comfort.

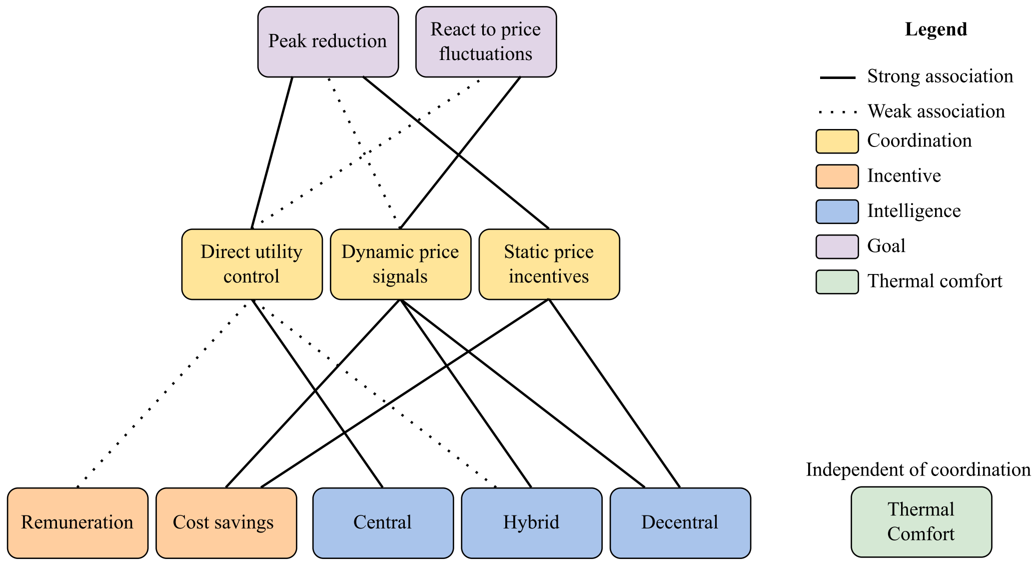
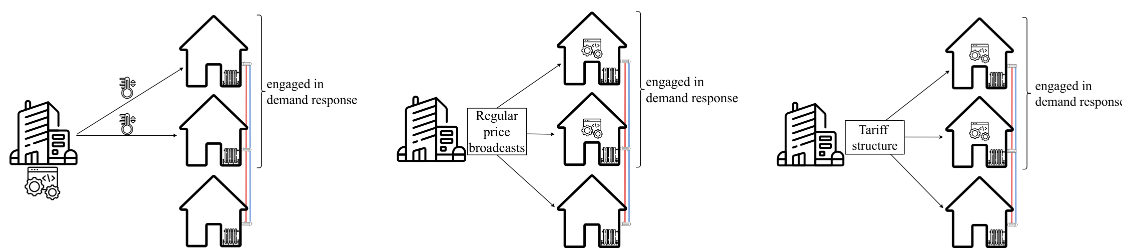


Fig. 4. The interplay between coordination style and other dimensions of utility customer interaction present in the considered literature. Strong association indicates a dimension is present in more than 30% of studies with a given coordination approach, weak associations appear in less than 30% of the respective studies, but at least once. No association indicates a dimension is not present in any of the reviewed studies for a given coordination type.



(a) Direct utility control. (b) Dynamic price signals. (c) Static price incentives.

Fig. 5. The three fundamental interaction styles between utility and residential customer: (a) direct utility control, (b) dynamic price signals, and (c) static price incentives.

These relationships manifest in three distinct interaction patterns between utilities and residential customers, characterized by the underlying coordination mechanism, as shown in Fig. 5. In direct utility control, the utility centrally optimizes heat loads and directly adjusts household consumption. Importantly, different households can receive individualized control signals depending on their preferences. If the program is opt-in, participants can also choose not to receive any signals at all. Dynamic price signals shift decision-making to customers, who respond to real-time economic incentives through cost-optimizing behavior. Static price incentives establish long-term cost frameworks that guide adjustments in heating behavior without requiring frequent communication. In the case of dynamic prices and static price incentives, engaging in demand response means reacting to the incentive provided. Customers who do not wish to participate thus have the option of not reacting to the provided economic incentive and do not have to invest in smart devices. However, they might miss out on potential savings or even face elevated costs.

Based on these insights, this section examines these interaction patterns across their key operational dimensions and strategic implications. First, we analyze how each coordination approach shapes practical aspects such as information flow, infrastructure requirements, and risk distribution. Then, we explore the strategic factors that influence utilities' selection decisions and implementation challenges.

5.1. Operational dimensions

Each interaction style exhibits distinct characteristics across several practical implementation dimensions that determine the feasibility and effectiveness of demand response programs in DH systems. These dimensions include information exchange and technical requirements, risk distribution between stakeholders, response flexibility, implementation complexity, privacy considerations, and scalability potential. The following analysis examines these operational differences across the three coordination approaches.

5.1.1. Information exchange and technical requirements

The effectiveness of each interaction pattern depends heavily on its underlying communication systems and technological components, which determine how information flows between utilities and customers and what physical infrastructure is required. All three coordination approaches share a fundamental requirement for smart sensors and actuators at the building level to enable any form of automated demand response (Christensen et al., 2022; Hedegaard et al., 2019; Kontu et al., 2019). These base technologies allow for monitoring thermal conditions and adjusting heat consumption, regardless of who controls them or how decisions are made. Beyond this common foundation, the approaches diverge significantly in their communication patterns and additional technological requirements.

Direct utility control establishes a high-frequency, bidirectional information exchange system where thermal state data flows from buildings to central utility systems, and control commands return to local heating systems (Christensen et al., 2022). This approach requires a comprehensive infrastructure, including reliable communication networks capable of handling substantial data traffic. The entire system must function cohesively, with utility control signals reliably translating to physical adjustments in household heating. With respect to the practical implementation of this coordination mechanism, this creates significant questions about equipment procurement, installation, and maintenance responsibilities.

Dynamic price signals operate through less frequent, primarily unidirectional communication, where utilities broadcast price updates reflecting current system conditions (Golmohamadi and Larsen, 2022). Although this reduced exchange frequency simplifies network requirements, it shifts the technological burden predominantly to customers who need Home Energy Management Systems (HEMSs) capable of autonomous optimization in response to these signals (Hedegaard et al., 2019). In addition, smart heat meters become essential for accurate consumption measurement and dynamic time-varying billing. Without investment in these technologies, the benefits of dynamic pricing remain largely inaccessible.

Static price incentives function with minimal ongoing communication, relying on predefined incentives rather than real-time signals (Håkansson et al., 2024). The technological requirements vary depending on the specific pricing mechanism: peak-based pricing requires meters capable of recording maximum consumption values, while time-of-use pricing necessitates meters that track consumption during different predefined time blocks. Although these approaches can operate with a simpler metering infrastructure than real-time pricing, accessing their full benefits still requires some form of automation or HEMS. Without automated responses to tariff incentives, customers are unlikely to optimize their consumption patterns consistently (Eguiarte et al., 2022), particularly for peak avoidance, where timing precision is crucial. When it comes to static time-of-use tariffs, devices allowing programmable heat plans would most likely already be sufficient.

5.1.2. Risk distribution

Each pattern creates a distinct allocation of financial, operational, and comfort-related risks between utilities and customers. Direct control concentrates operational responsibility at the utility level, guaranteeing thermal comfort while optimizing system performance (Christensen et al., 2020). Customers only trade a certain degree of autonomy for the possibility of financial remuneration (Christensen et al., 2022). Dynamic pricing shifts the economic risk towards customers, who must optimize their consumption in response to fluctuating prices or face potentially increased cost (Golmohamadi and Larsen, 2022; Hedegaard et al., 2019). Utilities face reduced operational complexity but must accurately predict aggregate responses to price signals to avoid inducing potentially costly peak loads (Hedegaard et al., 2019). In addition, dynamic heat prices can affect revenue management and complicate financial planning, particularly for capital-intensive technologies that require pricing consistently above marginal costs to ensure cost recovery (Dominković et al., 2018). Static price incentives establish more predictable risk frameworks. The static nature of these incentives provides customers with transparent cost structures for long-term planning, while utilities gain consistent behavioral changes but surrender immediate load flexibility (Kontu et al., 2019). The primary risk for utilities lies in correctly calibrating incentives to achieve desired consumption patterns and to anticipate the customer's reaction to the incentive structure correctly.

5.1.3. Flexibility and responsiveness

The different interaction patterns offer distinct response capabilities. Direct control provides immediate, deterministic load management, which is particularly valuable during critical periods. This approach excels at addressing acute system constraints like extreme peaks, as demonstrated by field trials showing load reductions of 25%–85% during intervention periods (Christensen et al., 2020; Beltram et al., 2019; Romanchenko et al., 2019). The immediate responsiveness to system needs makes this approach particularly effective for handling morning peaks (Christensen et al., 2022) or other predictable high-demand periods. Dynamic pricing creates market-mediated responses dependent on customer price sensitivity. While less immediate than direct control, this approach effectively shifts loads when price differentials adequately reflect system needs (Hedegaard et al., 2019). Studies show that dynamic pricing can achieve meaningful cost savings of 1%–53% (Suhonen et al., 2020; Mokhtari et al., 2025) and in some cases, when applied with hybrid intelligence, even peak reductions of 4%–65% by incentivizing customers to adjust their consumption patterns based on price signals (Mokhtari et al., 2025; Hedegaard et al., 2019). Static price incentives generate minimal short-term flexibility but potentially strong long-term behavioral adaptation. As customers align consumption patterns with standing incentives, the system benefits from durable demand reshaping. Research demonstrates that appropriately designed static price incentives can lead to sustained peak reduction by 10%–20% and overall demand changes as customers adjust their consumption patterns in response to the incentive posed by a fixed tariff structure (Håkansson et al., 2024; Kontu et al., 2019).

5.1.4. Implementation complexity

Implementation pathways of the different coordination approaches vary substantially. Direct control faces significant technical challenges: system integration across diverse buildings, optimization algorithm development, and thermal comfort guarantees. This approach requires substantial expertise and careful customer engagement. Studies implementing centralized optimization models highlight the complexity of co-optimizing both heat generation scheduling and space-heating demands (Romanchenko et al., 2019) while addressing computational efficiency challenges (Hamp and Levihn, 2022). The need to respect individual thermal comfort preferences adds further complexity, as highlighted by research on the equitable distribution of thermal discomfort across participating households in direct control systems (Bhattacharya et al., 2016). Dynamic pricing requires market mechanisms that accurately reflect system conditions without creating unintended consequences like excessive, synchronous customer behaviors. Balancing price responsiveness with stability presents ongoing challenges. Research acknowledges that high participation rates among flexible customers could potentially lead to avalanche effects overwhelming network constraints (Hedegaard et al., 2019). Some approaches address this challenge by incorporating network constraints into their dynamic-pricing coordinated model. There, an additional instance, a network agent receiving the schedules of multiple participating households, ensures the network constraints are met while allowing autonomous customer decisions (Cai et al., 2020). Lastly, static price incentives present operational challenges primarily in the planning phase. The key difficulty lies in accurately forecasting customer responses to price structures before implementation (Håkansson et al., 2024). Unlike direct control's real-time challenges, static price incentives require advance prediction of aggregate consumption changes, with limited ability to make quick adjustments if responses do not match expectations. This forecasting uncertainty complicates system planning when attempting to leverage price-based incentives for flexibility.

5.1.5. Privacy considerations

The coordination approaches differ in their data requirements and external access considerations. Direct control systems typically utilize building thermal models that require temperature data and building parameters (Romanchenko et al., 2019; Hamp and Levihn, 2022). A notable aspect is that these systems require external entities to have direct access to building control settings, specifically temperature setpoints. Dynamic pricing approaches function with local optimization, but still require higher-resolution heat consumption measurements to enable response to time-varying prices (Golmohamadi and Larsen, 2022). Peak pricing, the most prevalent static price incentive, operates with less frequent measurements, typically requiring only standard billing data such as energy use and peak demand Kontu et al. (2019) and Håkansson et al. (2024).

Table 2
Strategic implications of coordination mechanisms for utilities.

Coordination mechanism	Strategic drivers	Implementation barriers	Optimal context
Direct utility control (Christensen et al., 2022, 2020; Beltram et al., 2019; Sweetnam et al., 2018; Romanchenko et al., 2019; Hamp and Levihn, 2022; Bhattacharya et al., 2016; Romanchenko et al., 2021; Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Wernstedt and Johansson, 2008; Li and Wang, 2015)	• Critical peak management • Guaranteed system response • Allows reactive management	• Unclear incentive • Significant infrastructure investment • Privacy and data concerns • Equipment responsibility	• Smaller networks • Systems requiring immediate response • High reliability needs
Dynamic price signals (Hedegaard et al., 2019; Suhonen et al., 2020; Golmohamadi and Larsen, 2022; Eguiarte et al., 2022; Amato et al., 2023; Cai et al., 2020; Knudsen et al., 2021, 2025; Langner et al., 2025; Mokhtari et al., 2025)	• Accomodate variable heat production costs • Distributes optimization to customer systems	• Risk of synchronized responses • Technological participation barriers • Equity and access concerns • Potential regulatory constraints	• Volatile energy procurement costs • Diverse customer base • Flexible regulatory environment
Static price incentives (Ala-Kotila et al., 2020; Håkansson et al., 2024; Kontu et al., 2019)	• Long-term peak reduction • Lowest implementation barriers • Operates with limited smart infrastructure • Transparent incentives	• Customer education requirements • Balancing simplicity and effectiveness • Limited short-term flexibility	• Customer segments with low technological adoption • Gradual transition strategies

5.1.6. Scalability and computational complexity

The coordination approaches face different scaling limitations. Direct control's centralized approach encounters increasing computational complexity as the building portfolio grows (Mayne et al., 2000). This challenge is acknowledged in research aimed at reducing computational demands in centralized control applications (Hamp and Levihn, 2022). Studies implementing centralized approaches typically demonstrate their application to limited building portfolios, such as the 134 buildings analyzed in Romanchenko et al. (2019). To overcome these computational limitations, several implementations employ heuristic approaches rather than full optimization (Christensen et al., 2022, 2020; Beltram et al., 2019). Dynamic pricing distributes computational processing across customer systems. This means that scaling does not lead to increased computational cost on the utility side. Studies show successful implementation with larger numbers of households using decentralized optimization (Hedegaard et al., 2019). The same is true for static price incentives (Håkansson et al., 2024).

5.2. Strategic implications for utilities

Based on the implications of the different interaction patterns discussed in Section 5 The choice of coordination mechanism represents a strategic decision for utilities that must align with their specific circumstances and objectives. While the dimensional analysis in the previous section highlighted operational differences, utilities must ultimately evaluate coordination approaches based on their alignment with business goals, system constraints, and customer relationships.

Table 2 highlights the key drivers and barriers associated with each coordination approach. These factors interact with the utility's specific context to determine the most appropriate strategy.

Direct utility control represents a strategic option especially well suited for scenarios that require highly reliable and deterministic responses. Its fundamental strength lies in providing utilities with guaranteed load management capabilities during critical periods, addressing acute system constraints when predictability is essential. The inherent thermal inertia of buildings, supplemented by secondary network capacity in building-level implementations, creates a natural buffer that makes direct utility control technically viable with manageable comfort impacts. While thermal buffering benefits all coordination strategies, it is particularly critical for direct control because the utility determines the timing and magnitude of heating adjustments based on system needs rather than decisions the customer is responsible for. This is especially important in building-level control scenarios where individual inhabitants cannot influence or override automated adjustments, making the thermal buffer the primary mechanism for maintaining acceptable comfort during control events. The implementation strategy must consider that complete network-scale optimization may be feasible for smaller systems, while selective deployment offers a more scalable approach for larger networks. For utilities considering this pathway, the primary strategic considerations involve balancing the clear operational advantages of direct control against the significant implementation requirements: infrastructure investment, clearly defined equipment responsibility arrangements, customer acceptance challenges, and long-term system integration. The strategic value of this approach increases in systems where flexibly dispatchable peak demand management delivers substantial operational or financial benefits.

Dynamic price signals offer a strategic advantage for utilities operating systems with variable heat production costs. This approach aligns particularly well with modern DH configurations where external factors such as electricity market fluctuations significantly influence production economics. By distributing the optimization burden to customer systems, this approach overcomes the computational scalability limitations of centralized methods while enabling more personalized comfort management. The strategic implementation challenges primarily involve market design: creating price formation mechanisms that accurately reflect system conditions, addressing the challenge of synchronized customer responses that can create problematic secondary demand peaks, overcoming technological barriers to customer participation, ensuring equitable access across diverse customer segments, and navigating the regulatory framework for variable pricing. Hybrid intelligence approaches – which combine dynamic pricing with centralized coordination mechanisms – show promise in mitigating these risks, particularly synchronized responses that can create new peak loads. However, evidence for hybrid implementations remains predominantly simulation-based. These hybrid frameworks also introduce additional complexity around price formation transparency and fairness: when central coordination influences dynamic prices or constrains customer responses, questions arise about equitable cost allocation across participants and regulatory acceptance of such intervention mechanisms. Nevertheless, the dynamic pricing approach represents a market-based strategy that leverages economic incentives to achieve system objectives while preserving customer autonomy.

Static price incentives present the lowest implementation barriers for utilities initiating demand response strategies. This approach can function effectively with limited smart infrastructure, making it accessible even without extensive technology deployment. A key strategic advantage is the provision of predictable, transparent incentives that customers can readily understand and incorporate into their decision-making processes. This predictability creates a stable framework conducive to long-term behavioral adaptation as customers gradually adjust their consumption patterns in response to consistent price signals. Strategic implementation considerations focus on structural design rather than technical complexity: carefully crafting incentive structures such as peak-based pricing that effectively influence consumption patterns, developing clear communication strategies for customer education about program benefits, balancing simplicity in design with effectiveness in achieving system objectives, and accepting the inherent trade-off of limited short-term flexibility in exchange for long-term behavioral change and system stability.

The strategic evaluation indicates that system-specific factors, including production portfolio characteristics, network constraints, existing technical infrastructure, and regulatory environment, should guide the selection of the coordination approach. Rather than viewing these approaches as mutually exclusive alternatives, utilities may benefit from considering hybrid coordination frameworks that integrate complementary elements as their systems evolve. For instance, combining static price incentives with dynamic price signals could balance stable long-term peak reduction incentives with the flexibility to respond to production cost fluctuations. Such integrated approaches, which have shown promise in electricity demand response systems (Stute and Klobasa, 2024), represent an emerging direction for DH demand response that warrants further investigation. Beyond hybrid strategies, different coordination approaches can mutually reinforce each other because they often rely on the same underlying infrastructure. For example, both static price incentives and dynamic price signals require smart meters, local sensors, or HEMS to function effectively. Leveraging this shared infrastructure can make it easier for utilities to implement multiple mechanisms simultaneously or in sequence, without duplicating investment. In some cases, the infrastructure initially installed to enable price-based strategies could later support more advanced approaches, such as limited direct utility control-but only if devices follow standardized interfaces and interoperable protocols. As DH systems continue to incorporate greater renewable integration and market connectivity, coordination approaches will likely need to evolve towards more sophisticated frameworks that address multiple operational objectives simultaneously. Phased approaches could facilitate this evolution by gradually expanding operational capabilities as infrastructure and customer engagement mature.

6. Research gaps and technological opportunities

Our systematic review of utility-customer interaction patterns in residential DH demand response has uncovered several significant research gaps that warrant further investigation. Regarding economic frameworks, the reviewed literature demonstrates a critical gap in developing effective incentive structures for direct utility control. Ten of thirteen studies examining direct utility control (Christensen et al., 2020; Beltram et al., 2019; Romanchenko et al., 2019; Hamp and Levihn, 2022; Romanchenko et al., 2021; Van Oevelen et al., 2020, 2023; Guelpa et al., 2019; Wernstedt and Johansson, 2008; Li and Wang, 2015) did not address incentives at all, while the remaining three (Christensen et al., 2022; Sweetnam et al., 2018; Bhattacharya et al., 2016) acknowledged their importance without proposing specific frameworks. This gap is particularly pronounced in building-level implementations, where the literature provides no documentation of how incentives are structured or how benefits are distributed between building owners who make participation decisions and residents who experience comfort impacts. More broadly, studies comparing residential customers' willingness to participate across different coordination approaches or incentive structures are entirely absent. This knowledge gap creates uncertainty for utilities in program design and implementation decisions, as they lack empirical guidance on how various demand response options might affect customer acceptance and participation rates across different implementation levels. However, one recent study focused on customer perceptions identified four main aspects that shape how households perceive and accept central interventions: the baseline indoor climate conditions, the timing and intensity of temperature adjustments, the degree of control residents have, and the quality of communication about the measures (Hagejärd et al., 2021). Notably, participants became less willing to accept temperature variations after a trial period with emulated interventions, suggesting that user acceptance cannot be assumed even when comfort impacts are minimal.

When it comes to human factors, while various thermal comfort approaches were identified in the literature, from uniform temperature bounds to individualized set point deviations, little research has systematically evaluated how these approaches are understood and accepted by residential customers. Given the central importance of thermal comfort to program participation, this represents a critical knowledge gap. The reviewed studies also did not thoroughly investigate how additional forms of utility-customer collaboration, such as enhanced data sharing or co-created energy management strategies, might improve the effectiveness of demand response programs. As residential energy management systems become more sophisticated, exploring these collaborative dimensions could yield valuable insights. Several methodological limitations were also identified. All reviewed studies were conducted in European contexts, primarily in Nordic countries (see Fig. 2), which limits the generalizability of findings to regions with different climate conditions, building characteristics, cultural contexts, or regulatory frameworks. This geographic concentration highlights the need for research in more diverse contexts. Only one of the reviewed papers (Christensen et al., 2020) provides open-source code, limiting reproducibility. We advocate for wider adoption of open science practices to improve transparency and collaboration (National Academies of Sciences and Policy and Global Affairs and Board on Research Data and Information and Committee on Toward an Open Science Enterprise, 2018). Additionally, the reviewed studies employed diverse and often incomparable metrics to evaluate demand response performance, making systematic comparison across approaches difficult. Developing standardized metrics for evaluating both technical performance and customer experience would facilitate more robust comparative analyses. Addressing these research gaps would advance the practical implementation of residential demand response in DH systems.

In summary, future research directions should include developing robust incentive structures for direct utility control, exploring hybrid coordination mechanisms, and expanding the geographical scope of field studies to more diverse contexts. Motivated by these research gaps and the practical challenges identified throughout the review, we now outline technological opportunities that could address barriers for each coordination approach.

For direct utility control, computational scalability and infrastructure requirements present significant barriers to widespread deployment. Control architectures operating at building level-adjusting heat supply through substations serving multi-family buildings-while monitoring indoor thermal conditions in selected representative dwellings, represent an underexplored middle ground between comprehensive household-level control and purely building-level operation. Such approaches could enable verification of thermal comfort maintenance and calibration of control strategies based on actual thermal response, without requiring control points and sensors in every dwelling. Edge computing frameworks that distribute optimization tasks across local controllers while maintaining system-level coordination could simultaneously address scalability constraints and privacy concerns. Development of low-cost, interoperable controllers compatible with existing heating infrastructure could reduce deployment barriers by enabling retrofit rather than requiring new installations. Additionally, the lack of established incentive structures suggests a need for technology supporting automated benefit tracking and compensation distribution, particularly for building-level implementations where arrangements between building owners and residents remain undocumented.

For dynamic pricing, the risk of synchronized customer responses creating secondary demand peaks represents a persistent challenge. While individual HEMS with price-responsive optimization have been demonstrated, coordination mechanisms to prevent avalanche effects remain underdeveloped. Hybrid intelligence approaches combining dynamic price signals with coordination elements show promise but introduce regulatory challenges: price formation algorithms that incorporate network constraints or coordination objectives beyond marginal heat provision costs may face regulatory scrutiny regarding pricing transparency and fairness. Technology enabling explainable hybrid price formation – clearly communicating how prices reflect both heat provision costs and system coordination needs – warrants development to address these concerns. Combining static price components with dynamic signals represents another approach that could mitigate overload risks while maintaining flexibility; such hybrid tariff structures have shown promise in electricity demand response systems (Stute and Klobasa, 2024) but remain underexplored in DH contexts.

For static incentives, while peak-based pricing structures already exist in several countries, customer awareness and engagement remain limited, leaving significant savings potential unrealized. Technology supporting customer understanding of savings opportunities and available automation solutions could enable broader participation in existing programs. Tools visualizing consumption patterns relative to tariff structures, estimating potential savings from behavioral changes, and guiding technology adoption decisions warrant development. Simple automation solutions enabling effective response to static tariffs – such as tariff-aware programmable thermostats with intuitive feedback – could lower participation barriers. Beyond their immediate value, such technologies could serve as stepping stones towards dynamic coordination, familiarizing customers with automated demand response concepts while operating under simpler tariff structures.

Across all coordination approaches, development of open communication standards and interoperable platforms enabling evolutionary implementation pathways receives limited attention, yet appears critical for reducing vendor lock-in risks and allowing utilities to progress from simpler to more sophisticated coordination without infrastructure replacement.

7. Conclusion

This systematic review synthesizes evidence from 26 studies and identifies three distinct coordination patterns for residential demand response in DH: direct utility control, dynamic price signals, and static price incentives. These coordination approaches shape implementation requirements, stakeholder relationships, performance characteristics, and the distribution of decision-making across the system. Understanding these interaction patterns is essential for translating technical capabilities into operational demand response programs.

The quantitative evidence highlights both the performance potential and the heterogeneity of evaluation approaches. Direct utility control demonstrates targeted peak management capabilities, with maximum power reductions of 5%–35% and intervention-period reductions of 25%–85%. Field implementations using central heuristic control have demonstrated household-level viability, while centralized MPC remains predominantly at aggregated infrastructure levels or in simulation studies. Dynamic price signals yield the widest range of outcomes (4%–65% peak reduction, 1%–53% cost savings), reflecting sensitivity to customer responsiveness and coordination design. Purely decentralized implementations face risks of synchronized reactions that may amplify rather than reduce peaks. Hybrid approaches incorporating central coordination mechanisms can mitigate these risks but introduce additional implementation complexity and remain primarily at the simulation scale. Static price incentives deliver consistent 10%–20% reductions with minimal communication requirements, though they offer limited short-term flexibility for addressing acute system imbalances. The diversity of performance metrics, including maximum power reduction, intervention-period reduction, threshold-based energy reduction, and cost savings, underscores that coordination mechanisms support different system objectives.

Consistent trade-offs emerge across approaches. Greater operational control and reliability tend to require higher infrastructure investment and more complex institutional arrangements, while lower-barrier approaches provide less predictable flexibility and face greater uncertainty in performance outcomes. Field validation maturity varies substantially, and the geographic concentration in Northern Europe limits generalizability across diverse building typologies, climates, and regulatory environments.

As detailed in Section 6, significant research gaps remain, particularly regarding incentive design for direct control, benefit distribution mechanisms in building-level implementations, and comparative evidence on customer acceptance. Addressing these gaps will become increasingly important as DH systems integrate larger shares of renewable and variable heat sources, requiring greater demand-side flexibility to balance supply and demand.

This review provides a structured framework for understanding how coordination choices shape implementation requirements and performance characteristics. By synthesizing evidence from field studies and simulations, our analysis helps utilities assess the operational implications and identify research limitations associated with different coordination patterns, supporting more informed planning for residential demand response programs aligned with specific operational, regulatory, and infrastructural contexts.

CRediT authorship contribution statement

Oliver Resch: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Leo Semmelmann:** Writing – review & editing, Validation, Supervision, Conceptualization. **Christof Weinhardt:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude and ChatGPT 4o and 5 for language refinement and grammar correction. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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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Table A.1
Identified key aspects and associated categories per study.

Study	Goal			Thermal comfort							Intelligence				Coordination			Incentive		
				Uniform		Individual			Other		Central		Decentral							
	Peak reduction	Accommodate fluctuating prices	Other	Set point deviation bounds	Temperature bounds	Set point deviation bounds	Temperature bounds	In objective function	Only certain rooms	No automatic actuation	MPC	Heuristic	MPC	Heuristic	Direct utility control	Dynamic price signals	Static price incentives	Cost savings	Remuneration	Not addressed
Christensen et al. (2022)	×			×								×			×				×	
Hedegaard et al. (2019)	×			×								×	×			×		×		
Suhonen et al. (2020)		×			×								×			×		×		
Ala-Kotila et al. (2020)	×			×										×			×	×		
Christensen et al. (2020)	×			×					×			×			×					×
Beltram et al. (2019)	×			×					×			×			×					×
Sweetnam et al. (2018)	×			×								×	×		×				×	
Golmohamadi and Larsen (2022)		×						×					×			×		×		
Håkansson et al. (2024)	×						×						×				×	×		
Eguiarte et al. (2022)		×								×				×		×		×		
Romanchenko et al. (2019)	×			×							×				×					×
Kontu et al. (2019)	×												×				×	×		
Hamp and Levihn (2022)			×			×					×				×					×
Amato et al. (2023)			×						×					×		×		×		
Bhattacharya et al. (2016)			×					×			×				×				×	
Cai et al. (2020)		×						×					×			×		×		
Romanchenko et al. (2021)		×		×							×				×					×
Van Oevelen et al. (2023)	×				×						×				×					×
Van Oevelen et al. (2020)	×				×						×				×					×
Guelpa et al. (2017, 2019), Vittorio et al. (2019)	×			×								×			×					×
Wernstedt et al. (2007), Wernstedt and Johansson (2008)	×				×							×			×					×
Li and Wang (2015)	×			×								×			×					×
Knudsen et al. (2025)		×				×						×	×			×		×		
Mokhtari et al. (2025)	×	×			×							×		×		×		×		
Langner et al. (2025)		×			×								×			×		×		
Knudsen et al. (2021)		×			×								×			×		×		
Count	15	9	3	10	7	2	1	3	3	1	6	9	10	5	13	10	3	13	3	10

Appendix. Supplementary tables

Table A.1 provides a comprehensive overview of how each analyzed study addresses the five key dimensions of utility-customer interaction in residential demand response in DH: goals, thermal comfort considerations, mechanisms for intelligent control, coordination approaches, and incentive structures.

For a detailed evaluation of the key concepts associated with each study included in the review refer to Table A.2.

Table A.2
Complete evaluation of the considered studies.

Study	Goal	Thermal Comfort	Intelligence	Coordination	Building Thermal Model	Incentive	Technological Prerequisites Customer	Experimental Setup
Christensen et al. (2022)	Reduction of morning peak	Limit off period to 2 h, maximum pre-heating of 2 degrees above set point	None, typical behavior of EMPC of radiators by utility was simulated	During study: Direct remote control of radiators either turning them off or pre-heat before anticipated peak time	Not addressed as only fixed set point variations were considered	Not tested, but participates mentioned economic benefit as key motivator to participate in DR	Thermostats allowing remote actuation	Real world test in three one storey buildings in Denmark
Hedegaard et al. (2019)	Reduction of fluctuating heat consumption caused by domestic hot water consumption peaks	User specified lower and upper temperature bounds, in simulation uniform bounds used for sake of interpretation	EMPC employed by each consumer, utility optimizes peak prices by simulating demand response	Indirect control through price signals at the time of demand peaks	Modification of RC-network based building energy model in ISO 13790 calibrated with Bayesian statistical framework	Time varying prices with increased prices during peaks	Energy management system capable of price-based optimization, remote controlled thermostats	Simulation study including 159 single family houses in Denmark
Suhonen et al. (2020)	Cost reduction for flexible DH customers by optimizing based on electricity price CHP can capture	Uniform temperature bounds: Use of acceptable indoor temperatures defined by the Finnish Society of Indoor Air Quality	Rule-based demand response control at customer site based on hourly future energy price	Indirect control through dynamic prices based on marginal cost	IDA Indoor Climate and Energy Simulation Software (IDA ICE)e	Dynamic prices dependent on electricity price	Thermostats allowing remote actuation, decentral ICT for price-based optimization, IDA ICE	Simulation study for three building types, one of which is residential in German and Finnish climate
Ala-Kotila et al. (2020)	Peak demand reduction by DHW priorization	Uniform bounds of 0.5 degrees Celsius around set point	Algorithm prioritizing DHW at the expense of space heating deployed by customer or building owners	Indirect through pricing policy incentivizing reduction of individual peaks	Talotohtori Building Management System	Price-based: prices composed of usage price and peak price component	Real time tap water sensors, remote controlled DH valves, cloud based Energy Management System (EMS)	Field test was conducted in 27 residential student buildings in Finland
Christensen et al. (2020)	Reduce heating demand in peak load hours	Integrated into control algorithm: Maximum setpoint offset is 2 degrees Celsius, exclusion of bathrooms from the rooms participating in DR	Time-based set point intervention coordinated by penalty signals to reduce morning peak	Remotely controlled change of set points	Not addressed as only fixed set point variations were considered, however, empirical data of thermal behavior was collected and analyzed	Not mentioned	Remotely controllable sensors and actuators, ICT, centralized optimization handled by supplier or third party	Living Lab experiment in selected flats of multi-storey residential building with 72 apartments in Denmark
Beltram et al. (2019)	Peak demand shaving	Integrated into control algorithm: Maximum setpoint offset is 1.5 degree Celsius, exclusion of bathrooms	Fixed schedule based on set point heuristic	Direct remote control of set points in individual rooms	Not mentioned	Not mentioned	Remotely controllable sensors and actuators and corresponding ICT, control handled by supplier or third party	16 apartments in multi-storey building of 72 apartments in Denmark that participated in field test

(continued on next page)

Table A.2 (*continued*).

Study	Goal	Thermal Comfort	Intelligence	Coordination	Building Thermal Model	Incentive	Technological Prerequisites Customer	Experimental Setup
Sweetnam et al. (2018)	Reduce load factor	Limit temperature fluctuation to 1 degree Celsius around set point during occupancy	Combination of MPC optimization at customer site and active demand shaping algorithm coordinating aggregated demand	Sending demand constraint signals directly to HEMS which integrates the signal into the local operation schedule based on MPC	Building model from PassivSystems HEMS calibrated with data from the first four weeks of the experiment	Fixed remuneration is proposed by participants as incentive	Remotely controllable thermostats, HEMS capable of communicating with cloud based demand coordination service	Field trial with 28 homes built between 2010 and 2015 in England
Golmohamadi and Larsen (2022)	Minimize individual energy consumption cost	Set point deviations are punished by weighted penalty in objective function, individual upper and lower temperature thresholds	EMPC	Indirect: Hourly dynamic heat price is provided 24 h ahead, based on which households optimize their heat demand	State-space RC model for thermal dynamics in multi-room buildings using 3-state differential equations and Continuous-Time Stochastic Model (CTSM)	Dynamic hourly prices of heat	Remotely controllable mixing loop, ICT for local EMPC	Simulations of a 150sqm danish test house with four temperature zones
Håkansson et al. (2024)	Reduce linear combination of peak demand and average demand	Individual and time varying comfort levels can be set	EMPC, on house and on group level	Indirect through definition of pricing policy	Linear gray-box model	Two price components: tariffs are based on both energy consumption and peak demand	Means for physically varying heat demand not specifically addressed, but presumably some form of remotely controllable actuator and ICT for local EMPC	Simulations based on data of 20 multi-family dwellings in Sweden
Eguiarte et al. (2022)	Reduce costs for consumers in scenario where DH is complemented by distributed HPs	Ensured by only providing recommendations to users which adjust heating settings themselves	Rule based decision on prioritizing either HP or DH	Indirect through day-ahead recommendations based on weather forecasts, tariff predictions, and system performance	Linear heat demand model based on heat transfer coefficient and difference between indoor and outdoor temperature	Time varying electricity prices	Some internet connected device for receiving recommendations	Field experiment including 6 dwellings in Serbia
Romanchenko et al. (2019)	Reduction in peak demand through pre-heating	Maximum upwards variation of 3 degrees to comply with ISO 7730:2005 for Ergonomics of the Thermal Environment	Centralized demand–supply optimization model co-optimizing dispatch and space-heating demands	Direct control of set points in participating buildings	Physical space heating demand model of building stock based on the Energy Carbon and Cost Assessment of Building Stocks model Mata et al. (2013) incorporating ISO 13790	Not modeled	Remotely controllable set points	134 representative buildings of the building stock in Gothenburg, Sweden
Kontu et al. (2019)	Reduction of individual heating costs by peak demand reduction	Not discussed but possibly included in the commercial solution used by customers- most probably some form of EMPC	Commercial solution implemented locally at customers	DH company not involved, but can modify incentive through pricing scheme	Part of the commercial model	Pricing policy: Heat price consisting of two components: heat energy consumed and peak load	Autonomous heat flow control, HEMS capable of price-based heat load optimization	Empirical real life study of 109 households with DH in Finland, with 31 of these implementing DSM measures including DR

(*continued on next page*)

Table A.2 (*continued*).

Study	Goal	Thermal Comfort	Intelligence	Coordination	Building Thermal Model	Incentive	Technological Prerequisites Customer	Experimental Setup
Hamp and Levihn (2022)	Unlock flexibility in thermal demands through centrally controlled DR	Individual accepted set point fluctuation	MPC	Direct control through centralized unit that determines optimal control strategy	3R3C resistance–capacitor building model	Not addressed	Remotely controllable DH valve	Simulation on multi-zoned building based of data from 10 inhabited Swedish residential buildings
Amato et al. (2023)	Enabling use of EMP to facilitate DR in DH-connected buildingsC	Separation of the house into active and passive rooms with only active rooms participating in DR	None, typical behavior of EMPC of radiators was simulated	In the study, the set point changes are controlled locally by a home automation system	Not used but mentioned as crucial aspect for future implementation of EMPC	Not addressed	Remotely controllable radiator valves, remotely accessible temperature sensors, home automation system	Field study in single family building in Denmark
Bhattacharya et al. (2016)	Identify DR mechanisms that promote thermal fairness	Discomfort defined by linear deviation from individual setpoint with utility function minimizing the time averaged total discomfort	Convex optimization problem with linear constraints	Direct control of set points in participating buildings	1R1C resistance–capacitor thermal model	Not modeled, yet some form of monetary incentive acknowledged to be crucial part of DR	Remotely controllable set points	Simulation study of 10 buildings connected to DH grid in parallel topology
Cai et al. (2020)	Reduce energy cost	Set point deviations are punished by discomfort cost in objective function	exchange ADMM	Dynamic prices and network agent ensuring network constraints are met	1R1C resistance–capacitor thermal model	Dynamic heat prices	Remotely controllable set points, at-home microcontrollers, ICT for communicating with substations	Simulation study and subsequent real world experiments in a set of 21 residential and one commercial building in Copenhagen
Romanchenko et al. (2021)	Reduce energy cost	Fixed temperature range around setpoints assumed to be uniform	Energy balance unit commitment optimization	Direct utility control	Physical space heating demand model of building stock based on the Energy Carbon and Cost Assessment of Building Stocks model Mata et al. (2013) incorporating ISO 13790	Not addressed	Remotely controllable setpoints	Simulation of 134 buildings, including residential and non-residential in Gothemburg considering projected heat demand in 2050
Van Oevelen et al. (2023)	Reduce peak loads	Uniform temperature bounds	Central MPC with time horizon of 24 h in 15 min time increments	Direct control of MFH substation to adjust the secondary side supply temperature	Linear gray box model for heating demands, heat transfer models for heat exchangers, Network model for DH Network	Not addressed	Remote access to substations and mixing stations	Field test with one multi family and 34 single family homes in Brescia, Italy
Van Oevelen et al. (2020)	Reduce peak Loads, accommodate market prices	Uniform temperature bounds (but no explicit comfort modeling or validation)	Centralized demand–supply matching using self-learning algorithms and predictive control	Direct control of building thermal systems via sensor override and flow restrictions	Physical space heating demand model based on building thermal mass and weather forecasting	Not modeled	Buildings with existing building management systems; external sensor override capability or gateway integration required	Field test in 134 buildings across two demonstration sites (Heerlen, Netherlands and Rottne, Sweden)

(*continued on next page*)

Table A.2 (*continued*).

Study	Goal	Thermal Comfort	Intelligence	Coordination	Building Thermal Model	Incentive	Technological Prerequisites Customer	Experimental Setup
Guelpa et al. (2017, 2019) and Vittorio et al. (2019)	Minimize thermal peaks	Short timeframe of interventions effectively limiting setpoint deviation to under 0.5 degrees Celsius	Centralized optimization using genetic algorithm with network physical modeling	Direct control of substation schedules via remote control system	No thermal building model	Not modeled	Remote substation control and flow or temperature sensors	Simulation on 103 buildings and a field test on 104 buildings with 32 controllable (Turin, Italy)
Wernstedt et al. (2007), Wernstedt and Johansson (2008)	Even out daily load fluctuations	Setpoint deviations capped to 2 degrees Celsius	Distributed multi-agent coordination system (computational distribution among building controllers for scalable utility control)	Automated direct control with agent-based allocation (utility system automatically controls building heating through coordinated software agents)	Physical thermal time constant model for thermal capacity	None	Buildings with automated controllable heat exchangers, two-way communication capability, and utility-installed control hardware	Field study in 14 multi-family buildings with 350 apartments in Karlshamn, Sweden
Li and Wang (2015)	Peak load reduction	Uniform setpoint deviation bounds	Centralized optimization with heuristic allocation rules	Direct utility control	None	None	Buildings with controllable heating systems and communication capability for temperature reporting	Simulation Study of 5 building groups (Denmark)
Knudsen et al. (2025)	Match the demand in a DH network with fluctuating waste heat supply	Uniform temperature bounds	Hybrid optimization with central signal and building-level MPC	Indirect coordination with dynamic price signal	Reduced-order RC-model	Dynamic heat price	Requires smart metering and HEMS for predictive control based on price signals	Simulation study in Trondheim, Norway in a residential area with roughly 2000 dwellings
Mokhtari et al. (2025)	Reduce household costs by adjusting to dynamic heat prices; Supplier: peak reduction and flexibilisation to accommodate fluctuating cost possible	Uniform temperature bounds (18–26 degrees Celsius)	Central price setting via inverse optimization provided flexibility function, local cost-based optimization using different controller types (rule-based, linear, sigmoid, manual)	Indirect coordination via price signal	Whitebox building models (MODELICA)	Savings based on dynamic price	Smart thermostats, controllers and ICT for bidirectional price signal communication	Simulation of 9 multi family buildings (45 flats) in Sønderborg, Denmark
Langner et al. (2025)	Household cost optimization under dynamic heat prices	Uniform temperature bounds (18–24 degrees Celsius)	Building level MPC benchmarked against fuzzy logic	Indirect coordination via prica signal	Gray boc multi-zone RC-model	Savings based on dynamic price	HEMS with access to remotely controllable sensors and actuators	Field experiment at KIT Living Lab with 3 identical single family homes in Karlsruhe, Germany
Knudsen et al. (2021)	Cost savings of individual households under dynamic heat prices	Uniform temperature bounds (21–24 degrees Celsius)	Building level Economic MPC	Indirect coordination via price signal	Black-Box state-space model	Savings based on dynamic price	Connected Heat Meter, temperature sensors and some local device for optimization	Experimental test in NTNU Living Lab in Trondheim, Norway

Data availability

No data was used for the research described in the article.

References

Ala-Kotila, P., Vainio, T., Heinonen, J., 2020. Demand response in district heating market—Results of the field tests in student apartment buildings. Smart Cities 3 (2), 157–171. http://dx.doi.org/10.3390/smartcities3020009.

Amato, V., Hedegaard, R.E., Knudsen, M.D., Petersen, S., 2023. Room-level load shifting of space heating in a single-family house – A field experiment. Energy Build. 281, 112750. http://dx.doi.org/10.1016/j.enbuild.2022.112750.

Beltram, L., Christensen, M.H., Li, R., 2019. Demonstration of heating demand peak shaving in smart homes. J. Phys.: Conf. Ser. 1343 (1), 012055. http://dx.doi.org/10.1088/1742-6596/1343/1/012055.

Bhattacharya, S., Chandan, V., Arya, V., Kar, K., 2016. Thermally-fair demand response for district heating and cooling (DHC) networks. In: Proceedings of the Seventh International Conference on Future Energy Systems. In: E-Energy '16, Association for Computing Machinery, New York, NY, USA, pp. 1–11. http://dx.doi.org/10.1145/2934328.2934343.

vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., Cleven, A., 2009. Reconstructing the giant: On the importance of rigour in documenting the literature search process. pp. 2206–2217, https://Aisel.Aisnet.Org/Ecis2009/.

Cai, H., You, S., Wu, J., 2020. Agent-based distributed demand response in district heating systems. Appl. Energy 262, 114403. http://dx.doi.org/10.1016/j.apenergy.

2019.114403.

Carpaneto, E., Lazzeroni, P., Repetto, M., 2015. Optimal integration of solar energy in a district heating network. Renew. Energy 75, 714–721. http://dx.doi.org/10.1016/j.renene.2014.10.055.

Christensen, L.R.L., Broholt, T.H., Barthelmes, V.M., Khovalyg, D., Petersen, S., 2022. A mixed-methods case study on resident thermal comfort and attitude towards peak shifting of space heating. Energy Build. 276, 112501. http://dx.doi.org/10.1016/j.enbuild.2022.112501.

Christensen, M.H., Li, R., Pinson, P., 2020. Demand side management of heat in smart homes: Living-lab experiments. Energy 195, 116993. http://dx.doi.org/10.1016/j.energy.2020.116993.

Dominković, D.F., Wahlroos, M., Syri, S., Pedersen, A.S., 2018. Influence of different technologies on dynamic pricing in district heating systems: Comparative case studies. Energy 153, 136–148. http://dx.doi.org/10.1016/j.energy.2018.04.028.

Drgoňa, J., Arroyo, J., Cupeiro Figueroa, I., Blum, D., Arendt, K., Kim, D., Ollé, E.P., Oravec, J., Wetter, M., Vrabie, D.L., Helsen, L., 2020. All you need to know about model predictive control for buildings. Annu. Rev. Control. 50, 190–232. http://dx.doi.org/10.1016/j.arcontrol.2020.09.001.

Egüez, A., 2021. District heating network ownership and prices: The case of an unregulated natural monopoly. Util. Policy 72, 101252. http://dx.doi.org/10.1016/j.jup.2021.101252.

Eguiarte, O., de Agustín-Camacho, P., Garrido-Marijuan, A., Vukovic, M., del Portillo, L., Romero-Amorrortu, A., 2022. Engaging domestic users on demand response for heating cost reduction with a recommendation tool: Case study in Belgrade. Energy Rep. 8, 325–331. http://dx.doi.org/10.1016/j.egyr.2022.01.069.

El Gohary, F., Stikvoort, B., Bartusch, C., 2023. Evaluating demand charges as instruments for managing peak-demand. Renew. Sustain. Energy Rev. 188, 113876. http://dx.doi.org/10.1016/j.rser.2023.113876.

European Commission, 2021. 'Fit for 55': Delivering the EU's 2030 climate target on the way to climate neutrality. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021DC0550.

European Commission and Directorate-General for Communication, 2021. European Green Deal – Delivering on Our Targets. Publications Office of the European Union, http://dx.doi.org/10.2775/373022.

European Commission and Directorate-General for Energy, 2022. Renewable space heating under the revised Renewable Energy Directive – ENER/C1/2018-494 – Final report. Publications Office of the European Union, http://dx.doi.org/10.2833/525486.

European Environment Agency, 2024. Share of energy consumption from renewable sources. https://www.eea.europa.eu/en/analysis/indicators/share-of-energy-consumption-from. (Accessed 13 August 2024).

European Parliament and Council of the European Union, 2023. Directive (EU) 2023/2413 of the European parliament and of the council of 18 october 2023 amending directive (EU) 2018/2001, regulation (EU) 2018/1999 and directive 98/70/EC as regards the promotion of energy from renewable sources, and repealing council directive (EU) 2015/652. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202302413. (Accessed 13 August 2024).

Eurostat, 2024. Database - energy statistics - data browser. http://dx.doi.org/10.2908/NRG_D_HHQ, (Accessed 05 August 2024).

Golmohamadi, H., Larsen, K.G., 2022. Economic heat control of mixing loop for residential buildings supplied by low-temperature district heating. J. Build. Eng. 46, 103286. http://dx.doi.org/10.1016/j.jobe.2021.103286.

Greening, L.A., 2010. Demand response resources: Who is responsible for implementation in a deregulated market? Energy 35 (4), 1518–1525. http://dx.doi.org/10.1016/j.energy.2009.12.013.

Guelpa, E., Barbero, G., Sciacovelli, A., Verda, V., 2017. Peak-shaving in district heating systems through optimal management of the thermal request of buildings. Energy 137, 706–714. http://dx.doi.org/10.1016/j.energy.2017.06.107.

Guelpa, E., Marincioni, L., Deputato, S., Capone, M., Amelio, S., Pochettino, E., Verda, V., 2019. Demand side management in district heating networks: A real application. Energy 182, 433–442. http://dx.doi.org/10.1016/j.energy.2019.05.131.

Guelpa, E., Verda, V., 2019. Thermal energy storage in district heating and cooling systems: A review. Appl. Energy 252, 113474. http://dx.doi.org/10.1016/j.apenergy.2019.113474.

Guelpa, E., Verda, V., 2021. Demand response and other demand side management techniques for district heating: A review. Energy 219, 119440. http://dx.doi.org/10.1016/j.energy.2020.119440.

Hagejärd, S., Dokter, G., Rahe, U., Femenías, P., 2021. My apartment is cold! household perceptions of indoor climate and demand-side management in Sweden. Energy Res. Soc. Sci. 73, 101948. http://dx.doi.org/10.1016/j.erss.2021.101948.

Håkansson, H., Önnheim, M., Gustavsson, E., Jirstrand, M., 2024. Effects on district heating networks by introducing demand side economic model predictive control. Energy Build. 309, 114051. http://dx.doi.org/10.1016/j.enbuild.2024.114051.

Hamp, Q., Levihn, F., 2022. Model predictive control for dynamic indoor conditioning in practice. Energy Build. 277, 112548. http://dx.doi.org/10.1016/j.enbuild.2022.112548.

Hampton, H., Foley, A., Del Rio, D.F., Smyth, B., Laverty, D., Caulfield, B., 2022. Customer engagement strategies in retail electricity markets: A comprehensive and comparative review. Energy Res. Soc. Sci. 90, 102611. http://dx.doi.org/10.1016/j.erss.2022.102611.

Hedegaard, R.E., Kristensen, M.H., Pedersen, T.H., Brun, A., Petersen, S., 2019. Bottom-up modelling methodology for urban-scale analysis of residential space heating demand response. Appl. Energy 242, 181–204. http://dx.doi.org/10.1016/j.apenergy.2019.03.063.

Idowu, S., Saguna, S., Åhlund, C., Schelén, O., 2016. Applied machine learning: Forecasting heat load in district heating system. Energy Build. 133, 478–488. http://dx.doi.org/10.1016/j.enbuild.2016.09.068.

International Energy Agency, 2023a. Buildings-related energy demand for heating and share by fuel in the Net Zero Scenario, 2022–2030. International Energy Agency, Paris, https://www.iea.org/data-and-statistics/charts/buildings-related-energy-demand-for-heating-and-share-by-fuel-in-the-net-zero-scenario-2022-2030. Licence: CC BY 4.0.

International Energy Agency, 2023b. Tracking Clean Energy Progress 2023. IEA, Paris, https://www.iea.org/reports/tracking-clean-energy-progress-2023. Licence: CC BY 4.0.

International Organization for Standardization, 2008. Energy Performance of Buildings — Calculation of Energy Use for Space Heating and Cooling. https://www.iso.org/standard/41974.html, ISO Standard 13790:2008.

Joskow, P.L., 2007. Chapter 16 regulation of natural monopoly. In: Polinsky, A., Shavell, S. (Eds.), In: Handbook of Law and Economics, vol. 2, Elsevier, pp. 1227–1348. http://dx.doi.org/10.1016/S1574-0730(07)02016-6, URL https://www.sciencedirect.com/science/article/pii/S1574073007020166.

Knudsen, M.D., Georges, L., Skeie, K.S., Petersen, S., 2021. Experimental test of a black-box economic model predictive control for residential space heating. Appl. Energy 298, 117227. http://dx.doi.org/10.1016/j.apenergy.2021.117227.

Knudsen, B.R., Zotică, C., Rohde, D., Foslie, S.S., Walnum, H.T., 2025. Assessing demand response in district heating with waste-heat utilization. Sustain. Cities Soc. 124, 106270. http://dx.doi.org/10.1016/j.scs.2025.106270.

Kontu, K., Penttinen, P., Vimpari, J., Junnila, S., 2019. From partial optimization to overall system management – real-life smart heat load control in district heating systems. Energy Build. 204, 109481. http://dx.doi.org/10.1016/j.enbuild.2019.109481.

Langner, F., Kovačević, J., Spatafora, L., Dietze, S., Waczowicz, S., Çakmak, H.K., Matthes, J., Hagenmeyer, V., 2025. Experimental evaluation of model predictive control and fuzzy logic control for demand response in buildings. Appl. Energy 401, 126666. http://dx.doi.org/10.1016/j.apenergy.2025.126666.

Li, H., Wang, S.J., 2015. Load management in district heating operation. Energy Procedia 75, 1202–1207. http://dx.doi.org/10.1016/j.egypro.2015.07.155, Clean, Efficient and Affordable Energy for a Sustainable Future: The 7th International Conference on Applied Energy (ICAE2015).

Li, X., Wen, J., 2014. Review of building energy modeling for control and operation. Renew. Sustain. Energy Rev. 37, 517–537. http://dx.doi.org/10.1016/j.rser.2014.05.056.

Luc, K.M., Heller, A., Rode, C., 2019. Energy demand flexibility in buildings and district heating systems – a literature review. Adv. Build. Energy Res. 13 (2), 241–263. http://dx.doi.org/10.1080/17512549.2018.1488615.

Lund, H., Möller, B., Mathiesen, B.V., Dyrelund, A., 2010. The role of district heating in future renewable energy systems. Energy 35 (3), 1381–1390. http://dx.doi.org/10.1016/j.energy.2009.11.023.

Lund, H., Werner, S., Wiltshire, R., Svendsen, S., Thorsen, J.E., Hvelplund, F., Mathiesen, B.V., 2014. 4Th Generation district heating (4GDH): Integrating smart thermal grids into future sustainable energy systems. Energy 68, 1–11. http://dx.doi.org/10.1016/j.energy.2014.02.089.

Ma, Z., Knotzer, A., Billanes, J.D., Jørgensen, B.N., 2020. A literature review of energy flexibility in district heating with a survey of the stakeholders' participation. Renew. Sustain. Energy Rev. 123, 109750. http://dx.doi.org/10.1016/j.rser.2020.109750.

Marszal-Pomianowska, A., Motoasca, E., Pothof, I., Felsmann, C., Heiselberg, P., Cadenbach, A., Leusbrock, I., O'Donovan, K., Petersen, S., Schaffer, M., 2024. Strengths, weaknesses, opportunities and threats of demand response in district heating and cooling systems. From passive customers to valuable assets. Smart Energy 14, 100135. http://dx.doi.org/10.1016/j.segy.2024.100135.

Mata, É., Kalagasidis, A.S., Johnsson, F., 2013. A modelling strategy for energy, carbon, and cost assessments of building stocks. Energy Build. 56, 100–108. http://dx.doi.org/10.1016/j.enbuild.2012.09.037.

Mayne, D.Q., Rawlings, J.B., Rao, C.V., Scokaert, P.O.M., 2000. Constrained model predictive control: Stability and optimality. Automatica 36 (6), 789–814. http://dx.doi.org/10.1016/S0005-1098(99)00214-9.

Meng, F., Lu, Z., Li, X., Han, W., Peng, J., Liu, X., Niu, Z., 2024. Demand-side energy management reimagined: A comprehensive literature analysis leveraging large language models. Energy 291, 130303. http://dx.doi.org/10.1016/j.energy.2024.130303.

Mokhtari, R., Madsen, H., Li, R., 2025. Exploring the impacts of consumer reaction to dynamic heat prices in district heating. Energy Build. 347, 116347. http://dx.doi.org/10.1016/j.enbuild.2025.116347.

National Academies of Sciences and Policy and Global Affairs and Board on Research Data and Information and Committee on Toward an Open Science Enterprise, 2018. Open Science by Design: Realizing a Vision for 21st Century Research. National Academies Press.

Prívara, S., Cigler, J., Váňa, Z., Oldewurtel, F., Sagerschnig, C., Žáčeková, E., 2013. Building modeling as a crucial part for building predictive control. Energy Build. 56, 8–22. http://dx.doi.org/10.1016/j.enbuild.2012.10.024.

Rezaie, B., Rosen, M.A., 2012. District heating and cooling: Review of technology and potential enhancements. Appl. Energy 93, 2–10. http://dx.doi.org/10.1016/j.apenergy.2011.04.020.

Romanchenko, D., Nyholm, E., Odenberger, M., Johnsson, F., 2019. Flexibility potential of space heating demand response in buildings for district heating systems. Energies 12 (15), 2874. http://dx.doi.org/10.3390/en12152874.

Romanchenko, D., Nyholm, E., Odenberger, M., Johnsson, F., 2021. Impacts of demand response from buildings and centralized thermal energy storage on district heating systems. Sustain. Cities Soc. 64, 102510. http://dx.doi.org/10.1016/j.scs.2020.102510.

Sayegh, M.A., Danielewicz, J., Nannou, T., Miniewicz, M., Jadwiszczak, P., Piekarska, K., Jouhara, H., 2017. Trends of European research and development in district heating technologies. Renew. Sustain. Energy Rev. 68, 1183–1192. http://dx.doi.org/10.1016/j.rser.2016.02.023.

Schmidt, D., Kallert, A., Blesl, M., Svendsen, S., Li, H., Nord, N., Sipilä, K., 2017. Low temperature district heating for future energy systems. Energy Procedia 116, 26–38. http://dx.doi.org/10.1016/j.egypro.2017.05.052.

Skoczkowski, T., Bielecki, S., Wołowicz, M., Sobczak, L., Węglarz, A., Gilewski, P., 2024. Participation in demand side response. Are individual energy users interested in this? Renew. Energy 232, 121104. http://dx.doi.org/10.1016/j.renene.2024.121104.

Sloot, D., Lehmann, N., Ardone, A., 2022. Explaining and promoting participation in demand response programs: The role of rational and moral motivations among German energy consumers. Energy Res. Soc. Sci. 84, 102431. http://dx.doi.org/10.1016/j.erss.2021.102431.

Song, J., Wallin, F., Li, H., 2017. District heating cost fluctuation caused by price model shift. Appl. Energy 194, 715–724. http://dx.doi.org/10.1016/j.apenergy.2016.09.073.

Srivastava, A., Van Passel, S., Laes, E., 2018. Assessing the success of electricity demand response programs: A meta-analysis. Energy Res. Soc. Sci. 40, 110–117. http://dx.doi.org/10.1016/j.erss.2017.12.005.

Stute, J., Klobasa, M., 2024. How do dynamic electricity tariffs and different grid charge designs interact? - Implications for residential consumers and grid reinforcement requirements. Energy Policy 189, 114062. http://dx.doi.org/10.1016/j.enpol.2024.114062.

Suhonen, J., Jokisalo, J., Kosonen, R., Kauppi, V., Ju, Y., Janßen, P., 2020. Demand response control of space heating in three different building types in Finland and Germany. Energies 13 (23), http://dx.doi.org/10.3390/en13236296.

Sweetnam, T., Spataru, C., Barrett, M., Carter, E., 2018. Domestic demand-side response on district heating networks. Build. Res. Inf. 47 (4), 330–343. http://dx.doi.org/10.1080/09613218.2018.1426314.

Torío, H., Schmidt, D., 2010. Development of system concepts for improving the performance of a waste heat district heating network with exergy analysis. Energy Build. 42 (10), 1601–1609. http://dx.doi.org/10.1016/j.enbuild.2010.04.002.

Van Oevelen, T., Neven, T., Brès, A., Schmidt, R.-R., Vanhoudt, D., 2023. Testing and evaluation of a smart controller for reducing peak loads and return temperatures in district heating networks. Smart Energy 10, 100105. http://dx.doi.org/10.1016/j.segy.2023.100105.

Van Oevelen, T., Vanhoudt, D., Johansson, C., Smulders, E., 2020. Testing and performance evaluation of the STORM controller in two demonstration sites. Energy 197, 117177. http://dx.doi.org/10.1016/j.energy.2020.117177.

Vandermeulen, A., van der Heijde, B., Helsen, L., 2018. Controlling district heating and cooling networks to unlock flexibility: A review. Energy 151, 103–115. http://dx.doi.org/10.1016/j.energy.2018.03.034.

Vittorio, V., Capone, M., Elisa, G., 2019. Optimal operation of district heating networks through demand response. Int. J. Thermodyn. 22, 35–43. http://dx.doi.org/10.5541/ijot.519101.

Webster, J., Watson, R.T., 2002. Analyzing the past to prepare for the future: Writing a literature review. MIS Q. 26 (2), xiii–xxiii, arXiv:4132319.

Werner, S., 2017. International review of district heating and cooling. Energy 137, 617–631. http://dx.doi.org/10.1016/j.energy.2017.04.045.

Wernstedt, F., Davidsson, P., Johansson, C., 2007. Demand side management in district heating systems. In: Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems. AAMAS '07, Association for Computing Machinery, New York, NY, USA, http://dx.doi.org/10.1145/1329125.1329454.

Wernstedt, F., Johansson, C., 2008. Intelligent distributed load control. In: Proceedings of the 11th International Symposium on District Heating and Cooling. Reykjavík, Iceland.

Yao, Y., Shekhar, D.K., 2021. State of the art review on model predictive control (MPC) in heating ventilation and air-conditioning (HVAC) field. Build. Environ. 200, 107952. http://dx.doi.org/10.1016/j.buildenv.2021.107952.