ANNEX 84

EBC

Energy in Building and Communities Programme

International Energy Agency

Demand management of buildings in thermal networks: Tools and methods to leverage the thermal demand response potential in buildings connected to thermal networks (Annex 84, Subtask C)

Energy in Buildings and Communities Technology Collaboration Programme

April 2025

Technology Collaboration Programme

by iea

ANNEX **84**

EBC

Energy in Building and Communities Programme

International Energy Agency

Demand management of buildings in thermal networks: Tools and methods to leverage the thermal demand response potential in buildings connected to thermal networks (Annex 84, Subtask C)

Energy in Buildings and Communities Technology Collaboration Programme

April 2025

Authors

Hicham Johra, SINTEF Community, Norway (hicham.johra@sintef.no)
Markus Schaffer, Aalborg University, Denmark (msch@build.aau.dk)
Daniel Leiria, Danfoss, Denmark (daniel.leiria@danfoss.com)
Roberto Boghetti, Idiap Research Institute and EPFL, Switzerland (roberto.boghetti@idiap.ch)
Elisa Guelpa, Politecnico di Torino, Italy (elisa.guelpa@polito.it)
Christopher Graf, Fraunhofer Institute for Energy Economics and Energy System Technology, Germany (christopher.graf@iee.fraunhofer.de)
Benedetto Nastasi, Tor Vergata University of Rome, Italy (benedetto.nastasi@outlook.com)
Ingo Leusbrock, AEE Intec, Austria (i.leusbrock@aee.at)
Anders Rhiger Hansen, Aalborg University, Denmark (arhansen@build.aau.dk)
Stefano Mazzoni, University of Roma Tor Vergata, Italy (stefano.mazzoni@uniroma2.it)
Salam Al-Saegh, University College London, United Kingdom (s.saegh@ucl.ac.uk)
Qian Wang, KTH Royal Institute of Technology, Sweden (qianwang@kth.se)
Yangzhe Chen, KTH Royal Institute of Technology, Sweden (yangzhec@kth.se)
Zeng Peng, KTH Royal Institute of Technology, Sweden (zengp@kth.se)
Jad Al Koussa, VITO, Belgium (jad.alkoussa@vito.be)

Contributing Authors

Steffen Petersen, Aarhus University, Denmark (stp@cae.au.dk)
Jérôme H. Kämpf, (jerome.kaempf@idiap.ch)

Published by Aalborg University, Fredrik Bajers Vej 7K 9220 Aalborg East Denmark

ISBN (13-digits): 978-87-94561-40-2

DOI: 10.54337/aau978-87-94561-40-2

Participating countries in the EBC TCP: Australia, Austria, Belgium, Brazil, Canada, P.R. China, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Republic of Korea, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States of America.

Additional copies of this report may be obtained from: EBC Executive Committee Support Services Unit (ESSU), C/o AECOM Ltd,
The Colmore Building, Colmore Circus Queensway, Birmingham B4 6AT, United Kingdom
www.iea-ebc.org
essu@iea-ebc.org

Preface

The International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the framework of the Organisation for Economic Co-operation and Development (OECD) to implement an international energy programme. A basic aim of the IEA is to foster international co-operation among the 30 IEA participating countries and to increase energy security through energy research, development and demonstration in the fields of technologies for energy efficiency and renewable energy sources.

The IEA Energy in Buildings and Communities Programme

The IEA co-ordinates international energy research and development (R&D) activities through a comprehensive portfolio of Technology Collaboration Programmes (TCPs). The mission of the IEA Energy in Buildings and Communities (IEA EBC) TCP is to support the acceleration of the transformation of the built environment towards more energy efficient and sustainable buildings and communities, by the development and dissemination of knowledge, technologies and processes and other solutions through international collaborative research and open innovation. (Until 2013, the IEA EBC Programme was known as the IEA Energy Conservation in Buildings and Community Systems Programme, ECBCS.)

The high priority research themes in the EBC Strategic Plan 2019-2024 are based on research drivers, national programmes within the EBC participating countries, the Future Buildings Forum (FBF) Think Tank Workshop held in Singapore in October 2017 and a Strategy Planning Workshop held at the EBC Executive Committee Meeting in November 2017. The research themes represent a collective input of the Executive Committee members and Operating Agents to exploit technological and other opportunities to save energy in the buildings sector, and to remove technical obstacles to market penetration of new energy technologies, systems and processes. Future EBC collaborative research and innovation work should have its focus on these themes.

At the Strategy Planning Workshop in 2017, some 40 research themes were developed. From those 40 themes, 10 themes of special high priority have been extracted, taking into consideration a score that was given to each theme at the workshop. The 10 high priority themes can be separated in two types namely 'Objectives' and 'Means'. These two groups are distinguished for a better understanding of the different themes.

Objectives - The strategic objectives of the EBC TCP are as follows:

- reinforcing the technical and economic basis for refurbishment of existing buildings, including financing, engagement of stakeholders and promotion of co-benefits;
- improvement of planning, construction and management processes to reduce the performance gap between design stage assessments and real-world operation;
- the creation of 'low tech', robust and affordable technologies;
- the further development of energy efficient cooling in hot and humid, or dry climates, avoiding mechanical cooling if possible;
- the creation of holistic solution sets for district level systems taking into account energy grids, overall performance, business models, engagement of stakeholders, and transport energy system implications.

Means - The strategic objectives of the EBC TCP will be achieved by the means listed below:

- the creation of tools for supporting design and construction through to operations and maintenance, including building energy standards and life cycle analysis (LCA);
- benefitting from 'living labs' to provide experience of and overcome barriers to adoption of energy efficiency measures;
- improving smart control of building services technical installations, including occupant and operator interfaces;
- addressing data issues in buildings, including non-intrusive and secure data collection;
- the development of building information modelling (BIM) as a game changer, from design and construction through to operations and maintenance.

The themes in both groups can be the subject for new Annexes, but what distinguishes them is that the 'objectives' themes are final goals or solutions (or part of) for an energy efficient built environment, while the 'means' themes are instruments or enablers to reach such a goal. These themes are explained in more detail in the EBC Strategic Plan 2019-2024.

The Executive Committee

Overall control of the IEA EBC Programme is maintained by an Executive Committee, which not only monitors existing projects, but also identifies new strategic areas in which collaborative efforts may be beneficial. As the Programme is based on a contract with the IEA, the projects are legally established as Annexes to the IEA EBC Implementing Agreement. At the present time, the following projects have been initiated by the IEA EBC Executive Committee, with completed projects identified by (*) and joint projects with the IEA Solar Heating and Cooling Technology Collaboration Programme by (☼):

Annex 1: Load Energy Determination of Buildings (*)
Annex 2: Ekistics and Advanced Community Energy Systems (*)
Annex 3: Energy Conservation in Residential Buildings (*)
Annex 4: Glasgow Commercial Building Monitoring (*)
Annex 5: Air Infiltration and Ventilation Centre
Annex 6: Energy Systems and Design of Communities (*)
Annex 7: Local Government Energy Planning (*)
Annex 8: Inhabitants Behaviour with Regard to Ventilation (*)
Annex 9: Minimum Ventilation Rates (*)
Annex 10: Building HVAC System Simulation (*)
Annex 11: Energy Auditing (*)
Annex 12: Windows and Fenestration (*)
Annex 13: Energy Management in Hospitals (*)
Annex 14: Condensation and Energy (*)
Annex 15: Energy Efficiency in Schools (*)
Annex 16: BEMS 1- User Interfaces and System Integration (*)
Annex 17: BEMS 2- Evaluation and Emulation Techniques (*)
Annex 18: Demand Controlled Ventilation Systems (*)
Annex 19: Low Slope Roof Systems (*)
Annex 20: Air Flow Patterns within Buildings (*)
Annex 21: Thermal Modelling (*)
Annex 22: Energy Efficient Communities (*)
Annex 23: Multi Zone Air Flow Modelling (COMIS) (*)
Annex 24: Heat, Air and Moisture Transfer in Envelopes (*)
Annex 25: Real time HVAC Simulation (*)
Annex 26: Energy Efficient Ventilation of Large Enclosures (*)
Annex 27: Evaluation and Demonstration of Domestic Ventilation Systems (*)
Annex 28: Low Energy Cooling Systems (*)
Annex 29: Daylight in Buildings (*)
Annex 30: Bringing Simulation to Application (*)
Annex 31: Energy-Related Environmental Impact of Buildings (*)
Annex 32: Integral Building Envelope Performance Assessment (*)
Annex 33: Advanced Local Energy Planning (*)
Annex 34: Computer-Aided Evaluation of HVAC System Performance (*)
Annex 35: Design of Energy Efficient Hybrid Ventilation (HYBVENT) (*)
Annex 36: Retrofitting of Educational Buildings (*)
Annex 37: Low Exergy Systems for Heating and Cooling of Buildings (LowEx) (*)
Annex 38: Solar Sustainable Housing (*)
Annex 39: High Performance Insulation Systems (*)
Annex 40: Building Commissioning to Improve Energy Performance (*)
Annex 41: Whole Building Heat, Air and Moisture Response (MOIST-ENG) (*)
Annex 42: The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (FC+COGEN-SIM) (*)
Annex 43: Testing and Validation of Building Energy Simulation Tools (*)
Annex 44: Integrating Environmentally Responsive Elements in Buildings (*)
Annex 45: Energy Efficient Electric Lighting for Buildings (*)
Annex 46: Holistic Assessment Tool-kit on Energy Efficient Retrofit Measures for Government Buildings (EnERGo) (*)
Annex 47: Cost-Effective Commissioning for Existing and Low Energy Buildings (*)
Annex 48: Heat Pumping and Reversible Air Conditioning (*)
Annex 49: Low Exergy Systems for High Performance Buildings and Communities (*)
Annex 50: Prefabricated Systems for Low Energy Renovation of Residential Buildings (*)
Annex 51: Energy Efficient Communities (*)
Annex 52: Towards Net Zero Energy Solar Buildings (*)
Annex 53: Total Energy Use in Buildings: Analysis and Evaluation Methods (*)
Annex 54: Integration of Micro-Generation and Related Energy Technologies in Buildings (*)
Annex 55: Reliability of Energy Efficient Building Retrofitting - Probability Assessment of Performance and Cost (RAP-RETRO) (*)
Annex 56: Cost Effective Energy and CO2 Emissions Optimization in Building Renovation (*)
Annex 57: Evaluation of Embodied Energy and CO2 Equivalent Emissions for Building Construction (*)

Annex 58: Reliable Building Energy Performance Characterisation Based on Full Scale Dynamic Measurements (*)
Annex 59: High Temperature Cooling and Low Temperature Heating in Buildings (*)
Annex 60: New Generation Computational Tools for Building and Community Energy Systems (*)
Annex 61: Business and Technical Concepts for Deep Energy Retrofit of Public Buildings (*)
Annex 62: Ventilative Cooling (*)
Annex 63: Implementation of Energy Strategies in Communities (*)
Annex 64: LowEx Communities - Optimised Performance of Energy Supply Systems with Exergy Principles (*)
Annex 65: Long-Term Performance of Super-Insulating Materials in Building Components and Systems (*)
Annex 66: Definition and Simulation of Occupant Behavior in Buildings (*)
Annex 67: Energy Flexible Buildings (*)
Annex 68: Indoor Air Quality Design and Control in Low Energy Residential Buildings (*)
Annex 69: Strategy and Practice of Adaptive Thermal Comfort in Low Energy Buildings
Annex 70: Energy Epidemiology: Analysis of Real Building Energy Use at Scale
Annex 71: Building Energy Performance Assessment Based on In-situ Measurements
Annex 72: Assessing Life Cycle Related Environmental Impacts Caused by Buildings
Annex 73: Towards Net Zero Energy Resilient Public Communities
Annex 74: Competition and Living Lab Platform
Annex 75: Cost-effective Building Renovation at District Level Combining Energy Efficiency and Renewables
Annex 76: Deep Renovation of Historic Buildings Towards Lowest Possible Energy Demand and CO_2 Emissions
Annex 77: Integrated Solutions for Daylight and Electric Lighting
Annex 78: Supplementing Ventilation with Gas-phase Air Cleaning, Implementation and Energy Implications
Annex 79: Occupant-Centric Building Design and Operation
Annex 80: Resilient Cooling
Annex 81: Data-Driven Smart Buildings
Annex 82: Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems
Annex 83: Positive Energy Districts
Annex 84: Demand Management of Buildings in Thermal Networks
Annex 85: Indirect Evaporative Cooling
Annex 86: Energy Efficient Indoor Air Quality Management in Residential Buildings
Annex 87: Energy and Indoor Environmental Quality Performance of Personalised Environmental Control Systems
Annex 88: Evaluation and Demonstration of Actual Energy Efficiency of Heat Pump Systems in Buildings
Annex 89: Ways to Implement Net-zero Whole Life Carbon Buildings
Annex 90: EBC Annex 90 / SHC Task 70 Low Carbon, High Comfort Integrated Lighting
Annex 91: Open BIM for Energy Efficient Buildings
Annex 92: Smart Materials for Energy-Efficient Heating, Cooling and IAQ Control in Residential Buildings
Annex 93: Energy Resilience of the Buildings in Remote Cold Regions
Annex 94: Validation and Verification of In-situ Building Energy Performance Measurement Techniques
Annex 95: Human-centric Building Design and Operation for a Changing Climate
Annex 96: Grid Integrated Control of Buildings
Annex 97: Sustainable Cooling in Cities

Working Group - Energy Efficiency in Educational Buildings (*)
Working Group - Indicators of Energy Efficiency in Cold Climate Buildings (*)
Working Group - Annex 36 Extension: The Energy Concept Adviser (*)
Working Group - HVAC Energy Calculation Methodologies for Non-residential Buildings (*)
Working Group - Cities and Communities
Working Group - Building Energy Codes

Summary

Subtask C of the IEA EBC Annex 84 aims to explore and review the current body of knowledge in data-driven methods and tools for smart thermal operation of buildings and district heating and cooling networks.

This report summarizes the key findings of the IEA EBC Annex 84 Subtask C. It aims to provide a comprehensive overview of state-of-the-art methods, frameworks, software, numerical tools and algorithms relevant to smart thermal management of individual buildings and building clusters connected to district heating and cooling (DHC) networks. It covers aspects such as dynamic modelling, large data treatment and analysis, automated fault detection and digital twins for the orchestration of the smart thermal operation, and demand response of buildings integrated into thermal grids. The focus lies on achieving energy-efficient, cost-effective and sustainable district heating and cooling grids. The objective of this document is to guide professionals, researchers, policymakers, and stakeholders interested in the latest advancements in building energy management that benefit district heating and cooling systems.

The key findings of the IEA EBC Annex 84, Subtask C are as follows:

- Limited suitability of existing modelling tools and co-simulation frameworks for smart control and optimization of large DHC networks with multiple buildings performing demand response and building-to-grid services.
- Future tools should be easier to use, better documented, and capable of balancing accuracy and performance when simulating large building clusters.
- The increasing availability of high-resolution smart meter data provides valuable insights into building energy use, but data challenges such as missing values, low resolution, and lack of load disaggregation need to be addressed to fully leverage smart meter data.
- Digital twins can support real-time monitoring, forecasting, optimization, and fault detection, improving overall system efficiency and reliability. They are considered a key technology for the optimal control and operation of future smart thermal grids with building clusters performing demand response.
- Machine learning approaches are being developed for automated fault detection and diagnosis, but progress is constrained by the lack of labeled and standardized data with ground truth on the fault occurrence and nature.
- Real-world implementation of smart building and smart DHC solutions is challenged by diverse data formats, hardware, control systems, and protocols. Standardization through ontologies, BIM (Building Information Modelling), and semantic principles is key to enabling interoperability and scalability.

Table of content

Abbreviations

Abbreviations	Meaning
AFDD	Automated fault detection and diagnosis
API	Application programming interface
B2G	Building-to-grid
BEM	Building energy modelling
BIM	Building information modelling
BSEC	Building and socio-economic characteristic
CHP	Combined heat and power
DC	District cooling
DH	District heating
DHC	District heating and cooling
DHN	District heating network
DHW	Domestic hot water
DMKD	Data mining and knowledge discovery
DR	Demand response
DSM	Demand-side management
EMS	Energy management system
FD	Fault detection
FMI	Functional mock-up interface
HP	Heap pump
KPI	Key performance indicator
MPC	Model-predictive control
OWL	Web ontology language
RC	Resistance-capacitance
RDF	Resource description framework
RES	Renewable energy sources
SCADA	Supervision control and data acquisition
SH	Space heating
SHM	Smart heat meter
SVR	Support vector regression
SVM	Support vector machine
TES	Thermal energy storage

Definitions

Energy performance: definition according to EN 15603:2008 (Official Journal of the EU, 19.4. 2012, p. C 115/9) and econcept (embodied energy).

Energy source: source from which useful energy can be extracted or recovered either directly or by means of a conversion or transformation process.

Energy carrier: substance or phenomenon that can be used to produce mechanical work or heat or to operate chemical or physical processes.

1. Introduction

1.1 General Context

Buildings are becoming smarter due to the widespread availability of connected devices, sensors, actuators and appliances, which can improve the indoor comfort of occupants while reducing total building operational costs, energy, and environmental footprint. At the same time, space and water heating contribute to 45% of CO2 emissions in the building sector, accounting for 12% of global energy-related CO2 emissions [1]. Space cooling, which currently represents only 15% of the energy used for heating [1], along with heating, makes up the largest portion of carbon emissions in buildings. Over the next 30 years, building floor areas are expected to double by 2070, cooling demand is projected to grow by 3% annually, but heating demand is not expected to balance out this increase, thus these energy uses are key targets for interventions aimed at a swift and effective transition to zero-carbon energy systems [2].

District heating and cooling (DHC) systems are recognized as the most sustainable solutions for meeting heating and cooling needs in densely populated areas where individual heat pump installations are impractical [2][3]. It is estimated that district heating (DH) systems supply 9% of the global heating demand in buildings and industry [4]. According to the IEA's "Net Zero by 2050" strategy [5], DH is expected to supply over 20% of the global space heating demand. The district cooling (DC) systems are in the development stage delivering around 300 PJ/year globally [6]. Yet, they are gaining the interest of the international community since the impact of climate change on global warming is now clearly visible, and the cooling demand increases even in heating-dominated locations, e.g., Austria, the Netherlands, Poland, and Canada. Additionally, the European Union has raised its CO2 emissions reduction target for 2030 from 40% to 55%. The EU's "Fit-for-55" proposal aims to achieve this goal through enhanced energy efficiency and increased reliance on renewables. As a result of these international targets, both the DHC and electrical power sectors are undergoing significant transformations, striving to eliminate fossil fuels and boost the share of renewable energy sources (RES).

The planned decarbonization of the energy system necessitates a revolution across all energy sectors and a shift towards smart energy systems, markets, and social restructuring [7][8][9][10]. A high integration of RES, such as geothermal, solar, and wind energy, either directly at DHC production units or indirectly through the electricity grid via large-scale heat pumps (HPs), may result in fluctuating heat production [11]. Consequently, DHC systems could play a critical role in buffering energy system intermittency. However, this variability presents additional challenges in DHC system operation and planning, increasing the need for long- and short-term energy storage and flexibility and, thus, interoperability between the existing and new components and functionalities located at the production and demand sides. Thus, DH systems are undergoing major changes to meet decarbonization goals and manage intermittent heat supplies to ensure consistent heat availability while stable operation and cost-optimal performance.

Thermal energy storages (TESs) offer a promising solution to enhance the controllability of DHC systems during short- and long-term operational challenges [12][13]. According to [14], TES in DHC systems can be classified by a) physical phenomenon: sensible, latent, and chemical; b) storage duration: short-term and long-term; c) location: distributed/decentralized and localized/centralized; and d) transportability: fixed and mobile. TES can be integrated into the production unit or strategically placed within the distribution network, centrally controlled by DHC operators. Water circulating in DHC network pipelines has also been explored as a source of thermal storage or driven in a decentralized manner via broadcasted incentive signals [15][16]. These TES solutions involve actions and investments on the primary side.

At the same time, every building connected to the DHC network can be seen as a decentralized TES solutions with characteristics fluctuating according to the heat demand profile of the building. The main concept behind utilizing buildings for energy storage is that for a specific time, the heat supply to the building exceeds current demand, with the stored heat used later [17]. This concept, known as energy-flexible building or demand response (DR), has been studied by international experts for over a decade, focusing on initial concept definition, formulation, simulation studies [18], general discussions on applications and challenges [19][20], and extensive reviews of evaluation metrics [21]. However, these studies are mostly academic, with generic definitions and evaluation metrics applied across different scopes, mainly in the electricity sector, without accounting for hydronics in thermal DHC systems. Despite its potential, large-scale implementation of demand response and utilisation of buildings for energy storage in DHC systems has not yet materialised, as utilities are hesitant to adopt it in daily operations. Integrating solutions for flexibility activation and control into existing DHC systems and building heating installations while ensuring customer satisfaction, economic viability, interoperability and regulatory compliance is a complex task that requires collaboration among various stakeholders with sometimes conflicting goals. These challenges limit the large-scale adoption of the demand response concept in DHC systems.

The overarching goal of IEA EBC Annex 84 "Demand Management of Buildings in Thermal Networks" is to develop comprehensive knowledge used as guidelines for the successful activation of the DR in DHC systems. The work of IEA EBC Annex 84 explores both the social and technical challenges and how they can be overcome, as well as how digitalization of the demand side (e.g., smart meters, sensors, monitoring equipment) can further facilitate large-scale DR utilization with the minimum investments.

To fulfil the aim the following specific objectives were defined for IEA EBC Annex 84:
- Provide knowledge on partners/actors involved in the energy chain and on collaboration models/instruments for successful demand management.
- Classify, evaluate and provide design solutions for new and existing building heating and cooling installations for successful demand management in various DHC networks.
- Develop methods and tools to utilize data from energy and IEQ monitoring equipment for real-time data modelling of thermal demand response potential in buildings and urban districts.
- Disseminate lessons learned from case studies collected by the Annex.

To address these objectives, the research and development work in the Annex is divided into four sub-tasks, each of which is further divided into several specific work items (see Figure 1 below).

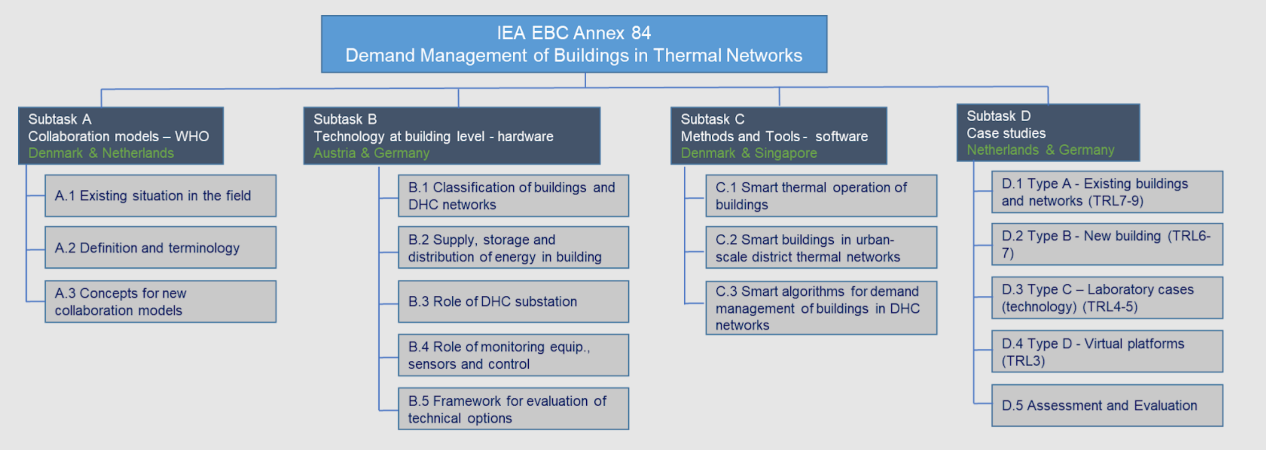

Figure 1: Structure of the IEA EBC Annex 84.

Subtask A: Collaboration Models

It investigates the motivations, challenges and limitations of key actors involved in DR. It reviews existing terminology and indicators describing the DR concept followed by the development of a common language understandable for all involved actors. It reviews the existing collaboration models and provides recommendations for the commercial utilisation of the DR concept by DHC utilities in the case studies in Subtask D.

Subtask B: Technology at Building Level

It investigates the technological options integrated at the building level to enable DR. Special attention is given to the evaluation of their ability to maintain the thermal and DHW comfort demands of the end-users while reacting to the DHC signals, to their market readiness level, and to their economic and adaptation potential in different generations of DHC systems.

Subtask C: Methods and Tools

It develops new data-driven algorithms for modelling the smart thermal operation of individual buildings and for aggregation, orchestration and feasibility studies of individual smart buildings in urban DHC systems and techno-economic system-wide optimization of DHC systems.
It provides an overview of state-of-the-art methods, frameworks, software, numerical tools and algorithms relevant to smart thermal management of individual buildings and building clusters connected to district heating and cooling networks. It covers aspects such as dynamic modelling, large data treatment and analysis, techno-economic optimization, fault detection and orchestration of the smart thermal operation and demand response of buildings integrated into thermal grids.

Subtask D: Case studies

It reviews the existing real-life and virtual buildings or cluster of buildings delivering thermal storage to DHC systems and thereby being demand-response-ready. The investigation includes the applied technological solutions, control strategies, collaboration agreements between DHC utilities and the customers, and finally the motivation of the actors to initiate the DR action.

Finally, to address the topic comprehensively and uniformly the Annex 84 has adopted the terminology, which is technology agnostic and presented in Figure 2.

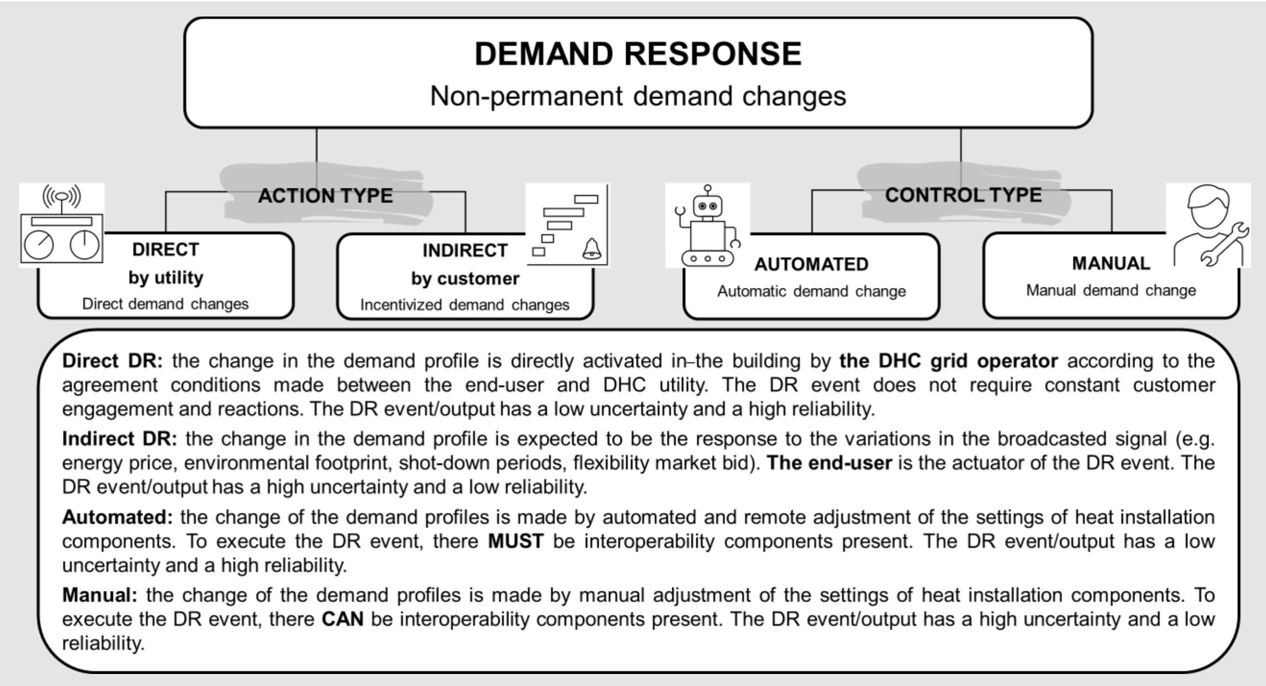

Figure 2: Terminology applied in IEA EBC Annex 84.

Combining the two action and control types there can be four different demand response types: 1) **Direct Automated** (e.g. model predictive control in the building executing a forecast of the DHC grid operator), it is characterised by high & high reliability; 2) **Indirect Automated** (e.g. model predictive control in the building reacting to the DHC broadcasted signal), it is characterised by low & high reliability; 3) **Direct Manual** (e.g. DHC operator vising the house or sitting in the control room and pressing the button), it is characterised by high & low reliability; 4) **Indirect Manual** (e.g. end users changing the settings physically of via using the remote technology (walking in the house, sitting on the sofa and using app) as the reaction to the broadcasted signal), it is characterised by low & low reliability. Figure 3 is presenting the visualisation of the four DR types.

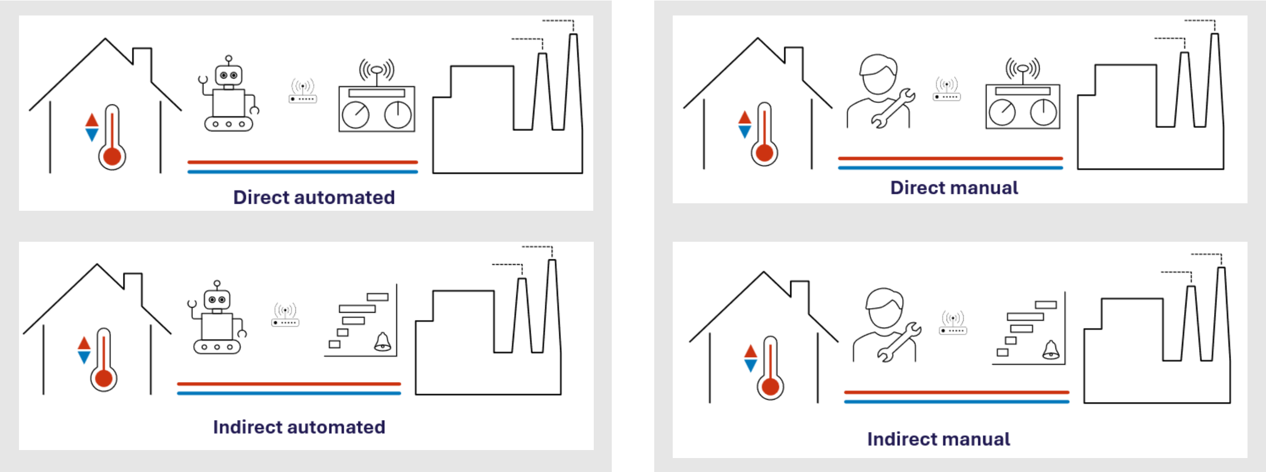

Figure 3. Illustration of the four type of DR according to Annex 84.

Finally, the direct and indirect action types proposed by Annex 84 are preferable DR mechanisms employed by the DHC operators; they indicate the level of operator involvement in the DR programme. From the customers' perspective, i.e., a more sociological viewpoint, these action types can be classified as explicit or implicit DR mechanisms. In the explicit DR, the customers receive a direct payment from the DHC utility for shifting their demand as part of the DR programme. In implicit DR, various incentives, e.g., price or CO2 signals, are used to encourage customers to modulate their demand.

1.2 Challenges and Opportunities for Demand Response in District Heating and Cooling Networks

The urgent need to decarbonise energy grids and transition away from fossil fuels toward RES to mitigate climate change, improve energy supply security, reduce pollution and address sustainability challenges requires an important paradigm shift for the largest energy end-user: the building sector. Previously considered as immutable and non-responsive loads, buildings are now becoming more and more energy-efficient, with decentralised energy production and storage assets (prosumers), operating sector coupling between the different energy grids, and capable of adapting their short-term energy demand profile to provide building-to-grid (B2G) services and help to match the energy demand with the intermittent energy supply from RES (see Figure 4).

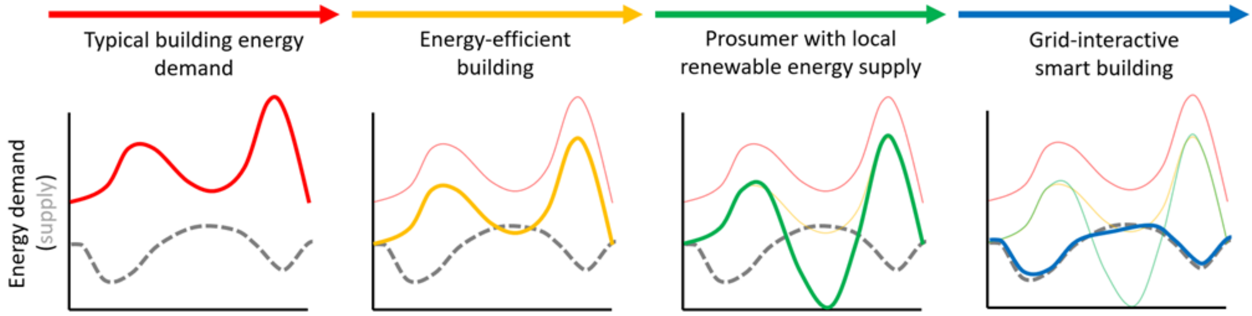

Figure 4. The emergence of a paradigm shift with energy-efficient smart building prosumers providing B2G services to optimise the operation of smart energy grids [22].

DHC systems stand out as a key technology for achieving greenhouse gas emission reduction targets by enhancing energy efficiency and increasing the share of RES. However, this relies on the transformation of current DHC networks into 4^{th}- or 5th-generation DHC with a low-temperature supply for heating grids and a relatively high-temperature supply for cooling grids.

The shift to 4th generation DHC not only facilitates integration with other energy sectors (sector coupling) and low-grade RES, but it also enables synergies by harvesting, leveraging and upcycling various local sources of industrial heat surplus.

However, DHC systems face several challenges: the need to reduce the usage or and phase out CO2-intensive district heating and cooling plants, eliminate peak power and flow limitation at local bottlenecks in energy networks, lower costly needs for reinforcement and extension of energy infrastructures and prevent the deterioration of hydronic networks caused by the unstable operation.

The building stock possesses tremendous potential for energy storage in its different distributed storage systems (hot water tanks, electrical batteries, schedulable appliances, electric vehicles), but also in the thermal mass of the indoor space and construction elements [23]. This energy storage potential can be employed to provide B2G services (in the form of demand response and building energy flexibility strategies) that can alleviate the aforementioned challenges of future thermal grids with large shares of RES.

However, orchestrating the energy flexibility assets of smart buildings and smart energy communities requires a new class of numerical modelling tools for planning, designing, controlling and operating such complex systems. In addition, the continuous digitalisation of the building stock plays a major role in unlocking the various B2G service opportunities needed to achieve sustainable thermal grids. Moreover, the large amount of data generated by the building stock can also be leveraged for the optimisation of building systems: e.g., the automated fault detection and diagnosis of district heating and cooling substations, distribution networks and heating/cooling building emitters [24]. Big-data analysis can also provide crucial insights on energy-related occupant behaviour to optimize smart home and smart building automation and building services, but also nudge highly-inefficient energy-related behaviours or provide tailored tariff structures for demand response programs [25]. All these data-driven smart building applications can only develop their full potential if interoperable data management systems using ontologies and semantic principles are deployed and maintained to ensure reliable data quality and alleviate cybersecurity risks.

2. Modelling Demand Response and Smart Thermal Operation of Buildings

2.1 Current Landscape of Available Tools

The current commercial simulation tools used by engineering and utility companies for the design, sizing, large-scale planning, and operation of DHC networks are typically unsuitable for integrating B2G services in the form of building demand response and energy flexibility strategies. Indeed, the former usually lack the required time and spatial resolution, the fully dynamic modelling of the building's indoor environment, the capacity to implement advanced control schemas, or the possibility to be coupled (co-simulation) with other building energy modelling tools. These DHC network simulation tools only account for building as pre-calculated demand profiles which cannot change the latter based on an external incentive signal or an advanced predictive controller. Most of the time, this limitation cannot be mitigated easily as these tools do not integrate interoperability mechanisms such as the Functional Mock-up Interface (FMI) framework [26].

More advanced and versatile DHC modelling tools exist, such as TRNSYS [27], Modelica (with specialized modelling libraries for buildings and DHC systems [28][29][30][31][32]), SIM-VICUS [33], IDA Districts [34], DIMOSIM [35], CitySim [36][37], APROS [38] or DistrictLab-H [39]. They allow for the dynamic thermo-hydraulic modelling of complex thermal networks with high temporal resolutions (usually down to the minute or second) and can be coupled to other simulation platforms via, most of the time, the FMI standard [26]. Recently, a number of network-only non-commercial open modelling tools developed with Python have been released, such as Pandapipes [40], PyDHN [41] and GridPenguin [42].

On the building and indoor environment modelling side, the bottom-up approach for the detailed dynamic modelling of single buildings and small clusters of buildings is often performed with white-box model tools, such as EnergyPlus [43], TRNSYS [27], IDA ICE [44], SIM-VICUS [33], IES.VE [45] or PLEIADES/COMFIE [46]. Although very accurate, white-box models are usually computationally heavy. Therefore, for the simulation of larger building clusters (or for optimization applications), simpler models (fewer input variables and model parameters) are usually employed. For instance, Modelica libraries [28][29][30][31][32] and CTSM-R [47] support the creation of Resistance-Capacitance (RC) network-based grey-box models that can be run with minimum computation burden. In addition, statistical modelling- and machine learning-based black-box approaches have gained popularity within the building energy modelling (BEM) community because of accessible libraries/packages on popular programming languages (often Python) to generate and calibrate regression models, tree-based models, support vector machines, or artificial neural networks: e.g., scikit-learn [48], and pymodconn [49][50].

Furthermore, multi-domain simulation tools, such as Modelica, SIM-VICUS, TRNSYS, or CitySim can handle both the thermodynamics of multiple buildings and thermal networks at the same time. These integrated tools do not require coupling and co-simulation frameworks, which can ease the study of DHC with demand response strategies. For instance, CitySim has been used to study the impact of DH substation's control strategies with variable building heat demand profiles to evaluate the mass flow needed in the pipes for a predefined temperature difference at the heat exchangers. If the demand of a building is not met, for instance, due to a too low distribution temperature, the insufficient supply to the building impacts the indoor operative temperature and/or the domestic hot water production temperature. Vice-versa, if the heat demand from buildings is reduced at specific periods of the day, the impact on the thermal network is properly accounted for. In that way, the impact of different demand response control logics and DHC configurations can be evaluated on a large scale. Future development directions in the CitySim tool include using Machine Learning to reproduce the physical behaviour of the DHC with a low computational burden to run optimization schemes for demand response controllers in large building clusters [36].

2.2 Modelling Approaches

White-box models require comprehensive knowledge of the system's internal mechanisms, including all governing equations and parameters. For buildings and DHC network simulations, white-box models allow for high-fidelity representation of system behaviour under varying boundary conditions and can integrate all types of energy systems, energy storages, and advanced controllers. They provide detailed insights into system dynamics, enabling engineers to accurately predict performance across different design scenarios. This facilitates the development of precise control strategies and aids in optimising system components for maximum efficiency. However, as white-box models rely on a detailed knowledge of the system's characteristics, they often require the user to make assumptions about unknown parameters that can have a significant impact on the simulation results. Furthermore, when a high level of detail in the system's components is used, white-box models' complexity can grow beyond the solver's capability, leading to poor scaling to larger systems. The simulation of hundreds or thousands of buildings in the same model with this white-box modelling approach is thus often impossible in terms of computation time and stability.

Grey-box models on the other hand, such as those available in Modelica or CTSM-R, can alleviate the limitations of white-box models by combining theoretical physical understanding with empirical data. They acknowledge that while some aspects of the system are well-understood, others are too complex or uncertain to model solely from first principles. Grey-box models achieve a balance between model complexity and computational efficiency. They can adapt to real-time data, improving prediction accuracy and offering enhanced flexibility in modelling components with partially known behaviours. In building and DHC optimisation, grey-box models are valuable for efficiently simulating system performance by incorporating theoretical knowledge and operational data, thus improving decision-making and operational strategies. Lumped RC networks the most common type of grey-box model to simulate the thermodynamics of buildings. They are widely employed for model-predictive control (MPC) applications in buildings [51].

As a relatively recent trend, black-box models rely exclusively on input-output data without any assumptions about the system's internal workings. They employ statistical or machine learning techniques to model system behaviour based solely on observed data. This approach has the advantages of rapid development using historical operational data and adaptability to complex, nonlinear system behaviours with uncertainty around the system's characteristics. Black-box models offer high flexibility in terms of what inputs can be used and which outputs should be estimated, as long as the necessary data is available or can be produced by physics-based simulations. However, the validity of the generated black-box models is limited to the specific use and problem space they were designed to consider: the particular case study characteristics and relative conditions on which the data was available. In other words, they typically sacrifice flexibility and generalisability but offer significant advantages in computational efficiency and a high degree of specialization, potentially reducing the reliance on design assumption of the modelled system. Furthermore, black-box models can require the development of specific scripts to interface with other tools, which can hinder integration. Currently, black-box models are predominantly implemented using Python-based frameworks, such as Scikit-learn [48] (random-forest, gradient-boosting, support vector machine, linear regression models), PyTorch [52] and Tensorflow/Keras [49][53] (deep learning and deep neural network), mainly because of its mature ecosystem for developing data-driven applications.

In DHC systems, black-box models are mostly used to predict energy demand, detect anomalies, and optimise operations through data-driven insights, especially when physical models are infeasible or too cumbersome to implement. Few attempts at using them as surrogate models for a more detailed simulation of the system have been recently made with promising results and a significant reduction of computational time, however more work in this direction is needed to assess their suitability for complex cases. In practice, a significant challenge with black-box models lies in the difficulty for the end-users to navigate the landscape of available possibilities for a specific use-case, especially since most comparative studies have been carried out on limited and proprietary data. Reliable and generalised benchmarks are not available yet.

A few tools are available for multi-domain modelling of both the building thermodynamics and the thermal networks. They typically employ a white-box or grey-box approach. Aside from general purpose modelling frameworks such as TRNSYS, Modelica and MATLAB, IDA District (coupled with IDA ICE), CitySim, City Energy Analyst [54], ESP-r [55], DIMOSIM and SIM-VICUS are suitable for the study of demand response control strategies of building clusters connected to DHC networks.

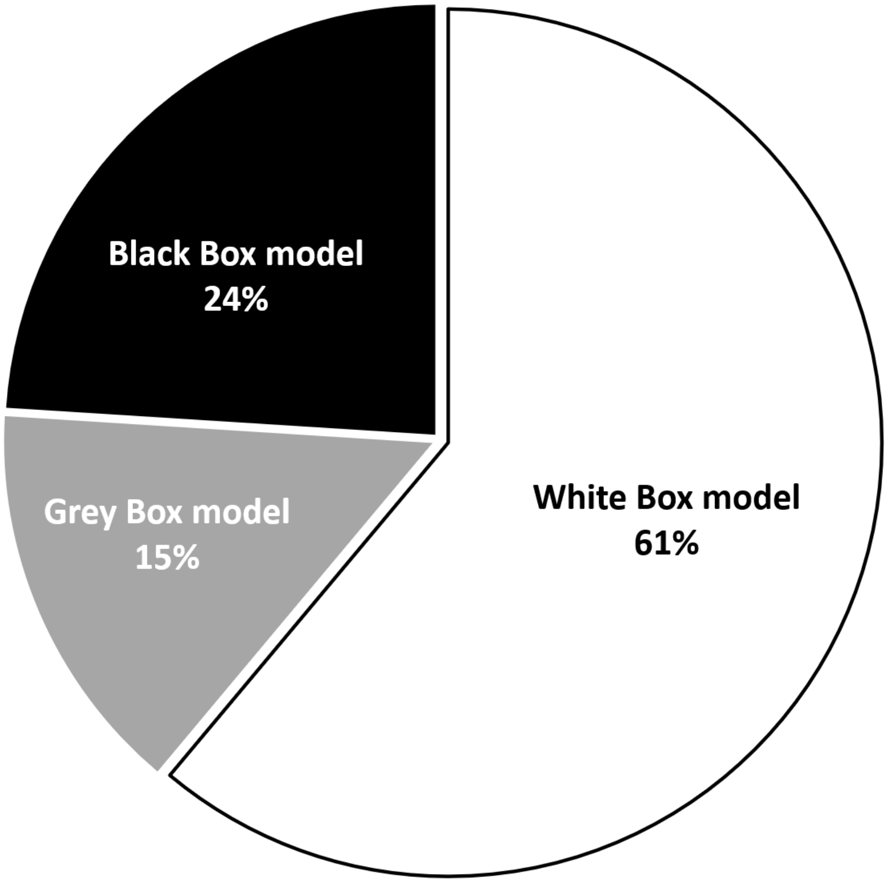

Figure 5. Distribution of modelling approaches in scientific studies on energy and buildings [56].

Finally, different modelling tools can be coupled via a co-simulation framework. For instance, Urban Opt [57] enables the coupling of EnergyPlus and Modelica; and BCVTB platform (Ptolemy II) is capable of coupling EnergyPlus with MATLAB-Simulink, Ansys and Python using FMI [58]. Another approach is to use general-purpose programming languages (typically Python or MATLAB) to manage the interfacing between two or more single-domain modelling tools. Nonetheless, the coupling of different modelling tools can be challenging and present a steep learning curve. Several researchers attempting to carry out co-simulation have reported difficulties to find adequate documentation, and have faced several issues such as computation instabilities, data flow corruption, or simulation desynchronization.

2.3 Outlook and Perspectives

Several key improvements are necessary to improve the suitability of simulation tools for demand response in buildings connected to district heating and cooling DHC networks. Addressing the primary challenges reported by users should be a priority to ensure accurate and efficient simulations.

Co-simulation, which integrates multiple modeling tools, remains particularly complex, requiring significant programming expertise and a steep learning curve. Limited interoperability and inconsistent workflows hinder seamless tool integration, necessitating improved compatibility and streamlined processes. Incomplete documentation further complicates tool coupling, emphasizing the need for comprehensive guides to facilitate smoother adoption. Additionally, frequent errors and inconsistencies (e.g., corrupted data flow in between models, misalignment of data sampling, and solver instability) require thorough testing, resolution, and clear documentation to support engineers and practitioners.

Scalability poses another major challenge, particularly for large-scale dynamic simulations involving clusters of hundreds or thousands of buildings. Each building's local control optimizers, stochastic occupancy patterns, and interactions with multi-energy systems introduce additional complexity. Currently, methodologies for modeling smart thermal operations in such large clusters are underdeveloped, making widespread adoption difficult for the building and energy industry.

To advance simulation tools for DHC networks, efforts should focus on improving interoperability, simplifying co-simulation frameworks, enhancing documentation, and addressing scalability issues. These improvements will be critical for developing more robust demand response strategies and optimizing energy-efficient DHC systems with a large share of intermittent RES supply.

3. Digital Twin Tools for District Heating and Cooling Networks in Future Smart Cities Performing Demand Response

3.1 The Role of Digital Twins in Building Demand Response

The rapid transformation of energy systems in response to climate change, the need for decarbonization, and the ever-increasing share of RES require innovative tools for managing and optimizing energy supply, distribution and use in DHC systems. In this context, digital twin technologies emerge as a key enabler, providing a virtual replica of physical assets to model, continuously re-calibrate, simulate, and optimize operation in real time. Digital twins are particularly suited for addressing the complexities of integrating distributed RES and unlocking the energy flexibility potential of smart buildings [59].

Digital twins serve as sophisticated computational models with a two-way communication that mirror the physical, operational, and functional aspects of systems in real time. For DHC networks, they enable predictive demand management by integrating data from sensors, weather forecasts, and building energy management systems. This facilitates the anticipation of variations in demand and supply, optimization of energy flows, and proactive decision-making. As DHC networks transition to 4th and 5th generation systems, digital twins play a critical role in ensuring seamless integration of decentralized renewable sources, energy storage, and sector coupling with electricity grids [59][60].

Moreover, digital twins advance the real-time optimization of DHC operations by simulating various scenarios, identifying inefficiencies, and recommending adjustments. Digital twins also enable buildings to participate actively in demand response programs by simulating their behavior as thermal storage assets and optimizing the use of distributed supply units such as heat pumps and hot water tanks [60]. By bridging the physical and digital domains, they provide the predictive, integrative, and optimization capabilities necessary for smart cities. The adoption of digital twins is not just a technological innovation but a strategic imperative for achieving sustainable, resilient, and efficient energy systems.

3.2 Digital Twin Tools for Thermal Networks

Future DHC systems will integrate diverse energy sources and storage options, creating multi-directional energy flows that require a holistic system-wide perspective. Digital twins provide this capability by continuously updating models with live data from sensors and IoT devices [59].

The application of digital twins in DHC networks relies on advanced modeling tools, data analytics, and interoperability frameworks. These tools enable detailed thermal modeling to predict heat and mass flows within DHC networks, accounting for fluctuating demand patterns and renewable energy inputs. The models at the core of digital twins can be multi-domain simulation tools, such as Modelica or TRNSYS, or leverage co-simulation frameworks, such as FMI, to couple several domain-specific tools for buildings, electricity, gas, and thermal grids, ensuring comprehensive sectoral integration [60]. The use of standardized interoperability frameworks improves the scalability of digital twins as they can integrate various modeling and simulation environments for diverse applications. Machine learning and AI method integration further enhance the predictive capabilities of digital twins by identifying patterns in historical and real-time data, enabling accurate demand forecasts and adaptive control strategies.

STORM (Simulation Tool for Operating Regimes in District Heating) is an example of the successful implementation of a digital twin for optimizing the operation of a thermal network. This tool, developed by VITO/EnergyVille (Belgium), can evaluate different operational regimes (e.g., constant supply temperature, variable supply temperature), simulate heat distribution in the network, and determine the most efficient operating strategy. It also supports the integration and optimization of RES within DH systems, and can forecast heat demand based on historical data, weather conditions, and other relevant factors. The economic analysis module enables to maintain cost-efficient operations while minimizing the environmental impact of district heating systems, including CO2 emissions and other pollutants. The demand response management module of STORM employs self-learning algorithms to modify the daily demand profiles of the building portfolio and achieve peak reduction, fossil fuel use and emission reduction (the thermal mass of the building is used as a thermal storage to reduce peak demand). The smart controller takes into account the energy storage capacity of the buildings' thermal mass, and the fluctuating electricity market [61].

4. Large-Scale Statistical Analysis of Smart Heat Meter Data from Clusters of Buildings Connected to District Heating Networks

Smart Heat Meters (SHMs) provide data on the heat energy usage of buildings with an unprecedented temporal resolution, thereby offering information that was previously unavailable. This capability facilitates a deeper understanding of the energy demand of buildings, which is crucial for the efficient operation of DHC networks and for implementing advanced control strategies such as demand response. Using SHM data often requires pre-processing steps to address issues such as missing data and the low resolution of commonly recorded integer kWh values. Disaggregation techniques have been developed to separate the total energy recorded by SHMs into energy for space heating (SH) and domestic hot water (DHW). Detailed knowledge about SH and DHW demand profiles can provide vital insights for district heating utility companies to implement advanced control strategies or automated fault detection and diagnosis (AFDD) methods [62]. Moreover, SHM data can be combined with Building and Socio-Economic Characteristics (BSECs) to gain insight into the factors driving energy demand and differentiation among buildings.

4.1 Data Pre-Processing

Pre-processing is an essential step when using smart meter data in general. Particular research focus has been on the imputation of missing data with methods ranging from simple moving averages [63] over methods based on finding similar days and copying data [64] to advanced autoencoder-based methods treating the time series as 2D picture-like information [65].

An aspect that has received considerably less attention is the artificially reduced resolution of the transmitted data from SHMs. The cumulative energy data is commonly rounded down to kilowatt integer values to fit with existing infrastructure at utility companies and reduce bandwidth when transmitting data. This introduces a considerable loss of information for fine granularity, such as in single-family dwellings [66].To overcome this problem for hourly data, Schaffer et al. (2023) proposed a framework (see Figure 2) that first applies smoothing using a moving average with linear weighting and a centered window with a length of 5 values. The smoothed values are then adjusted using the known maximum point-wise deviation and the assumption that, over one day, the same energy must be used [66].

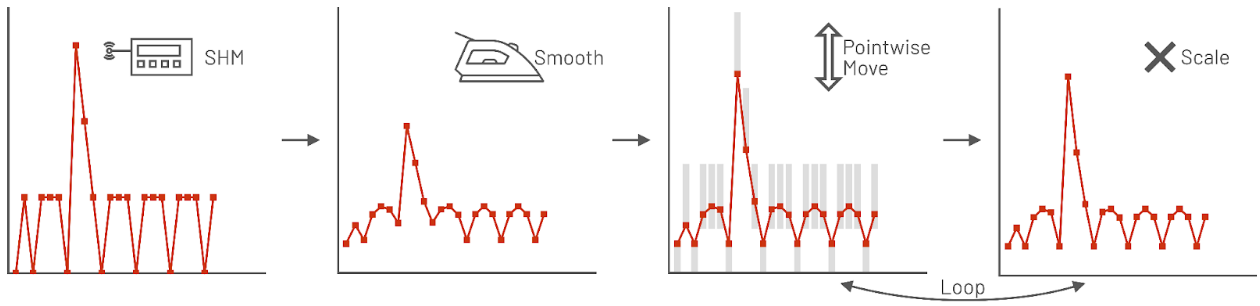

Figure 6. Framework proposed by Schaffer et al. (2023) to mitigate the issues introduced by the low transmitted resolution of SHMs [66].

Next to this established method, potential inspiration for future research could be drawn from the super-resolution methods, which aim at producing high-frequency data from low-frequency data, for which an extensive overview of their application on smart electricity meter data was given in Iversen et al. (2023) [67].

4.2 Disaggregation of Total Energy Demand Profiles

Disaggregating the total energy recorded by SHMs into SH and DHW is an important aspect, considering that these end-uses have different driving factors. Considerable research has been dedicated to disaggregating SHM data, acknowledging its importance. However, only a few studies use data with an hourly resolution rounded down to kilowatt hours and are thus applicable to most of the data collected by current commercial SHMs.

Hedegaard et al. (2020) [68] used a grey box model (5R2C) along with a switching model with 24-hour tapping to simulate DHW usage. The models were fitted to the data using a Bayesian calibration framework and evaluated using hourly data from 44 terraced houses. Their findings indicated that their method slightly overestimated DHW demand by approximately 0.5 kWh per day. Furthermore, their DHW model produced more accurate results than estimating DHW solely based on the summer period without SH. The latter method resulted in an underestimation of around 1 kWh per day.

The idea of training a regression model based on hours with only SH and predicting SH for all hours with potential DHW usage was proposed by Leiria et al. (2023) [69]. Evaluating five different approaches to identify SH-only values and five different prediction methods, they found that assuming the 17 lowest daily values were due to SH only led to the most accurate identification. At the same time, a Kalman filter combined with Support Vector Regression (SVR) gave the best prediction performance. Using this method, Leiria et al. (2022) [70] demonstrated that the performance significantly decreases if applied to SHM data that is rounded down to kilowatt values. However, this decrease in performance can be reduced if the above-mentioned approach developed by Schaffer et al. (2023) [66] is applied to the data beforehand.

Schaffer et al. (2024) [71] further investigated this idea with a focus on making it applicable to city-scale data. They found that data from smart water meters can help identify DHW hours. Additionally, they showed that a random forest can serve as a computationally efficient regression model without the need for hyperparameter optimization, outperforming the previously used SVR while being computationally more efficient. Furthermore, they demonstrated that using features different from those previously employed (specifically, the 1-hour and 2-hour lagged and leading energy use values plus cyclical encoded temporal information) enhanced the regression model's performance.

4.3 Smart Heat Meter Data Combined with Building and Socio-Economic Characteristics

Most approaches aimed at using SHM data combined with BSECs to gain more insight are based on a two-step process: first, clustering the data and second, using a classification algorithm to analyse BSECs as differentiating factors.

Gianniou et al. (2018) [72] used k-means clustering with KSC-distance to establish daily clusters from hourly SHM data from approximately 8300 single-family houses in Denmark, with a data duration of up to 81 months. Each day was considered independently, resulting in a building having daily profiles from several clusters. After identifying five daily energy use clusters, they used a logit regression model with five BSECs: building area and age, number of registered adults, number of teenagers and number of children to identify their influence on the likelihood of a building belonging to a cluster. Their results showed that building area, age, and the number of teenagers were statistically significant factors.

Carmo & Christensen (2016) [73] adopted a two-stage clustering approach to address seasonal variations. First, they clustered the daily profiles of each building into three categories (high, medium, low) and then clustered these groups across all buildings. They used k-means clustering on SH and DHW data from 139 heat pump-equipped dwellings in Denmark, mimicking data from SHMs. To analyse the differentiating factors for the two identified clusters, they used a logistic regression model with 15 BSECs. Their results showed that building area and year of construction, type of space heating distribution system, number of children and teenagers, and postcode were significant factors.

Schaffer et al. (2024) [74] used a co-clustering approach originally developed for smart electricity meters. This approach considers seasonal variation (time) as a feature, allowing the creation of co-clusters in a chessboard-like structure. Each building cluster shares the same time clusters, facilitating interpretation while incorporating seasonal variation into the clustering process. They applied this approach to two years of SHM data from nearly 5000 single-family houses in Aalborg Municipality, Denmark, creating six building clusters. They analysed 26 building characteristics and compared two multi-class classification and variable selection approaches. Overall, both approaches showed low performance (Matthew's correlation coefficient MCC of about 0.3). However, the variable selection approach based on Random Forests resulted in fewer selected variables while maintaining similar performance compared to multinomial logistic regression fitted with grouped lasso. They also found that the year of construction and, if applicable, the year of renovation of the buildings resulted in similar classification performance as detailed information such as transmission losses and information about the ventilation system. By merging the six clusters into three, based on similarities and domain knowledge, they improved classification performance (MCC of about 0.5) while retaining the overall selected information.

Extending this work, Schaffer et al. (2023) [75] investigated eight additional socio-economic characteristics using the variable selection approach based on random forest models. They found that when socio-economic information was combined with building information, the socio-economic variables were never selected. Furthermore, when used alone, socio-economic information resulted in poor classification performance (MCC of around 0.1).

Hansen et al. (2022) [76] used a different approach to investigate socio-economic household variation in heating use patterns based on SHM data. Rather than starting from the clustering of heating consumption data, they initially group households into occupational groups (blue-collar, white-collar, pensioner, and unemployed), demographic groups (child in household and age), and disposable income (six different groups). Using these categorizations, they compared daily heating load profiles for the various household groups. This is supplemented by models of household variation in the morning (5:00–9:00) and evening peaks (17:00–20:00). In this way, the study demonstrates an approach that focuses directly on the peak hours rather than various clusters reflecting shared patterns of the heating load. The study shows that higher-income households tend to consume more during the evening peak. The groups with at least one blue-collar worker or unemployed households tend to use less heat during the morning peak. However, the study reveals only minor differences across groups, which suggests that institutional rhythms, like working hours or school schedules, are the strongest structuring parameters of the daily load patterns in dwellings.

5. Data-driven Automated Fault Detection and Diagnosis for District Heating Network Consumers

The development and optimal orchestration of multiple energy flexibility assets connected to district heating networks (DHN) require that, in the first place, the hydronic components in the buildings operate as intended. However, this is far from being the case in most thermal grids, as studies estimate that approximately 74% of the buildings connected to the DHN have faults in their substation [77]. An interview and survey study on 56 Swedish DH utilities showed that faults in heat exchangers, control systems, customer's internal heating systems and control valves are common [78]. It is thus crucial to continuously detect and address the multiple faults that can be found in the systems of the building end-users to maximise the benefits of demand response strategies in thermal grids. The current section gives an overview of the current state of the art on (automated) fault detection and diagnosis for hydronic systems of buildings connected to thermal grids.

In DHNs, the return temperature of the heat-carrier fluid plays a key role in maintaining the overall efficiency and sustainability of the network, as it directly affects the heat losses in the thermal grid, system stability, and the longevity of infrastructure components [79]. Lower return temperatures indicate efficient heat transfer at the end-users, which enhances the energy efficiency of the entire system. Conversely, a higher return temperature (i.e., a small temperature difference between the supply and return temperature of the heat-carrier fluid) often indicates inefficiencies and potential faults within the building heating systems, leading to increased operational costs for the DHN [80][81]. As a result, monitoring and managing the return temperature (combined with other measured variables such as heat usage and fluid flow) is crucial for DHN utilities.

To encourage DHN consumers to maintain their return temperature at optimal levels, DHN utility companies may impose additional fees on those with a consistently high return temperature. This serves as an incentive for customers to adjust their usage patterns or address the faults within their heating systems that induce high return temperatures [82][83]. However, recent research suggests that utilities might benefit from reconsidering their business model, shifting towards offering continuous monitoring services to proactively detect, diagnose, and resolve these faults [83][84]. By fostering a closer relationship between utilities and their customers, this approach could provide them greater access to building heat substations and secondary heating systems, facilitating a deeper understanding of potential faults and improving overall system performance.

Over the last few years, the systematic deployment of SHM in buildings has enabled continuous heat monitoring and thus unlocks new services such as fault detection (FD) in the DHN systems. FD can be performed by finding anomalies in the recorded operational data. This anomaly detection process has been investigated and applied heavily in DHNs, as it does not require apriori information about the consumers, but only employs a data-driven algorithm that allows categorization of data points as normal or abnormal. In van Dreven et al. (2023) [85], the FD methodologies are classified into three groups: Data mining and knowledge discovery (DMKD), outlier detection, and leakage detection. DMKD refers to techniques for discovering concealed insights that could be valuable for FD, while outlier detection consists in identifying irregularities in the measurements. Lastly, leakage detection focus on spotting data anomalies specifically caused by leakage in networks [85].

On the other hand, fault diagnosis in DHN systems is a more difficult process to set up. Nonetheless, it plays an essential role in ensuring the reliability and efficiency of the heating grid by identifying the root causes of system malfunctions or inefficiencies. In DHN systems, faults can arise from a variety of sources, such as sensor failures, equipment degradation, incorrect heat distribution, or network leaks. Data-driven fault diagnosis leverages the vast amounts of data collected by SHM with machine learning techniques to automatically detect and diagnose irregularities in the system performance and classify these into appropriate fault categories. This enables a faster and more efficient fault-handling response, often addressing these issues before they escalate into major failures. The integration of these methods supports predictive maintenance strategies, reducing downtime and prolonging the lifespan of critical infrastructures, thus improving the resilience and cost-effectiveness of DHNs. However, contrary to FD, fault diagnosis requires a priori understanding of the system where the SHM is located. Therefore, this topic is much less studied in the current scientific literature. Table 1 below gives an overview of the current scientific literature regarding fault detection and fault diagnosis in the DHN sector (the denomination of the different terms is taken from van Dreven et al., 2023 [85]).

Table 1. Overview of the current scientific literature on fault detection and fault diagnosis for DHN.

Category	Topic	Number of publications
Fault detection	DMKD/Clustering	16
	Outlier detection	20
	Leakage detection	9
Fault diagnosis	Sensor failure	4
	Fouling	2
	Valves	2
	Pipes	3
	Multi-label	9

The geographical distribution of the reviewed studies on FDD for DHNs is presented in Figure 7 and Figure 8 (based on the affiliated institution of the first authors). One can observe that, naturally, countries with more extensive research on AFDD tend to be those with a higher proportion of buildings connected to district heating systems (e.g., Sweden and Denmark). However, there are notable exceptions with significant district heating coverage but very little to no scientific publication on AFDD for DHNs, such as Lithuania. This can be explained by the fact that AFDD requires available DHN data and resources to curate datasets, and test and develop AFDD algorithms.

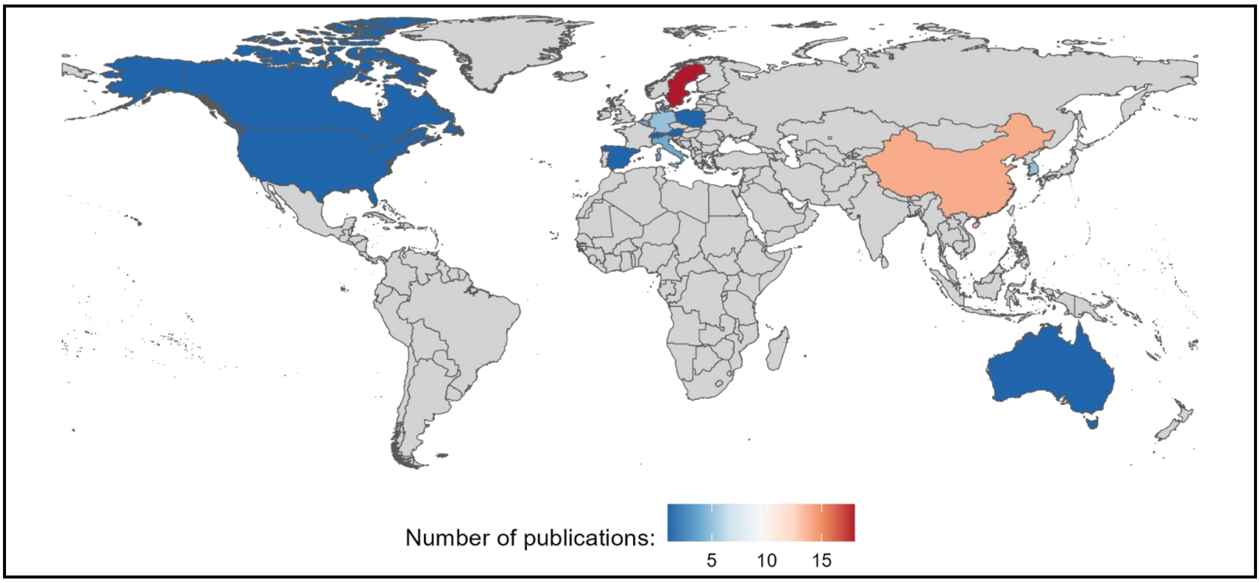

Figure 7. Geographical distribution of the reviewed studies on FDD for DHNs.

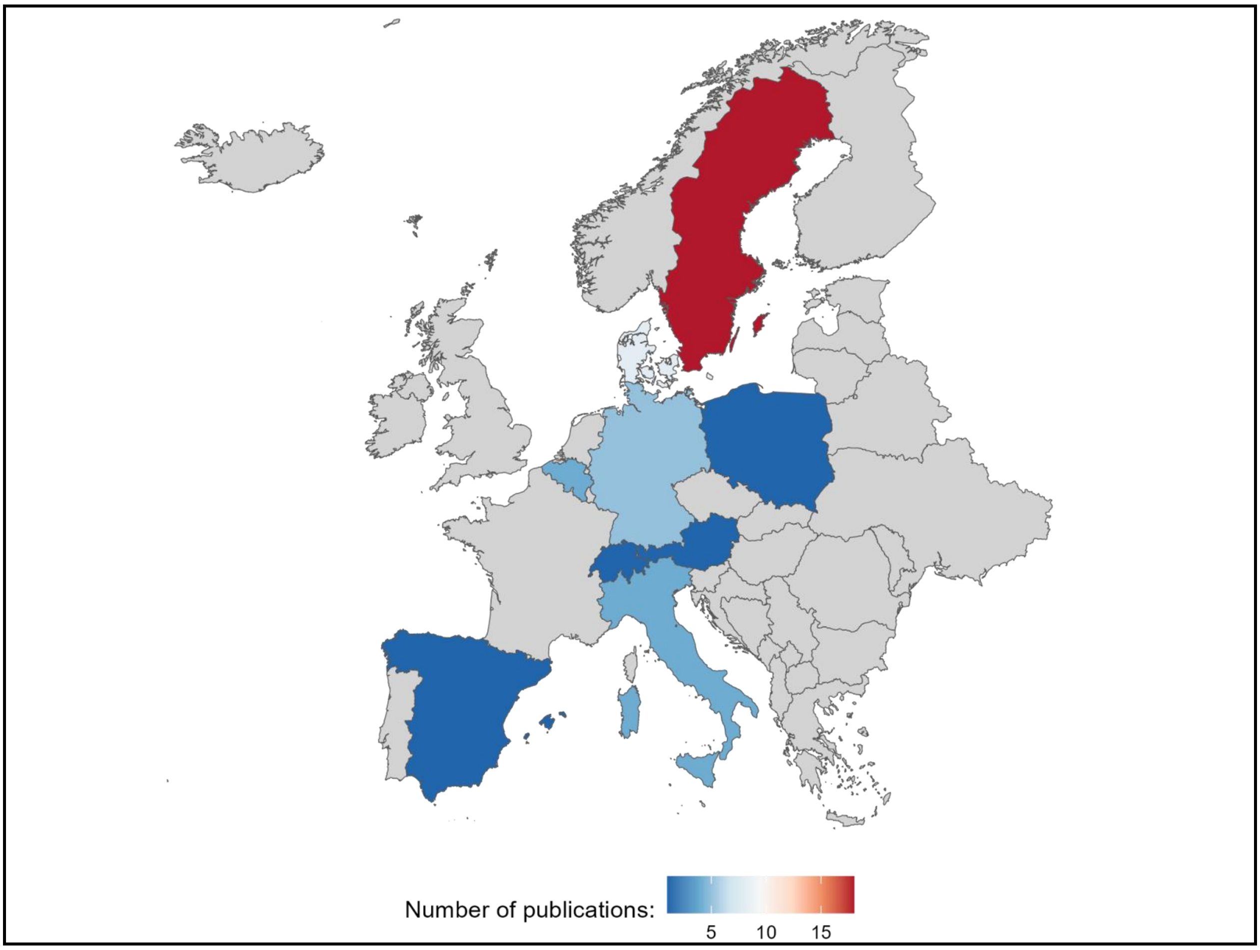

Figure 8. Geographical distribution of the reviewed studies on FDD for DHNs in Europe.

Figure 9 presents the distribution of scientific publications on AFDD per country and over the years. One can observe that Sweden is the leading contributor, followed by China and Denmark. Historically, fault detection is more prevalent in the literature, with a recent increase in papers about fault diagnosis.

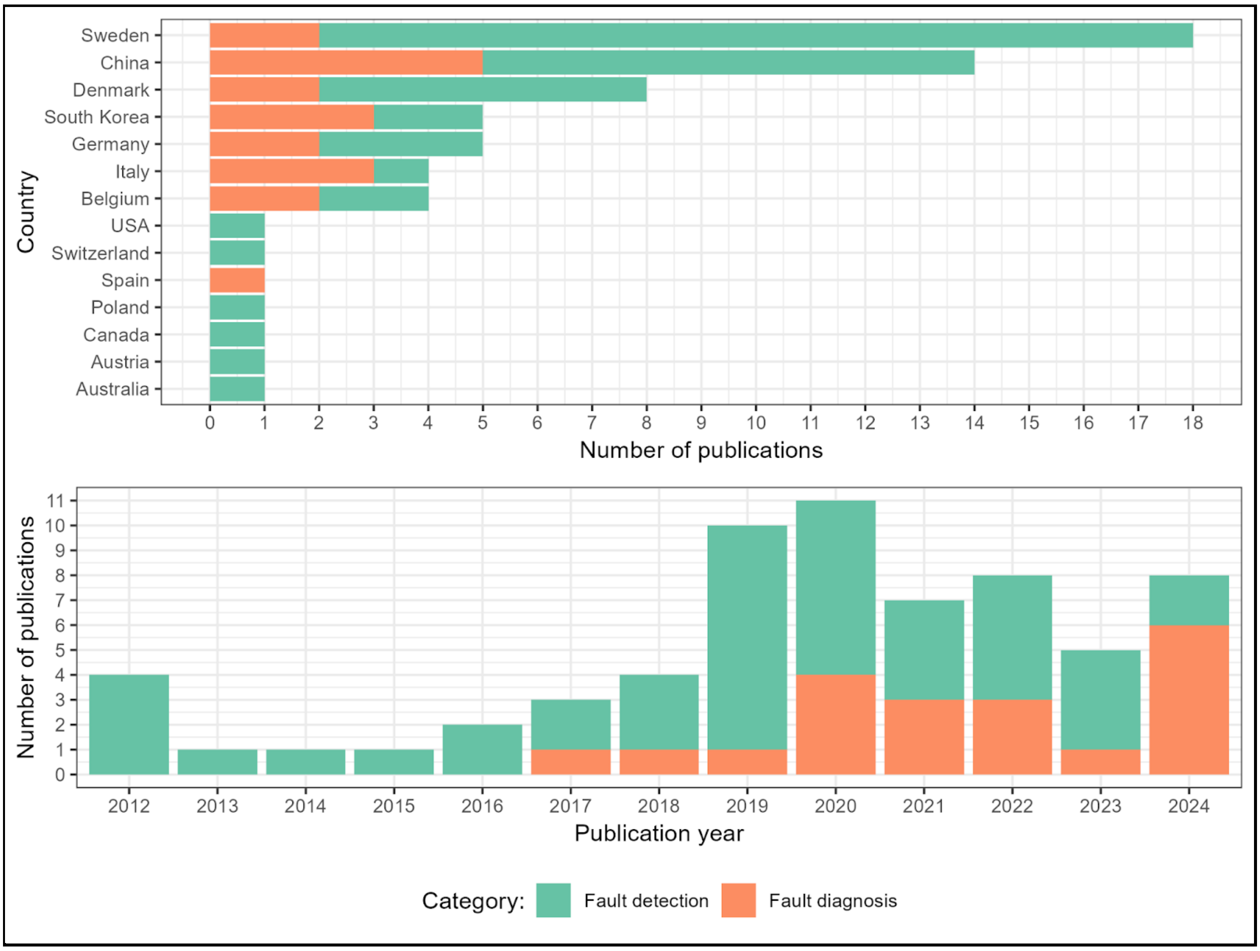

Figure 9. Distribution of scientific publications on AFDD per country and over the years.

A key factor contributing to the rise in research on this topic, particularly in fault diagnosis, is the increased availability of data from the rapid deployment of SHM on the demand side. This growth in data collection helps establish clear links between fault symptoms and under-performances observed in the SHM data and the actual root causes (ground truth) of these anomalies. Having this ground truth is crucial for developing AFDD algorithms that can be scaled up by utility companies, supporting their business models, improving service to their customers, and promoting the sustainability of DHNs:

- **Energy use and system efficiency optimisation:** FDD improves energy efficiency by ensuring that all system components are working properly, which reduces energy waste and lowers operating costs.
- **Proactive fault and anomaly detection to lower operating costs:** FDD algorithms can identify potential faults or anomalies at an early stage, enabling operators to address these issues before they escalate (predictive/preventive maintenance), thereby avoiding major failures and extending the lifespan of system components. FDD thus minimises the need for emergency repairs by facilitating preventive maintenance, which in turn reduces the frequency and severity of repairs, leading to significant cost savings for DHN utilities.
- **Reduced downtime and service disruptions:** Early FDD enables faster interventions and maintenance, reducing system downtime and interruptions of service, leading to a more reliable heating supply and increased customer satisfaction.
- **Improved maintenance prioritisation:** By identifying recurring issues, operators can prioritise maintenance tasks more effectively, ensuring that the most critical problems are addressed first and optimising resource management.

While the benefits of incorporating AFDD into DHN systems are clear, the path to implementation presents certain challenges that need to be addressed [62][86][87]:

- **Reliance on expert evaluations and dataset limitations:** Acquiring sufficient data for fault diagnosis often depends heavily on expert analysis, which can result in ambiguous fault labels and the potential for human error, as each case is evaluated individually.
- **Requirement for high-quality ground truth data:** In order to leverage machine learning and deep learning methods for AFDD in DHNs, a substantial amount of high-quality ground truth data is essential to achieve sufficient accuracy. At the moment, the available data with labelled ground truth is insufficient.
- **Data compilation, sharing, and standardisation:** District heating companies should prioritise the compilation, anonymisation, and sharing of data to drive advancements in the field. Developing standardised datasets through collaborative efforts would enable the validation and comparison of various models on consistent benchmarks, thus accelerating progress in AFDD solutions.
- **SHM data resolution:** Truncation errors from rounding measurements down to the nearest integer results drastically reduces the usefulness of this data for FDD purposes. This issue can be alleviated by aggregating the data over days. However, detecting certain types of faults requires higher measurement resolution and temporal granularity data from the SHM, which can compromise their battery lifespan and thus increase their maintenance costs.

To support the generation of ground truth data, to tackle the lack of structured way to label identified faults by the industry, and to facilitate the development of FDD methods for DHN, Manson et al. [86] suggested a taxonomy for labeling deviating patterns from customer data. Figure 10 illustrates this fault handling and labelling process.

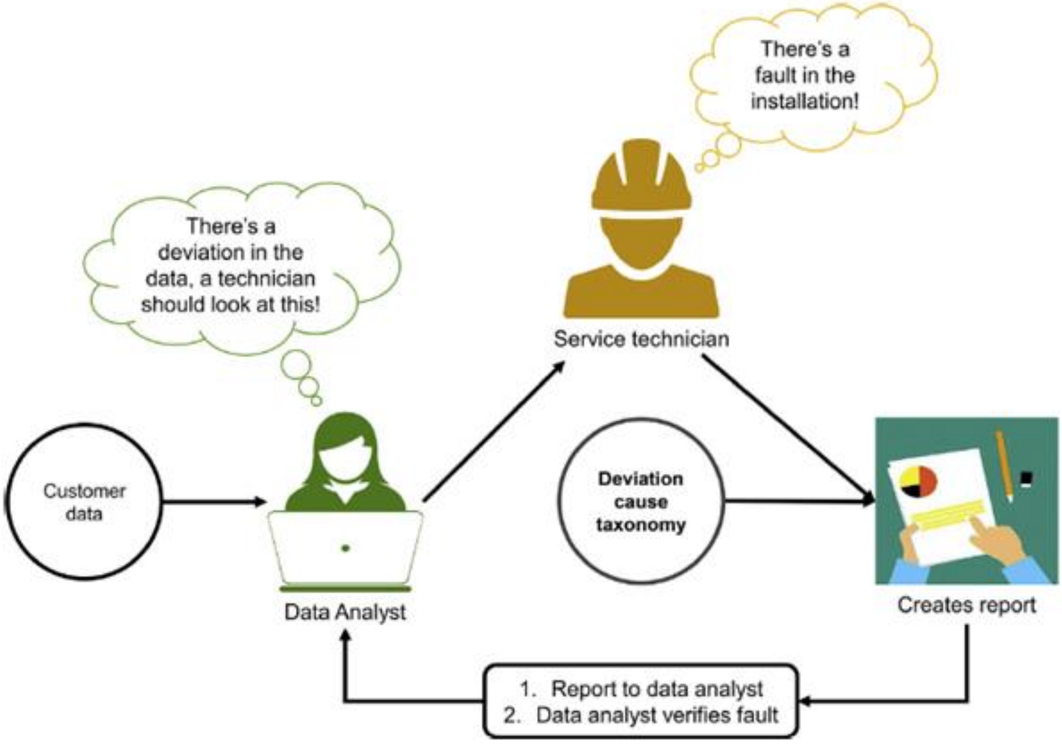

Figure 10. Illustration of a fault handling and labelling process [86].

This approach allows a closed loop between technicians performing interventions on the network and the data analyst to improve on the labelling of the data. This standardized framework helps the technician as well as the data analyst to better identify and characterize faults and technical interventions (see Figure 11).

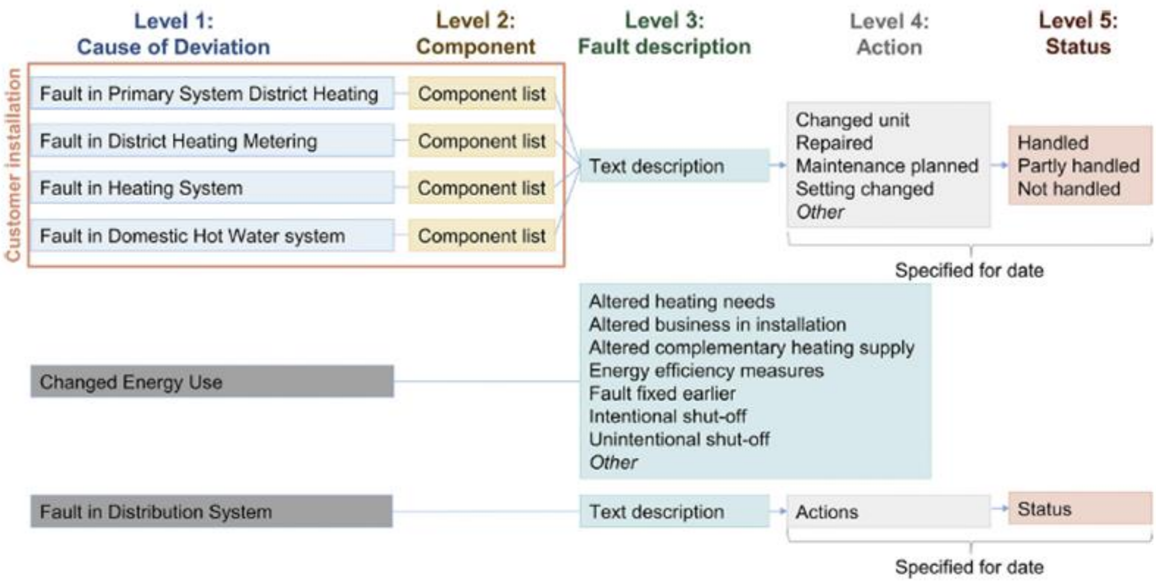

Figure 11. The structure of the deviation cause taxonomy suggested by Manson et al. [86].

An alternative approach to generate training datasets with labeled ground truth on system fault is to emulate faults in laboratory setups. For instance, Van Dreven et al. used a test rig to emulate different types of faults in the substation of an apartment or house connected to a DHN [88]. The generated data was then used to evaluate the performance of machine learning-based models for fault detection and fault diagnosis. For fault detection, semi- supervised learning methods one-class Support Vector Machine (SVM) and the isolation forests were used. The latter was selected for its ability to isolate anomalies in datasets with unlabeled. For fault diagnosis, random forest and SVM models were employed. The test results showed that, in that case, the isolation forest and the random forest models were the most accurate for detecting and diagnosing faults in DHN substations.

6. Model and Data Interoperability

The orchestration of multiple sub-systems and decentralized flexibility assets, and the scalable deployment of smart control, AFDD and analytics solutions require common data structures and inter-comprehensible languages or communication protocols.

Semantic modeling using ontologies is a methodology for creating standardized, machine-readable representations of buildings and energy networks. An ontology is a structured framework for representing knowledge within a specific domain by defining, organizing, and highlighting relationships among various concepts. Ontologies establish a shared language that facilitates seamless interaction between diverse systems and stakeholders. This is particularly essential in the property sector, where complex systems (such as those for energy optimization, ventilation, heating, cooling, and security) must function in harmony. Ontologies ensure consistent data interpretation throughout a building's lifecycle, supporting applications like intelligent control systems, digital twins, and integration with broader ecosystems, including smart cities. They are grounded in the principles of the semantic web and employ standards such as RDF (Resource Description Framework) and OWL (Web Ontology Language) to effectively structure and exchange information.

In the domain of building energy flexibility, the development and usage of ontologies is fairly recent. In 2022, Li & Hong created the semantic ontology EFOnt that is dedicated to the co-development and streamlining applications in the building energy flexibility domain [89]. EFOnt synthesizes demand response key performance indicators (KPIs) from existing literature and provides standardized definitions, data requirements, and calculation procedures for building energy flexibility quantification applications (see illustrative example in Figure 12). Moreover, this ontology can be linked with other ontologies that represent various useful knowledge domains in the building and energy grid sector. This fosters reusability, interoperability, and semantic integration [90].

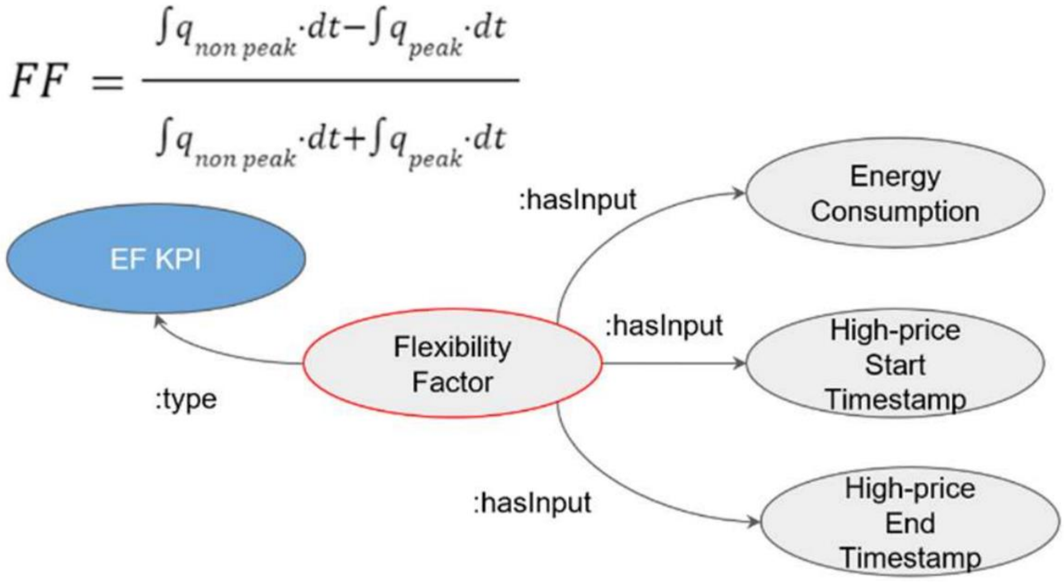

Figure 12. Semantic description of the flexibility factor KPI and its input variables in EFOnt [90].

Recent case studies have demonstrated the benefits of leveraging ontologies and semantic principles for the scalable deployment of building-to-grid services. For instance, in 2025, de Andrade et al. presented a semantics-driven framework for deploying demand response control applications in real buildings. It enables the creation of semantic models based on Brick and SAREF ontologies, integrating metadata from BIM (Building information modelling) and building automation systems. This framework can integrate diverse data sources, and execute demand response actuation in the building. Moreover, leveraging BIM data with this framework showed a 75% reduction in effort for developing, configuring, and deploying building controls compared to existing approaches [91].

Further research and development are needed to address the current limitations of BIM representations that can fully support data-driven applications in building demand response and optimization of DHN operation. This includes developing extensions to existing ontologies or creating new ontologies that can better represent the complexities of buildings integrated with district heating systems, particularly in the context of nearly zero-energy building prosumers.

7. Use Cases of Tools and Methods for Demand Response in Buildings Connected to Thermal Grids

A total of 30 case studies were analyzed in the Subtask D of the IEA EBC Annex 84, focusing on the integration of demand-side management in buildings connected to thermal networks. Among these, 7 cases explicitly described demand-side management using tools that incorporate numerical models of buildings and/or thermal grids. These cases are presented here below.

Table 2. Overview of relevant case studies using numerical modelling tools for demand response in buildings connected to thermal grids (IEA EBC Annex 84 - Subtask D).

Case Study	Title of Case Study / Research Project	Model Type	Reference
1	Peak shaving in Turin district heating (Politecnico di Torino, Italy)	Black Box	[92]
2	Data-driven automated demand-side management technology (Project "DataDrivenLM", AEE Intec, Austria)	Grey Box	[93]
3	100% renewable district heating Leibnitz (AEE Intec, Austria)	Grey + White Box	[94]
4	Flexible energy system integration (Project "Flexi-Sync", AIT, Austria)	Grey Box	[95]
5	Temperature optimisation for low-temperature district heating (Project "TEMPO", VITO/EnergyVille, Belgium)	Grey Box	[96][97]
6	Application of the STORM controller in Rottne (Project "STORM", VITO, Belgium)	Grey Box	[98]
7	Demand response in student apartment buildings (VTT Finland)	Black Box	[99]

7.1 Case study 1: Peak shaving in Turin district heating (Politecnico di Torino, Italy)

This case study investigates the implementation of demand response strategies within the largest DHN in Italy in Turin. The network comprises a singular transport pipeline connecting various thermal plants to the urban area, complemented by 182 distribution networks that link buildings to the transport system, resulting in a total of 6,500 substations. The system operates as a second-generation DHN, with supply temperatures reaching 120 °C and return temperatures varying between 50 °C and 70 °C.

The main challenge identified in this system is the significant thermal peak occurring in the morning, which is attributed to heating systems being switched off overnight (nighttime setback), leading to a cooling of building thermal mass. The subsequent high demand arises as water in the distribution network, heat exchangers, and building heating systems ramp up the temperature during the morning hours.

The objective of the demand-side management (DSM) in this system is peak shaving, which involves adjusting the start-up times for heating systems in buildings to mitigate the thermal peak. In this case study, only one distribution grid with about 100 connected buildings is considered. However, only a fraction of these buildings has a changeable schedule that can lead to load shifting. It is assumed that no significant indoor comfort degradation will occur as schedule modifications are always shorter than 20 minutes.

A genetic algorithm optimizer is used for dynamic adjustments of building heating schedules, taking into account real-time data inputs, and building heat load forecasting. This genetic algorithm optimizer can be conceptualized as a black box model. Key inputs to the model include substations data for demand forecasting, alongside sensors monitoring flow rates at the primary sides of heat exchanger, temperature at the inlet and outlet of the primary and secondary side of the heat exchangers, as well as ambient temperature. The effects of network dynamics are integrated by a thermo-fluid dynamic model, which helps capture the broader impact of load shifting on the system. The output of the optimizer involves control commands that switch off heating systems in buildings for up to 20 minutes, effectively reducing peak demand.

The experimental results indicate that a significant peak reduction is achievable: From 5% to 10% of peak reduction when activating less than 30% for a maximum of 20 minutes. Furthermore, simulation analysis reveals that when all buildings are included and the allowed activation extends to 60 minutes, it is possible to completely shave the morning peak [92].

7.2 Case study 2: Data-driven automated demand-side management technology (Project “DataDrivenLM”, AEE Intec)

The project "DataDrivenLM" explores an innovative, automated, data-driven approach for load management in small DHNs, specifically tailored for a typical Austrian medium-sized network. This network serves a few hundred customers in a rural area, utilizing a biomass/wood chip boiler as the primary heat source, supplemented by an oil boiler for rare peak demands. The main challenge addressed is the occurrence of infrequent peaks due to weather conditions and frequent peaks resulting from building operations, which are costly to manage.

The present demand-side management strategy aims to flatten the overall load, avoid peaks, and prevent very low partial loads. This is achieved by forecasting fixed customer demands and optimizing flexible customer usage. The system employs an MPC approach, integrating various components such as sensors at customer sites to monitor supply and return temperatures, setpoints, volume flow, power and energy, valve positions, pressure, and ambient temperature. A bi-directional data exchange is established between connected customers and central servers via an API (Application programming interface), facilitating real-time data flow.

The central server, on which the MPC is running, learns the heating curves of buildings and individual customer control settings from measurement data and can be seen as a grey box model. It utilizes data-driven thermal load models to predict 15-minute average power demands, forecast fixed customer needs, and optimize flexible customer operations. The ambient temperature value at the customer, that is used to control the heating curve of the building, is manipulated as a control variable to manage flexible customers, with optimization conducted at a 15-minute rate over a 36-hour horizon.

The results indicate that the implementation of this DSM strategy facilitates reusing existing infrastructure. Since there are no hardware requirements, there is a low barrier for implementation and this DSM strategy, and offers a cost-effective solution for existing infrastructure. Replication for larger DHNs is possible, but not economically feasible. In addition, the simplified building models at the core of the current MPC might not be suitable for controlling more complex building blocks [93].

7.3 Case study 3: 100% renewable district heating Leibnitz (AEE Intec, Austria)

This case study presents the implementation of a smart control system for interconnected DHNs, within the ThermaFlex research project. The primary aim was to facilitate the use of RES and fluctuating industrial waste heat, while increasing overall system efficiency. The project encompasses three DHNs in Leibnitz: Tillmitsch, Leibnitz, and Leibnitzerfeld, each with varying biomass and gas boiler capacities. The Tillmitsch network is equipped with two 800 kW biomass boilers and serves an annual heat demand of approximately 4 GWh, supported by a thermal storage of 25 m³. The Leibnitz network features a 3.2 MW biomass boiler and a 2.4 MW biomass boiler, collectively supplying around 12 GWh annually, with a thermal storage capacity of 75 m³. The Leibnitzerfeld network, on the other hand, has a 6 MW gas boiler for an annual heat demand of 14 GWh, relying on 223 m³ of thermal energy storage and the potential to harness 4.5 MW of industrial waste heat along with a constant 500 kW output from a biogas combined heat and power (CHP) system.

The central challenge here is the need to increase the efficiency of the DHN and its energy producers while coordinating multiple feed-in points across the interconnected grids. As part of the project's broader impact, a comprehensive communication campaign was launched across various channels to inform citizens about the DH system expansion, emphasizing the importance of the project for climate protection and positioning Leibnitz as a leader in proactive climate policy. Furthermore, a comprehensive strategy is employed consisting of two parts. First, energy management system (EMS) that utilizes MPC to optimally schedule DH production units by predicting thermal demands based on historical data and weather forecasts. The model incorporates energy supply characteristics, thermal energy storage, and consumer profiles, each represented by mathematical grey-box models that capture their operational dynamics and constraints. Secondly, a DSM controller employes a mixed-linear regression model for the demand forecasting of each consumer, distinguishing between workdays and non-workdays. The DSM controller performs mixed-integer linear optimization every 15 minutes to provide real-time operational commands to the SCADA (Supervision Control and Data Acquisition) systems managing the networks. During operation, the system distinguishes between day and night operation. The DSM further refines the supply capacity limits for substations, ensuring that demand peaks are managed efficiently while minimizing energy costs and CO2 emissions.

Preliminary evaluations using historical data and simulations revealed promising results. The approach demonstrated a cost reduction of approximately 9% and a remarkable 45% decrease in greenhouse gas emissions for the entire network. The CO_2 emissions were reduced by 35%, and the fuel costs were reduced by 7%. Further tests showed a reduction of larger peaks but also revealed oscillations in the load curve due to synchronization of safety measures. The differentiation between working days and non-working days appears to be crucial for the demand forecast. Improvements seem possible if the DSM is coordinated with the DH supply and the management of the TES. The energy storage capacity in the thermal inertia of the buildings' structure connected to the DHN could further improve the performance of the DSM. Notably, fossil fuel use could be further replaced by waste heat and biomass. In addition, not all customers' demand profile can be flattened by the DSM strategy. The reason could be that the consumer substation is oversized. Simulation studies indicate that direct control of gas boilers and longer prediction horizons may lead to further performance improvements [94].

7.4 Case study 4: Flexible energy system integration (Project "Flexi-Sync", AIT, Austria)

The project "Flexy-Sync" focuses on the district heating grid of Maria Laach, a rural area with 30 heat consumers and a 1.5 km network span. The grid is primarily powered by two 600 kW biomass boilers, serving key consumers such as restaurants, hotels, a school, public buildings, and multifamily apartments, which collectively account for approximately 50% of the annual demand of 1650 MWh/year. Several substations were equipped with buffer storage and new substation controllers to enhance grid capabilities. Customers were informed about the project at an early stage, though they were not directly involved in the testing phase.

The main challenge in this grid is its insufficient flexibility and missing DSM, which limits the integration of new customers, and high operation costs due to expensive peak loads. The new DSM objectives include integrating flexibility into the heating grid to better incorporate fluctuating renewable energy, reducing peak loads, leverage building thermal inertia. The project also aims to replace peak boilers with CHP systems, allow new customer integration, achieve cost savings, and enable remote adjustments of substation controllers.

The model at the core of the DSM is a data-driven approach, utilizing machine learning and historical data from each substation to calibrate simplified grey box models. An optimization software was used to find the optimal substation schedule, taking into account the weather forecast. The data transfer is done with an API connection between the DH grid and the EnergyPredict software. The optimization scheme creates a two-day operation plan, which is then communicated back to the thermal grid operating system via an API. The front end provides a basic web interface for user-initiated optimization requests.

The project results indicate that an increase of flexibility in actual day-to-day operation can be achieved. Peak load could be decreased by about 6% (80 kW). Live tests during a spring month show 7% energy savings (6 MWh). Furthermore, no increase in complaints by tenants about thermal comfort is noted. With a CHP plant in Maria Laach, excess electricity can also be used for stabilization of the power grid. However, tests with day-to-day operation including five different types of buildings show too high costs for the implementation in small rural grids. Therefore, a low-cost solution must be found [95].

7.5 Case study 5: Temperature optimisation for low-temperature district heating (Project "TEMPO", VITO/EnergyVille, Belgium)

The project "TEMPO" is conducted in the main DHN in Brescia, Italy, that is operational since 1972 and is serving 21,500 customers with an annual energy supply of 1000 GWh. The specific study was conducted in 2018, focusing on a multi-story residential complex comprising 43 buildings connected to the main DHN. The network operates with supply temperatures ranging from 90°C to 130°C and a return temperature of approx. 60°C. The demonstration site includes one apartment building and 35 single-family houses, where the return and supply temperatures are dynamically mixed at the substation to control the supply temperature to the demo network branch. A mixing station is located between the main network and the buildings, mixing hot water from the main network with return water from the building. The base load is supplied by a waste-to-energy plant, with additional heat recovery from two steel production plants. For winter peaks, a CHP and a gas boiler plant are used.

The primary challenge in this case is to address the high cost of peak power production plants. The goal of the current DSM is thus to achieve peak shaving and reduce the reliance on expensive fossil-based peak boiler operations.

The controller employed for this DSM strategy is a data driven MPC implemented on the VITO platform. It integrate data flow from sensors for supply and return temperatures on the secondary side of the building substation, heat meter data on the primary side, and indoor temperature sensors, all operating at a 15-minute logging frequency. The sensor data is collected via an API, and control signals are sent back to the systems of the demo site. Control signals are computed based on measurements and energy forecasts, and then sent to the customers to add a negative or positive offset to the outdoor temperature sensor, which in turns influence the heating curve of the heating system in the building. Throughout the project, it was observed that indoor temperature sensors were removed or relocated, highlighting the importance of stakeholder involvement in practical implementation, communication, and consultation.

Two test periods are investigated. The first test period during the fall has outdoor temperatures between 8°C and 14°C. The DSM strategy reduced the daily energy peak by 330 kWh on average, and achieved up to 700 kWh of peak reduction, which is a 60% to 70% reduction compared to the baseline. Most of the time, the supply temperature is kept to the lower limit of 80°C. In early mornings and afternoons, the supply temperature is increased to pre-charge the DH grid and lower the upcoming peaks. The second test period during winter has outdoor temperatures between 1°C and 6°C. During this test period, the substations behave unexpectedly. The Results cannot be attributed to control algorithm behavior. Capacity problems in heat exchangers lead to higher supply temperatures than the anticipated lower limit of 80°C. The low outdoor temperatures lead to high energy demand and therefore high supply temperatures.

This project exemplifies the integration of advanced control strategies in operational district heating networks, demonstrating the potential of MPC in enhancing demand response capabilities and optimizing energy use. The study underscores the complexity of dynamic temperature control in DHNs and the challenges of implementing such advanced control strategies across different seasonal conditions [96][97].

7.6 Case study 6: Application of the STORM controller in Rottne (Project "STORM", VITO, Belgium)

This project presents the implementation of the STORM Controller in the DHN of Rottne, Sweden, which comprises 180 connections and substations, predominantly serving small and large houses, with a significant proportion of multifamily houses, industries, public buildings, and offices. The project specifically focused on nine of the largest customer substations, which account for 34% of Rottne's total heat demand. The network, a 3rd generation DH system, operates with supply heat temperatures ranging from 75°C to 110°C, supported by two biomass boilers and a peak boiler using wood and bio-oil. The evaluation period ran from March 2018 to January 2019.

The primary challenge addressed in this project is the reliance on an costly boiler running on rapeseed methyl ester for peak loads during winter. The specific aim of this project is thus to minimize heat production from peak units by prioritizing base load units up to their full capacity.

The DSM objective is to shift and reduce heat demand on cold winter days to mitigate demand peaks. The STORM Controller, targeting large building owners, non-residential buildings, and housing cooperatives, operates on the VITO platform. The control strategy focused on shifting heat production from expensive peak loads (above 2.5 MW) to more economical baseloads. The model comprises several components: a forecaster predicting future demand profiles and estimating thermal flexibility, a planner creating optimized heat load control plans, a tracker dispatching control signals to building agents, and agents negotiating contributions to the heat load plan. Inputs to the model include sensor and measured data collected via an API, such as supply and return temperatures, heat meter data, and indoor temperature sensors. This data is sent to VITO, where the STORM Controller calculates control signals, which are then relayed back to the customers. The control strategy aims to reduce reliance on peak units with higher fuel costs by shifting heat loads above base load capacity to times of lower demand. This is achieved by manipulating the outdoor temperature sensor to influence the heating curve and demand of buildings.

Results of this project show that while the total heat load in all months except November increases by 69.1 MWh during the testing period, the controllable heat load decreases by 12.7 MWh during the testing period. However, overall higher heat load disturbs peak shaving testing and evaluation of the results. The overall peak heat production is reduced by 7.4 MWh (3.1%) compared to the reference period without STORM controller. Apart from January, all months show an absolute peak load reduction of up to 7.9 MWh. When excluding January, peak heat production is reduced by 19.8 MWh (12.7%). Notably, the controllable heat load remained consistently lower than the reference in all evaluated months, demonstrating the effectiveness of the STORM control strategy [98].

7.7 Case study 7: Demand response in student apartment buildings (VTT Finland)

This case study investigates demand response strategies in the district heating market through field tests conducted in 27 residential buildings in Tampere, Finland, with construction years ranging from 1929 to 2009. These multi-story concrete buildings, equipped with various types of ventilation systems, were tested between February and March 2018.

The primary challenge addressed in this study is the occurrence of high demand peaks, particularly during peak hot water usage times such as mornings and evenings when many residents are showering simultaneously. The DSM thus aims to reduce peak plant operation and fossil fuel usage, aligning with Finland's National Energy and Climate Strategy objectives for 2030. The strategy focuses on reducing heat demand without compromising comfort by managing demand in heating radiators during domestic hot water demand peaks, prioritizing domestic hot water demand over space heating.

The investigated controller employs a data-driven model hosted on the Talotohtori cloud, featuring a core standardized data model and a cloud-based building management system. The model's components include IoT sensors for real-time tap water monitoring, indoor temperature and humidity measurements, the Talotohtori cloud for monitoring and analysis, and a valve for DHW management. Inputs from the system’s sensor are sent to the cloud at ten-minute logging frequency. The building management system calculates the average temperature and adjusts heating based on deviations from the desired temperature. The algorithm monitors the DHW valve position and district heating supply to activate peak shaving. The DHW valve's actuator state is monitored, and energy for heating is reduced when a threshold is exceeded by restricting the valve.

The results of this project show that peak demand reduction of 12 to 15% on average is possible by activating demand response. The highest impact is achieved on the newest buildings, but improvements are also noticeable in older buildings. During the testing period from February to March, the normalized energy consumption of eight buildings is reduced by an average of 11%. This represents a 9% decrease in the annual energy consumption, costs and GHG emissions. Furthermore, since the case buildings have already had heating optimizations before, a bigger energy saving potential can be expected if buildings have no heating optimizations in the first place. Overall, demand response helps to achieve the objectives of the National Energy and Climate Strategy for 2030 [99].

8. Conclusions and Perspectives

This report provides a comprehensive overview of state-of-the-art methods, frameworks, software, numerical tools and algorithms relevant to smart thermal management of individual buildings and building clusters connected to district heating and cooling networks. It covers aspects such as dynamic modelling, large data treatment and analysis, automated fault detection and digital twins for the orchestration of the smart thermal operation, and demand response of buildings integrated into thermal grids.

Only a few of the existing commercial modelling tools used by engineers and operators are suited for the simulation, study and optimisation of cluster of buildings performing demand response and building-to-grid services for thermal networks. Advanced multi-domain modelling and co-simulation frameworks capable exist and can handle many aspects of the coupling between the indoor thermodynamics of the buildings, heating and cooling networks, and advanced control strategies. However, they come with a sharp learning curve. Moreover, despite the growing adoption of the Functional Mock-up Interface and the development of application programming interfaces for general-purpose programming languages like Python or MATLAB, interoperability issues remain and hinder seamless integration between different domain-specific modelling tools. Furthermore, model scalability remains a challenge in terms of computation time and solver stability. At the moment, it is difficult to run large-scale dynamic simulations with thousands of buildings operating under hourly time steps to provide demand response services to a thermal grid over a full year. Future development of building and thermal network modelling tools should be more user-friendly, simplifying co-simulation frameworks and improving documentation to lower the entry barrier for engineers and utility operators, while maintaining a balance between accuracy and computational efficiency when scaling up in building cluster size.

Several solutions and research directions are gaining traction and popularity as they present great potential to improve efficiency of district heating and cooling networks and the smart operation of building clusters providing building-to-grid services. The increasing availability of smart heat meter data with hourly temporal resolution unlocks new opportunities to gain key insights on the building end-users for district heating utility companies. Detailed knowledge about space heating and sanitary hot water demand profiles in large clusters of buildings is necessary to detect under-performing systems, optimize the operation of the entire thermal network, and develop new business models and advanced control strategies to improve supply/return fluid temperature and mitigate peak production bottlenecks. Active research is being carried out to ease and advance big data analytics for district heating and cooling systems, to tackle pre-processing challenges such as imputation of missing data, low measurement resolution of energy demand, or disaggregation of space heating and domestic hot water production from total main smart heat meter data.

The continuous stream of high-resolution building data can also be leveraged to generate and run digital twins of district heating and cooling systems (Virtual replicas of physical systems with two-way communication to the latter). Digital twins can help with real-time performance assessment and forecasting, energy and cost optimization of thermal network operation, peak load management, integration of renewable energy sources and fault detection and diagnosis. Regarding the latter, increasing efforts are dedicated to the development of AI- and machine learning-based algorithms for the automated detection and diagnosis of faults in district heating and cooling networks and their related sub-systems inside the buildings. The systematization of such frameworks would unlock predictive maintenance at scale and greatly contribute to the overall energy and cost efficiency and service reliability of thermal networks. However, the main challenge in the further development of automated fault detection and diagnosis algorithms remains to be the lack of high-quality data with standardized labeled ground truth on fault status, origine and consequences.

Finally, greater efforts should be dedicated to real-world implementation, deployment and demonstration of these aforementioned applications and demand response strategies across the large diversity of data structures, hardware, software, systems, customers, control strategies and communication protocols. Currently, their interoperability, portability, and scalability are limited, hindering business models supporting them. The use of standardized ontologies, building information models, and semantic principles are seen as key technologies to tackle these challenges and unlock seamless deployability.

References

[1] IEA (2020). Is cooling the future of heating? Paris.

[2] Werner S. (2017). International review of district heating and cooling. Energy 137, 617–31. https://doi.org/10.1016/j.energy.2017.04.045

[3] Mazhar AR, Liu S, Shukla A. (2018). A state of art review on the district heating systems. Renew Sustain Energy Rev 96, 420–39. https://doi.org/10.1016/j.rser.2018.08.005

[4] IEA. https://www.iea.org/energy-system/buildings/district-heating

[5] IEA (2021). Net zero by 2050. Paris:

[6] Werner S. (2017). International review of district heating and cooling. Energy 137, 617e31. https://doi.org/10.1016/j.energy.2017.04.045

[7] Lund H, Andersen AN, Østergaard PA, Mathiesen BV, Connolly D. (2012). From electricity smart grids to smart energy systems - a market operation based approach and understanding. Energy 42, 96–102. https://doi.org/10.1016/j.energy.2012.04.003

[8] Li Y, Rezgui Y, Zhu H. (2017). District heating and cooling optimization and enhancement – towards integration of renewables, storage and smart grid. Renew Sustain Energy Rev 72, 281–94. https://doi.org/10.1016/j. rser.2017.01.061

[9] Sorknæs P, Lund H, Skov IR, Djørup S, Skytte K, Morthorst PE, et al. (2020). Smart Energy Markets - future electricity, gas and heating markets. Renew Sustain Energy Rev 119. https://doi.org/10.1016/j.rser.2019.109655

[10] Reda F, Ruggiero S, Auvinen K, Temmes A. (2021). Towards low-carbon district heating: investigating the socio-technical challenges of the urban energy transition. Smart Energy 4. https://doi.org/10.1016/j.segy.2021.100054

[11] Sayegh MA, Danielewicz J, Nannou T, Miniewicz M, Jadwiszczak P, Piekarska K, et al. (2017). Trends of European research and development in district heating technologies. Renew Sustain Energy Rev 68, 1183–92. https://doi.org/10.1016/j.rser.2016.02.023

[12] Verda V, Colella F. (2011). Primary energy savings through thermal storage in district heating networks. Energy 36, 4278–86. https://doi.org/10.1016/j. energy.2011.04.015

[13] Olsthoorn D, Haghighat F, Mirzaei PA. (2016). Integration of storage and renewable energy into district heating systems: a review of modelling and optimization. Sol Energy 136, 49–64. https://doi.org/10.1016/j.solener.2016.06.054

[14] Guelpa E, Verda V. (2019). Thermal energy storage in district heating and cooling systems: a review. Appl Energy 252. https://doi.org/10.1016/j. apenergy.2019.113474

[15] Vandermeulen A, Reynders G, Van Der Heijde B, Vanhoudt D, Salenbien R, Saelens D, et al. (2018). Sources of energy flexibility in district heating networks: building thermal inertia versus thermal energy storage in the networks pipes. In: Proceedings of the urban energy simulation conference 2018, p. 1–9.

[16] Gu W, Wang J, Lu S, Luo Z, Wu C. (2017). Optimal operation for integrated energy system considering thermal inertia of district heating network and buildings. Appl Energy 199, 234–46. https://doi.org/10.1016/j.apenergy.2017.05.004

[17] Van Der Meulen SF. (1988). Load management in district heating systems, vol. 12.

[18] Jensen SØ, Marszal-Pomianowska A, Lollini R, Pasut W, Knotzer A, Engelmann P, et al. (2017). IEA EBC Annex 67 energy flexible buildings. Energy Build 155. https://doi.org/10.1016/j.enbuild.2017.08.044

[19] Li R, Satchwell AJ, Finn D, Christensen TH, Kummert M, Le Dréau J, et al. (2022). Ten questions concerning energy flexibility in buildings. Build Environ 223. https://doi.org/10.1016/j.buildenv.2022.109461

[20] Goy S, Ashouri A, Maréchal F, Finn D. (2017). Estimating the potential for thermal load management in buildings at a large scale: overcoming challenges towards a replicable methodology. Energy Proc 111, 740–9. https://doi.org/10.1016/j.egypro.2017.03.236

[21] Li H, Johra H, de Andrade Pereira F, Hong T, Le Dréau J, Maturo A, Wei M, Liu Y, Saberi-Derakhtenjani A, Nagy Z, Marszal-Pomianowska A, Finn D, Miyata S, Kaspar K, Nweye K, O'Neill Z, Pallonetto F, Dong

B. (2023). Data-driven key performance indicators and datasets for building energy flexibility: A review and perspectives. Applied Energy 343, 121217. https://doi.org/10.1016/j.apenergy.2023.121217

[22] Johra H. (2023). What is building energy flexibility – demand response? DCE Lecture Notes No. 81, Department of the Built Environment, Aalborg University. https://doi.org/10.54337/aau518320296

[23] Johra H, Goupy M, Wittchen KB. (2024). Expanding Building Archetypes to Estimate the Indoor Environment Thermal Storage Capacity in the Danish Building Stock when Performing Demand Response. BuildSim Nordic 2024 - Conference Proceedings, 9-11 June 2024, Espoo, Finland. https://doi.org/10.1051/e3sconf/202456204002

[24] Schaffer M, Fauth J, Johra H, Leiria D, Marszal-Pomianowska A, Pomianowski M. (2024). Digitalisation as potential game changer to foster energy efficiency in the building stock. The REHVA European HVAC Journal 61 (1). https://www.rehva.eu/rehva-journal/chapter/digitalisation-as-a-potential-game-changer-to-foster-energy-efficiency-in-the-building-stock

[25] Hansen AR, Leiria D, Johra H, Marszal-Pomianowska A. (2022). Who Produces the Peaks? Household Variation in Peak Energy Demand for Space Heating and Domestic Hot Water. Energies 15, 9505. https://doi.org/10.3390/en15249505

[26] Functional Mock-up Interface standard. https://fmi-standard.org/

[27] University of Wisconsin. TRNSYS. https://www.trnsys.com/

[28] RWTH Aachen University. AixLib Modelica library. https://github.com/RWTH-EBC/AixLib

[29] LBNL, Berkeley. Buildings Modelica library. http://simulationresearch.lbl.gov/modelica

[30] UdK Berlin. BuildingSystems Modelica library. http://www.modelica-buildingsystems.de/

[31] KU Leuven. IDEAS Modelica library. https://github.com/open-ideas/IDEAS

[32] International Building Performance Simulation Association (IBPSA). IBPSA Modelica library. https://github.com/ibpsa/modelica-ibpsa

[33] TU Dresden. SIM-VICUS. https://www.sim-vicus.de/

[34] EQUA Simulation AB. IDA Districts. https://equa.se/images/Fachtag_Lindau/Summary/Energienetze.pdf

[35] CSTB (Centre Scientifique et Technique du Bâtiment). DIMOSIM. https://dimosim.cstb.fr/index.html

[36] CitySim simulation software. https://www.epfl.ch/labs/leso/transfer/software/citysim/

[37] Walter E, Kämpf JH. (2015). A verification of CitySim results using the BESTEST and monitored consumption values, 2nd IBPSA-Italy conference Bozen-Bolzano, 4th – 6th February 2015.

[38] Fortum Power and Heat Oy, VTT Technical Research Centre of Finland Ltd. https://www.apros.fi/industries/district-heating/

[39] CEA-Liten. DistrictLab-H. https://www.districtlab.eu/

[40] Fraunhofer Institute, Kassel, and University of Kassel. Pandapipes. https://github.com/e2nIEE/pandapipes

[41] Idiap, EPFL. PyDHN. https://github.com/idiap/pydhn

[42] Flex Technologies, TU Delft. GridPenguin. https://github.com/ftbv/grid-penguin/tree/main

[43] U.S. DoE. EnergyPlus. https://energyplus.net/

[44] EQUA Simulation AB. IDA ICE. https://www.equa.se/en/ida-ice

[45] IES Virtual Environment. IES.VE-VE 2022. https://www.iesve.com/software/download/ve/archive

[46] Izuba. PLEIADES / COMFIE. https://www.izuba.fr/logiciels/outils-logiciels/

[47] DTU: Technical University of Denmark. CTSM-R. http://ctsm.info/installation.html

[48] Scikit-learn. https://scikit-learn.org/stable/index.html

[49] Chaudhary G, Johra H, Georges L, Austbø B. (2023). pymodconn: A python package for developing modular sequence-to-sequence control-oriented deep neural networks. SoftwareX 24, 101599. https://doi.org/10.1016/j.softx.2023.101599

[50] Chaudhary G, Johra H, Georges L, Austbø B. (2023). Synconn_build: A python based synthetic dataset generator for testing and validating control-oriented neural networks for building dynamics prediction. MethodsX 11, 102464. https://doi.org/10.1016/j.mex.2023.102464

[51] Drgoňa J, et al. (2020). All you need to know about model predictive control for buildings. Annual Reviews in Control 50, 190-232. https://doi.org/10.1016/j.arcontrol.2020.09.001

[52] PyTorch. https://pytorch.org/

[53] TensorFlow, Keras: The high-level API for TensorFlow. https://www.tensorflow.org/guide/keras
[54] ETH Zurich: Swiss Federal Institute of Technology Zurich. City Energy Analyst (CEA). https://www.city-energyanalyst.com/
[55] University of Strathclyde. ESP-r. https://www.strath.ac.uk/research/energysystemsresearchunit/applications/esp-r/
[56] Johra H, Schaffer M, Chaudhary G, Kazmi HS, Le Dréau J, Petersen S. (2023). What Metrics Does the Building Energy Performance Community Use to Compare Dynamic Models? In Proceedings of Building Simulation 2023: 18th Conference of IBPSA (International Building Performance Simulation Association). Shanghai, China, 4-6 September 2023. Pages 861-868. https://doi.org/10.26868/25222708.2023.1309
[57] National Renewable Energy Laboratory (NREL). Urban Opt. https://www.nrel.gov/buildings/urbanopt.html
[58] Lawrence Berkeley National Laboratory. BCVTB platform. http://simulationresearch.lbl.gov/bcvtb
[59] Schmidt, Dietrich (ed.) et al. (2023). Guidebook for the Digitalisation of District Heating: Transforming Heat Networks for a Sustainable Future, Final Report of DHC Annex TS4.
[60] G. Schweiger, R. Heimrath, B. Falay, K. O'Donovan, P. Nageler, R. Pertschy, G. Engel, W. Streicher, I. Leusbrock (2018). District energy systems: Modelling paradigms and general-purpose tools. Energy 164, 1326-1340. https://doi.org/10.1016/j.energy.2018.08.193
[61] EnergyVille. Storm district energy controller. https://energyville.be/en/product/storm-district-energy-controller/
[62] D. Leiria, H. Johra, J. Anoruo, I. Praulins, M.S. Piscitelli, A. Capozzoli, A. Marszal-Pomianowska, M.Z. Pomianowski (2025). Is it returning too hot? Time series segmentation and feature clustering of end-user substation faults in district heating systems. Applied Energy, 381, 125122. https://doi.org/10.1016/j.apenergy.2024.125122
[63] M. Schaffer, T. Tvedebrink, A. Marszal-Pomianowska (2022). Three years of hourly data from 3021 smart heat meters installed in Danish residential buildings. Sci Data 9, 420. https://doi.org/10.1038/s41597-022-01502-3
[64] M. Weber, M. Turowski, H.K. Çakmak, R. Mikut, U. Kühnapfel, V. Hagenmeyer (2021). Data-Driven Copy-Paste Imputation for Energy Time Series. IEEE Transactions on Smart Grid 12(6), 5409-5419. https://doi.org/10.1109/TSG.2021.3101831
[65] C. Fu, M. Quintana, Z. Nagy, C. Miller (2024). Filling time-series gaps using image techniques: Multidimensional context autoencoder approach for building energy data imputation. Applied Thermal Engineering 236(B), 121545. https://doi.org/10.1016/j.applthermaleng.2023.121545
[66] M. Schaffer, D. Leiria, J.E. Vera-Valdés, A. Marszal-Pomianowska (2023). Increasing the accuracy of low-resolution commercial smart heat meter data and analysing its error. In Proceedings of the 2023 European Conference on Computing in Construction and the 40th International CIB W78 Conference. Heraklion, Greece. July 10-12 2023. http://www.doi.org/10.35490/EC3.2023.208
[67] M. Iversen, M. Khan, A. Miraki, R. Arghandeh (2023). Advancements in super-resolution methods for smart meter data. Front. Energy Res. 11. https://doi.org/10.3389/fenrg.2023.1288683
[68] R.E. Hedegaard, M.H. Kristensen, S. Petersen (2020). Experimental validation of a model-based method for separating the space heating and domestic hot water components from smart-meter consumption data. In Proceedings of the 12th Nordic Symposium on Building Physics (NSB 2020). E3S Web of Conferences 172, 12001. https://doi.org/10.1051/e3sconf/202017212001
[69] D. Leiria, H. Johra, A. Marszal-Pomianowska, M.Z. Pomianowski (2023). A methodology to estimate space heating and domestic hot water energy demand profile in residential buildings from low-resolution heat meter data. Energy 263(B), 125705. https://doi.org/10.1016/j.energy.2022.125705
[70] D. Leiria, H. Johra, E. Belias, D. Quaggiotto, A. Zarrella, A. Marszal-Pomianowska, M. Pomianowski (2022). Validation of a new method to estimate energy use for space heating and hot water production from low-resolution heat meter data. In Proceedings of BuildSim Nordic 2022. E3S Web of Conferences 362, 10001. https://doi.org/10.1051/e3sconf/202236210001

[71] M. Schaffer, J. Widén, J.E. Vera-Valdés, A. Marszal-Pomianowska, T.S. Larsen (2024). Disaggregation of total energy use into space heating and domestic hot water: A city-scale suited approach. Energy 291, 130351. https://doi.org/10.1016/j.energy.2024.130351
[72] P. Gianniou, X. Liu, A. Heller, P.S. Nielsen, C. Rode (2018). Clustering-based analysis for residential district heating data. Energy Conversion and Management 165, 840-850. https://doi.org/10.1016/j.enconman.2018.03.015
[73] C. do Carmo, T.H. Christensen (2016). Cluster analysis of residential heat load profiles and the role of technical and household characteristics. Energy and Buildings 125, 171-180. https://doi.org/10.1016/j.enbuild.2016.04.079
[74] M. Schaffer, J.E. Vera-Valdés, A. Marszal-Pomianowska (2024). Exploring smart heat meter data: A co-clustering driven approach to analyse the energy use of single-family houses. Applied Energy 371, 123586. https://doi.org/10.1016/j.apenergy.2024.123586
[75] M. Schaffer, A.R. Hansen, J.E. Vera Valdés, A. Marszal-Pomianowska (2023). Analysing energy use clusters of single-family houses using building and socio-economic characteristics. Journal of Physics: Conference Series 2600, 052004. https://doi.org/10.1088/1742-6596/2600/5/052004
[76] A.R. Hansen, D. Leiria, H. Johra, A. Marszal-Pomianowska (2022). Who Produces the Peaks? Household Variation in Peak Energy Demand for Space Heating and Domestic Hot Water. Energies 15, 9505. https://doi.org/10.3390/en15249505
[77] H. Gadd, S. Werner (2015). Fault detection in district heating substations. Applied Energy 157, 51-59. https://doi.org/10.1016/j.apenergy.2015.07.061
[78] S. Månsson, P.J. Kallioniemi, M. Thern, T. Van Oevelen, K. Sernhed (2019). Faults in district heating customer installations and ways to approach them: Experiences from Swedish utilities. Energy 180, 163-174. https://doi.org/10.1016/j.energy.2019.04.220
[79] H.I. Tol, H.B. Madessa (2024). Return-Temperature Reduction at District Heating Systems: Focus on End-User Sites. Energies 17, 4901. https://doi.org/10.3390/en17194901
[80] H. Lund, S. Werner, R. Wiltshire, S. Svendsen, J.E. Thorsen, F. Hvelplund, B.V. Mathiesen (2014). 4th Generation District Heating (4GDH): Integrating smart thermal grids into future sustainable energy systems. Energy 68, 1-11. https://doi.org/10.1016/j.energy.2014.02.089
[81] D.S. Østergaard, S. Svendsen (2019). Costs and benefits of preparing existing Danish buildings for low-temperature district heating. Energy 176, 718-727. https://doi.org/10.1016/j.energy.2019.03.186
[82] K. Lygnerud, T. Nyberg, A. Nilsson, A. Fabre, P. Stabat, C. Duchayne, V. Gavan (2023). A study on how efficient measures for secondary district heating system performance can be encouraged by motivational tariffs. Energy, Sustainability and Society 13, 38. https://doi.org/10.1186/s13705-023-00417-0
[83] S. Månsson, P.O.J. Kallioniemi, M. Thern, T. Van Oevelen, K. Sernhed (2019). Faults in district heating customer installations and ways to approach them: Experiences from Swedish utilities. Energy 180, 163-174. https://doi.org/10.1016/j.energy.2019.04.220
[84] K. Lygnerud (2018). Challenges for business change in district heating. Energy, Sustainability and Society 8, 20. https://doi.org/10.1186/s13705-018-0161-4
[85] J. van Dreven, V. Boeva, S. Abghari, H. Grahn, J. Al Koussa, E. Motoasca (2023). Intelligent Approaches to Fault Detection and Diagnosis in District Heating: Current Trends, Challenges, and Opportunities. Electronics 12, 1448. https://doi.org/10.3390/electronics12061448
[86] S. Månsson, I.L. Benzi, M. Thern, R. Salenbien, K. Sernhed, P.O.J. Kallioniemi (2021). A taxonomy for labeling deviations in district heating customer data. Smart Energy 2, 100020. https://doi.org/10.1016/j.segy.2021.100020
[87] Q. Yang, R. Salenbien, K.M. Smith, M. Tunzi (2024). Identifying untraced faults associated with high return temperatures from heating systems in buildings connected to district heating networks. Energy 309, 133097. https://doi.org/10.1016/j.energy.2024.133097
[88] J. van Dreven, V. Boeva, S. Abghari, H. Grahn, J. Al Koussa (2024). A systematic approach for data generation for intelligent fault detection and diagnosis in District Heating. Energy 307, 132711. https://doi.org/10.1016/j.energy.2024.132711

[89] H. Li, T. Hong (2022). A semantic ontology for representing and quantifying energy flexibility of buildings. Advances in Applied Energy 8, 100113. https://doi.org/10.1016/j.adapen.2022.100113
[90] H. Johra, H. Li, F. de Andrade Pereira, K. Nweye, L. Chamari, Z. Nagy (2023). IEA EBC Annex 81 – Data-Driven Smart Buildings: Building-to-Grid Applications. In Proceedings of Building Simulation 2023: 18th Conference of IBPSA (International Building Performance Simulation Association). Shanghai, China, 4-6 September 2023. Pages 2537-2544. https://doi.org/10.26868/25222708.2023.1305
[91] F. de Andrade Pereira, K. Katsigarakis, D. Rovas, M. Pritoni, C. Shaw, L. Paul, A. Prakash, S. Martin-Toral, D. Finn, J. O'Donnell (2025). A semantics-driven framework to enable demand flexibility control applications in real buildings. Advanced Engineering Informatics 64, 103049. https://doi.org/10.1016/j.aei.2024.103049
[92] E. Guelpa, L. Marincioni, S. Deputato, M. Capone, S. Amelio, E. Pochettino, V. Verda (2019). Demand side management in district heating networks: A real application. Energy 182, 433-442. https://doi.org/10.1016/j.energy.2019.05.131
[93] K. Kreuter et al. (2022). DataDrivenLM project. Energieforschungsprogramm. Österreichische Forschungsförderungsgesellschaft. https://energieforschung.at/wp-content/uploads/sites/11/2023/02/871697_DDLM_publizierbarer_Endbericht_a.pdf
[94] V. Kaisermayer, J. Binder, D. Muschick, G. Beck, W. Rosegger, M. Horn, M. Gölles, J. Kelz, I. Leusbrock (2022). Smart control of interconnected district heating networks on the example of "100% Renewable District Heating Leibnitz. Smart Energy 6, 100069. https://doi.org/10.1016/j.segy.2022.100069
[95] Flexi-Sync: https://www.ivl.se/projekt/flexi-sync.html
[96] T. Van Oevelen, L. Scapino, J. Al Koussa, D. Vanhoudt (2021). A case study on using district heating network flexibility for thermal load shifting. Energy Reports 7(4), 1-8. https://doi.org/10.1016/j.egyr.2021.09.061
[97] T. Van Oevelen, T. Neven, A. Brès, R-R. Schmidt, D. Vanhoudt (2023). Testing and evaluation of a smart controller for reducing peak loads and return temperatures in district heating networks. Smart Energy 10(3), 100105. https://doi.org/10.1016/j.segy.2023.100105
[98] T. Van Oevelen, D. Vanhoudt, C. Johansson, E. Smulders (2020). Testing and performance evaluation of the STORM controller in two demonstration sites. Energy 197, 117177. https://doi.org/10.1016/j.energy.2020.117177
[99] P. Ala-Kotila, T. Vainio, J. Heinonen (2020). Demand Response in District Heating Market - Results of the Field Tests in Student Apartment Buildings. Smart Cities 3(2), 157-171. https://doi.org/10.3390/smartcities3020009

ANNEX 84

EBC

Energy in Building and Communities Programme

www.iea-ebc.org