

Renewable energy integration and modeling approaches in district heating networks: a review

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ABSTRACT

Integrating renewable energy sources (RES) into district heating networks (DHNs) is a promising strategy for achieving global decarbonization goals. This requires an understanding of viable RES options for DHNs to guide context-specific selection. Additionally, investors and operators must assess the performance of RES-based DHNs, necessitating accurate models to support optimal investment decisions and operational strategies. This paper addresses both of these aspects. We present a review of the integration of five selected RES into DHNs, alongside various modeling techniques used to analyze and characterize them. A multi-label classification of modeling approaches is proposed based on a detailed literature review and technological insights. A decision tree is included to help select an appropriate modeling technique based on specific objectives/tasks in DHNs. Furthermore, we discuss the integration pathways for RES in DHNs. Also, a qualitative overview of RES in DHNs is presented across six key criteria: cost, efficiency, storage potential, system complexity, flexibility, and carbon footprint. A multi-criteria overview suggests that hybrid systems seem to offer a more practical and effective solution for integrating RES into DHNs. However, their technical, economic, and environmental performance remains highly context dependent.

1. Introduction

1.1. Motivation

According to the International Energy Agency (IEA), 26 % of global energy-related emissions and 30 % of global final energy consumption are attributed to building operations, including heating, cooling, construction, and lighting [1]. Building heating accounts for approximately 9 % of worldwide energy consumption, and around 90 % of this energy still comes from fossil fuels [2]. To meet heating demand efficiently and reduce emissions, district heating networks (DHNs) can be utilized. DHNs are fuel-flexible and decarbonizing them is considered crucial to achieve net zero emissions (NZE) by 2050 [3]. One of the most effective ways to decarbonize DHNs is by integrating renewable energy sources (RES) [4]. This includes both sustainable heat sources (solar thermal, geothermal, sustainable biomass) and renewable electricity inputs for technologies like heat pumps, power-to-heat systems, and green hydrogen production.

The integration of RES into DHNs is already in progress, and significant changes are expected in the coming years to accelerate this transition. While several factors contribute to this anticipated shift, there are also key challenges [5,6]: (1) uncertainty from intermittent RES and waste heat, (2) technological challenges in integrating heat pumps and temperature boosters, and (3) the need to transition toward lower-temperature distribution grids to reduce losses.

Considering these challenges and the feasibility and availability of resources, local authorities and investors must determine the optimal mix of renewable sources, tailored to each case. To make informed decisions, stakeholders must (1) be familiar with the full range of available technologies, including their limitations and potential, and (2) possess the ability to model these systems for forecasting (to support investment decisions) and optimal real-time operation. The first point underscores the need to understand current RES-based DHN technologies. The second emphasizes the necessity of accurate and robust models to design, test, validate, and optimize DHN configurations, assess the effects of integrating various RES and their dynamics, and develop new control strategies [7,8]. RES-based DHNs represent large, complex

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Nomenclature

1D/2D/3D	One-, two-, or three-dimensional spatial model representation
CO ₂	Carbon dioxide
g CO ₂ /kWh _e	Carbon dioxide emissions per unit of electricity generated
g CO ₂ /kWh _{th}	Carbon dioxide emissions per unit of useful heat
kWh	Kilowatt-hour
°C	Temperature in degrees Celsius
\$/kWh	Cost per unit of energy or heat, as reported in cited studies
COP	Ratio of useful heat output to electrical energy input for a heat pump

Abbreviations

AI	Artificial intelligence	FVM	Finite volume method
ANN	Artificial neural network	HIU	Heat interface unit
ATES	Aquifer thermal energy storage	IEA	International Energy Agency
BTES	Borehole thermal energy storage	IES	Integrated energy system
CFD	Computational fluid dynamics	IRENA	International Renewable Energy Agency
CHP	Combined heat and power	LCA	Life cycle assessment
CNN	Convolutional neural network	LCOE	Levelized cost of electricity
COP	Coefficient of performance	LCOH	Levelized cost of heat
CSP	Concentrated solar power	LCOS	Levelized cost of storage
DES	District energy system	LR	Linear regression
DHCN	District heating and cooling network	MILP	Mixed-integer linear programming
DHN	District heating network	ML	Machine learning
DHS	District heating system	MLR	Multiple linear regression
DTN	Dynamic thermal network	MPC	Model predictive control
FEM	Finite element method	NZE	Net zero emissions
		O&M	Operation and maintenance
		PFST	Plug-flow N continuously stirred tanks
		PTES	Pit thermal energy storage
		PV	Photovoltaic
		RES	Renewable energy sources
		RF	Random forest
		SCADA	Supervisory control and data acquisition
		STC	Solar thermal collector
		SVM	Support vector machine
		TES	Thermal energy storage
		TSSC	Two-stage solar concentrator
		UTES	Underground thermal energy storage
		4GDH	Fourth-generation district heating
		5GDHC	Fifth-generation district heating and cooling

infrastructures that are costly and impractical to test experimentally, making thorough analysis and optimization essential before implementation [9]. Numerical modeling provides a feasible alternative for simulating DHN behavior, reducing investment risks, and exploring system variations [10]. Therefore, accurate modeling is critical for evaluating and validating the growing complexity of DHNs.

1.2. Background and research gap

District heating is considered a critical component of the energy transition due to its significance [11]. Accordingly, numerous studies have focused on integrating RES into DHNs and on modeling DHNs to support their design and operation. Concurrently, researchers have conducted extensive reviews on both fronts. To mirror the dual focus of the present paper, we first discuss reviews on RES integration in DHNs and related research gap, followed by reviews on DHN modeling and research gap.

Review studies have examined renewable energy integration in DHNs from multiple perspectives. Yuan *et al.* [12] review the potential, national policies, and status of RES in DHNs. They also explore the integration of waste heat as an energy source and the inclusion of thermal energy storage (TES). A review by Olsthoorn *et al.* [13] classifies RES based on their sustainability and their suitability for integration into DHNs. Perez-Mora *et al.* [14] provide a comprehensive summary of existing literature on solar district heating, and real-world case studies are included to offer deeper insights into integrating solar thermal technologies with DHNs. Agyekum *et al.* [15] present a bibliometric analysis of research on renewable energy and energy storage in DHNs. They identify major trends such as the growing role of thermal storage, heat pumps, and digitalization. Kassem and Moscariello [16] focus specifically on geothermal-based DHNs and systematically analyze the technical, economic, regulatory, and social factors influencing their

adoption, highlighting the key challenges such as high upfront costs and integration complexity. Malcher *et al.* [17] investigate decarbonization strategies in district heating using a supply-chain perspective and multi-criteria analysis. Further, they review data from 37 life cycle assessment (LCA) studies which indicate that RES-based systems consistently achieve the lowest emission levels. Sarbu *et al.* [18] provide an overview of renewable energy integration in DHNs, including solar, geothermal, biomass, and hybrid heat pump systems.

Generation wise evolution of DHNs and inclusion of RES is also discussed in the literature. Successive generations of DHNs primarily are distinguished by reductions in operating temperatures and increasing system integration. Fourth-generation district heating (4GDH) has been identified as a key for RES in DHNs. It is emphasized that low-temperature operation (below 70 °C) facilitates the integration of diverse RES and waste heat sources [19]. Studies have examined the challenges associated with integrating RES into 4GDH systems, including technical limitations related to heat source characteristics, storage requirements, and network operation [20]. Additionally, highlights the role of building-level adaptations and system design in enabling efficient low-temperature operation of modern DHNs [21]. Recent developments have introduced the concept of fifth-generation district heating and cooling (5GDHC), characterized by ultra-low or near-ambient temperature networks. They can have decentralized energy sources (including RES) and bidirectional flows enabling simultaneous heating and cooling [8].

Taken together, the reviews above address RES integration from distinct but partial angles: national policies and status [12], sustainability-based classification [13], energy source-specific [14,16], bibliometric trends [15], supply-chain and LCA perspectives [17], and broad overviews [18]. The generational literature [8,19–21] further situates RES within the evolution toward low-temperature networks. However, the literature remains fragmented for readers seeking a

concise pathway of how different RES are physically integrated in DHNs. In particular, a multi-criteria assessment of different RES that helps to judge their relative suitability in DHNs is lacking. Thus, there is still value in a synthesis that provides the integration pathways for RES in DHNs.

In parallel, several studies have focused on reviews Valentini for modeling of DHNs and classifications related to DHNs. Rezaie et al. [22] discusses the diverse definitions, classifications, and applications of DHNs, along with a detailed description of the key components of district energy networks. Abugabbara et al. [23] present bibliographic maps to link publications, research areas, and authors related DHNs. Sarbu et al. [9] provide a comprehensive overview of DHN modeling and optimization, focusing on the heat distribution network and system performance. Xu et al. [24] present a critical review of advanced modeling tools developed to enhance the design and management of district energy systems. Talebi et al. [25] propose a categorization of DHNs based on end-user demand, system scale, geographic location, and heat density. Further, they review component modeling and optimization approaches. Zhou et al. [26] offer guidelines for numerical modeling and validation methods for performance prediction and techno-economic-environmental feasibility analysis of cross-scale integrative energy systems, including DHNs.

Allegrini et al. [27] present a review of modeling approaches for district-scale energy systems, including DHNs. They emphasize on district level energy interactions and related simulation tools. Klemm and Vennemann [28] highlight that different energy sectors and scales are integrated in district energy systems. They evaluate a range of optimization-based tools to evaluate system performance under various criteria. Valentini et al. [29] evaluate different simulation tools for their ability to address operational requirements in renewable energy DHNs such as thermal energy storage (TES), demand response, and control strategies. In a similar line, Kuntuarova et al. [30] provide a review of software tools for DHN modeling, covering their mathematical formulations, capabilities, and application scope, while Brown et al. [31] offer a comparative assessment of modeling tools, highlighting key features with Pugh matrix for selecting appropriate tools for applications.

Reviews have provided classifications based on factors like system size, geographic location, and heat demand. Also, classification of modeling approaches is covered in literature, but it is mainly focused on modeling and simulation tools (Modelica, TRANSYS, TERMIS, etc.) [24,27–31] and covers their formulations, capabilities, and other aspects related to DHNs. Modeling approaches are also classified in terms of component level modeling, temperature level, single or multiple energy sources considered, thermal or hydraulic model, and others [9,25]. However, a classification in terms of physics behind the models (steady-state, dynamic, energy analysis, etc.) is missing. Also, the recent developments in data-driven models for DHNs need more attention. Most importantly, there is a lack of structured, decision-oriented guidance that helps researchers and practitioners select appropriate modeling techniques based on specific DHN tasks.

1.3. Contributions

Building on the previously discussed aspects, this review focuses on two core areas: the integration of RES in DHNs and the classification of modeling techniques. This dual focus aims to advance the field by supporting informed design and decision-making for future DHN development. The key contributions are as follows:

- We compile a multi-criteria overview of five primary RES-based DHNs, solar, geothermal, wind, biomass, and green hydrogen, selected through the bibliometric analysis in Section 3, highlighting their integration pathway in DHNs, advantages and limitations.
- We provide a broad classification of DHNs and introduce a novel framework for classifying DHN modeling approaches, offering insights into the strengths and limitations of each.

- We analyze various modeling approaches and present a decision-making flowchart to assist in selecting the most appropriate modeling technique for specific modeling objectives/tasks in DHNs.

Paper Organization: Section 2 presents an overview and taxonomy of DHNs. Section 3 describes the methodology used for literature selection. Section 4 examines the potential of RES in DHNs. Section 5 introduces the modeling classification framework and discusses representative techniques. Section 6 summarizes conclusions and highlights future research opportunities.

2. Components and general classification of DHNs

DHNs use water as the primary medium for transferring heat through a network of pipelines. As can be seen in Fig. 1, at the source, water is heated and travels through a supply pipeline to end users such as buildings, homes, and industries. A second pipeline carries the cooler, used water back to the source, where it can be reheated or recirculated [32]. The primary components of DHNs include: (1) heat sources, (2) transportation/distribution networks, (3) end users, and (4) thermal storage systems [31]. This section briefly overviews these elements and discusses how their characteristics form the foundation for classifying different types of DHNs.

2.1. Heat sources and working temperature

DHNs utilize a variety of heat sources, including fossil fuels, geothermal, RES-based heating systems (electric boilers, heat pumps), waste heat, and waste incineration. This gives rise to a source-based classification such as gas-based, coal-based, or geothermal-based DHNs [12]. A DHN may employ single or multiple sources, depending on operating temperature, network configuration, and end user's demand. Temperature levels and phases of water provide a further classification: high-temperature DHNs ($\geq 100^\circ\text{C}$, typically steam or pressurized water) [33], medium-temperature DHNs (65°C to 95°C), low-temperature DHNs (50°C to 70°C), and Ultra-low-temperature DHNs (30°C to 50°C) [34]. At even lower temperatures, networks support both heating and cooling and are regarded as district heating and cooling networks (DHCNs) [21]. An important term related to DHCNs is “prosumer network” which represents a network where users can act as both producers and consumers of thermal energy.

These temperature ranges also form the basis for the “generational classification” of DHNs. The “first-generation DHNs” use steam ($\geq 100^\circ\text{C}$), and “second-generation” (pressurized superheated water, $\geq 100^\circ\text{C}$), both primarily powered by fossil fuels or combined heat and power (CHP) systems. “third-generation DHNs” use hot water below 100°C and began incorporating RES, such as biomass and energy from waste incineration. “fourth-generation DHNs” operate below 70°C , aligning closely with end-user heating requirements and facilitating RES integration. The “fifth-generation DHNs/DHCNs” is sometimes treated as a distinct generation, but the IEA [35] regards it as a specialized subset of 4GDH. IEA promotes the term “thermal source networks” to describe 5th generation DHCNs, as pipe networks serve as heating and cooling sources through decentralized technologies like heat pumps.

2.2. Transportation/Distribution network

DHNs consist of an interconnected system of underground pipes designed for the transportation and distribution of heat.

The piping configuration provides another classification axis. Single-pipe DHNs use one insulated supply pipe and a separate (uninsulated or insulated) return pipe, representing the most basic design. Double-pipe DHNs enclose supply and return within a single insulated casing, offering better thermal insulation and reduced heat losses [36]. Triple-pipe DHNs share a common casing with three pipes, a primary supply, a secondary supply for peak demand, and a shared return. This provides

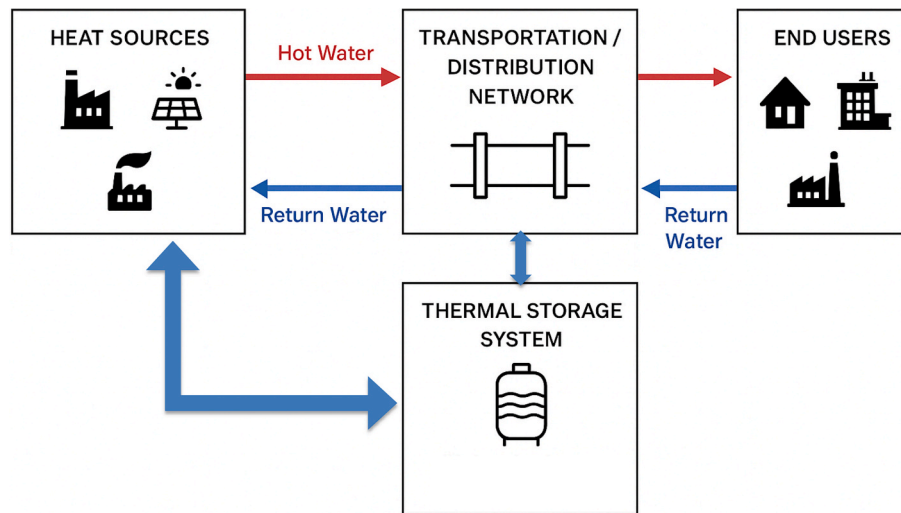


Fig. 1. Components of district heating network.

greater flexibility to accommodate variable demand and alternative heat sources [36]. Researchers have proposed that separating high-temperature supply for domestic hot water from low-temperature supply for space heating in a three-pipe configuration improves flexibility and efficiency relative to single- and double-pipe designs [37].

2.3. End user

Once heat reaches the receiving end of the distribution network, heat interface units (HIUs) comprising a heat exchanger supported by pumps, controls, and flow meters are typically used by end users to extract and utilize the thermal energy supplied by DHNs [38]. The number and density of end users provide a scale-based classification: small-scale DHN has a single distribution network to serve low-density areas such as villages or small towns, while large-scale DHNs comprise multiple heat production units to supply densely populated urban regions. Medium-scale DHNs fall between these two extremes in terms of coverage and infrastructure. Although some studies have proposed other criteria (heat supply capacity, source-to-consumer distance), user density remains the most widely adopted for defining the scale of a DHN [25,39].

2.4. Thermal storage system

DHNs utilize thermal storage systems (TES) to enhance operational flexibility, support the integration of RES, and manage fluctuations between heat supply and demand. DHNs can be classified by storage duration as daily/short-term heat storage (few hours), weekly/medium-term heat storage (few days), and seasonal heat storage (few weeks or months) [40]. Seasonal TES is often implemented as underground thermal energy storage (UTES), such as borehole thermal energy storage (BTES), aquifer thermal energy storage (ATES), and pit thermal energy storage (PTES) [41]. Another classification is based on the type of storage, like sensible heat storage (uses water tanks), latent heat storage (uses phase change materials), and thermochemical heat storage (uses chemical reactions) [42].

3. Methodology

This study is a structured narrative review rather than a formal systematic review. The objective was not to exhaustively catalogue all publications on district heating, but to identify and synthesize studies that are directly relevant with two focal themes: RES integration in DHNs and modeling approaches used to analyze such networks. The

literature search was conducted in two stages.

First, A bibliographic analysis was conducted using VOSviewer to identify keyword frequency and interrelationships within the DHN research landscape. The dataset was sourced from the Web of Science using the term “district heating,” and refined with the keyword “renewable” to target relevant studies. The resulting bibliographic data was imported into VOSviewer for keyword mapping and co-occurrence analysis, forming the basis for a visual understanding of research trends and thematic focus areas in the field.

As illustrated in Fig. 2, various keywords were selected to investigate their frequency and interconnections. To ensure comprehensive coverage, multiple terms related to DHNs, such as “district heating network,” “district heating system,” “district energy network,” and “district energy system,” along with their acronyms (e.g., DHN, DHS, DES), were included. We incorporated keywords associated with RES, including solar, wind, geothermal, biogas, and others. To capture the modeling dimension, terms such as “numerical,” “modeling,” and “simulation” were used, alongside related concepts like “objective function,” “correlation,” and “optimization.” Furthermore, keywords related to solution methods, including “genetic algorithm,” “machine learning,” and “mixed integer linear programming (MILP),” were included to reflect the analytical approaches employed in DHN studies.

The following inferences were drawn from the analysis, as visualized in Fig. 2:

- The term “district heating network” or “heating network” is used more frequently than “district heating system” or any other related terms. Therefore, throughout this paper, we will consistently use the term “district heating network.”
- Among RES in DHNs, solar, wind, and geothermal energy were the most prominent, with biomass and hydrogen following closely. Consequently, this article will explore the literature focusing on these RES for which the literature is found to be most established.
- Keywords related to system modeling were significantly present and are connected to various aspects of DHNs and energy sources. Therefore, as mentioned earlier, this paper will review studies focusing on the modeling of DHNs and the integration of RES.

Afterwards, a primary literature search was conducted using Web of Science as the core database. ScienceDirect, SCOPUS, Google Scholar, and key reports from International Renewable Energy Agency (IRENA) and the IEA were used as supplementary sources to identify additional relevant studies and grey literature. The reviewed literature was considered for approximately two decades (2005–2026) and were

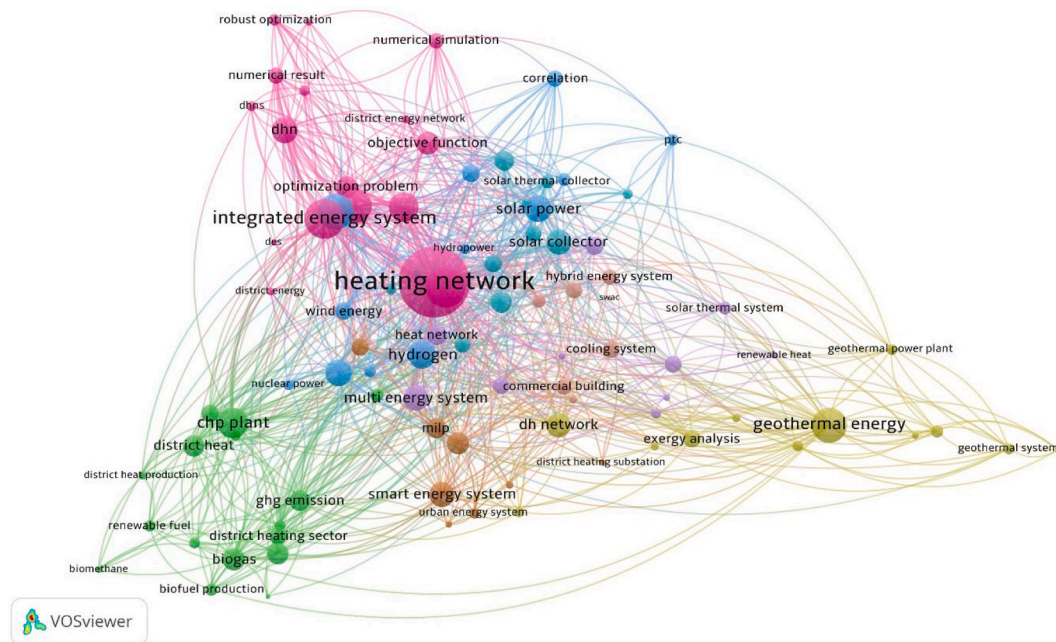


Fig. 2. Network visualization of various keywords related to DHNs.

limited to English-language journal articles, conference papers, review articles, and technical reports. The primary search terms included “district heating” OR “district heating system” OR “district heating network” which were refined using keywords as “modeling” and “renewable energy”. For [Section 4](#) focusing on RES-based DHNs, search was refined using the keywords “solar” OR “wind” OR “geothermal” OR “biomass” OR “hydrogen”. For [Section 5](#) on modeling approaches, search was refined using the keywords “Steady state” OR “Dynamic” OR “1D” OR “2D” OR “3D” OR “Energy” OR “Exergy” OR “Linear” OR “Nonlinear” OR “Data-driven/Machine learning/AI”.

The search identified 339 records after applying the search terms and filters, which formed the screening pool. Articles were screened based on their title, abstract, followed by full-text assessment where necessary. Because Web of Science served as the primary search database, duplicate records across supplementary databases were manually screened during title and abstract review and removed before full-text assessment. Supplementary databases were mainly used to identify additional studies that were not indexed in Web of Science, particularly recent conference papers and technical reports. Studies were retained if they (i) addressed DHNs at the network or multi-building level, (ii) discussed at least one renewable energy source integrated into a DHN or presented a modeling approach for a DHN, and (iii) were available in English. Studies were excluded if they (i) addressed only single-building heating systems without network-level scope, (ii) discussed RES or modeling outside a DHN context, or (iii) were not available in English. Overall, a total of 143 key scientific sources were shortlisted. The pool was then refined separately for the two focal themes of the review. Subsequently, 48 studies were used for analysis on renewable energy integration (Section 4) and 50 studies were used for analysis on modeling approaches in DHNs (Section 5). Other 45 are mainly used to establish the background, terminology, classification, and historical development of district heating networks and were not counted within the two thematic analytical subsets unless explicitly discussed in Sections 4 and 5. To improve transparency and reproducibility, the literature selection process is summarized in Table 1.

Additionally, this review is geographically inclusive, not limited to any specific country or region. In the next sections, we discuss the results of our review based on this search.

Table 1
Summary of literature screening and selection process.

Screening step	Number of articles
Records identified through database search	339
Records excluded after title/abstract screening	195
Studies retained for RES integration analysis	48
Studies retained for modeling approaches analysis	50
Additional contextual/background sources	45
Total references cited	143

4. Integration of RES into DHNs

In the introduction section, we discussed how the incorporation of RES could significantly contribute to the decarbonization of DHNs. Hence, this section examines the presence, benefits, and limitations of RES concerning DHNs. Additionally, to provide historical context, this section offers a brief overview of DHN development and its integration with RES.

RES-based DHNs have a long history, with their origins tracing back to the 14th century in Chaudes-Aigues, France, where geothermal energy was used to heat approximately 30 homes, making it the world's first functional renewable energy-based DHN [43]. Modern DHNs later emerged through steam-based systems in the United States in the 19th century, followed by wider adoption of water as the heat transfer medium in the early 20th century. A significant milestone came in 1898, when Copenhagen, Denmark, launched a CHP system powered by waste incineration, marking one of the earliest shifts toward more sustainable heat generation [11,44,45].

Over time, DHNs evolved through waste heat utilization, pipe insulation improvements, and system optimization advancements. Further, the reduction in operating temperatures, enabled the effective integration of RES, like geothermal and solar thermal energy [46,47]. This supported greater use of domestic energy resources and reduced reliance on imported fossil fuels.

More recently, RES-based DHNs have gained renewed importance in the context of NZE targets. By the end of 2023, 336 cities had adopted solar-powered DHNs [48], while geothermal-based DHNs have been implemented in several regions, including United States [49], Sweden, Denmark [50], France [51], China, Austria, and Belgium [52]. These

developments underscore the longstanding and growing role of RES in transitioning DHNs toward more sustainable and low-carbon energy systems.

Despite their potential, integrating RES into DHNs presents a complex challenge due to the diverse components involved and their inherent variability. Nevertheless, the benefits are substantial and justify the technical complexity. First, decarbonization is a significant advantage, as RES emit significantly less CO₂ than fossil fuels, helping achieve NZE goals. Second, RES can gain access to storage and operational flexibility when integrated into DHNs, by the inherent ability of thermal systems to store heat more cost-effectively and for longer durations than electricity. Finally, efficiency and long-term cost savings make RES-based DHNs economically attractive, despite higher upfront investment. These systems tend to have longer operational lifespans, stable operating costs, and can stimulate local economies through job creation [48,53–55].

Building on this foundation, the following sections of this paper examine RES in the context of DHNs. RES are catalogued by the way they supply usable heat to the DHNs. Further, to emphasize their potential for integration in DHNs, they are evaluated based on different factors.

4.1. Integration pathways of RES in DHNs

As mentioned in Section 3, a bibliographic analysis is conducted and five primary RES with the most established literature on DHN integration are selected for review: solar, geothermal, wind, biomass, and hydrogen. Thus, while several other RES are available, but only five are discussed here. Also, some other low-carbon heat sources for DHNs are not reviewed here. However, several of these (heat pumps, electric boilers, hydrothermal) function as conversion technologies or method of heat extraction and are covered in this paper's integration pathway-based framing. Some other heat sources, including industrial and data-center waste heat, waste incineration, and ambient heat are recovered-heat streams rather than primary renewable sources and are out of scope for this paper. Further, photovoltaic thermal (PVT) panels are a coupling technology between solar thermal and photovoltaic, not a distinct primary energy source, hence not covered here. To provide the reader with integration context of RES in DHNs, different integration pathways are discussed, and accordingly different RES are placed under them.

RES can be integrated into DHNs through different integration pathways, depending on how the primary renewable energy is converted into usable heat. These integration pathways strongly influence system performance, flexibility, and compatibility with network operating conditions such as supply and return temperatures [56]. To avoid conflating different system elements, we distinguish between primary energy sources, conversion technologies, intermediate energy carriers or storage options, and final heat-supply technologies. For example, solar irradiation and wind are primary energy sources; PV panels and wind turbines convert these resources into electricity; heat pumps or electric boilers then convert electricity into heat for DHNs. Similarly, hydrogen is treated as an intermediate energy carrier produced from renewable electricity, rather than as a primary renewable heat source. Broadly, RES integration in DHNs can be categorized into following main pathways:

4.1.1. Direct thermal integration

In this, heat is supplied directly to the DHNs. This pathway typically offers higher overall efficiency and simpler system configurations. Following RES can follow this pathway.

Solar thermal collectors (STCs) can convert solar energy into thermal energy to be used in DHNs [57]. The thermal output (heat gain and outlet temperature) depends on solar irradiation and STC type employed. Common types include non-concentrating technologies, such as flat plate collectors, and evacuated tube collectors, as well as concentrating solar power (CSP) technologies, such as parabolic trough

collectors or linear Fresnel reflectors [58]. Non-concentrating STCs are commonly relevant for low-temperature DHNs, while concentrating solar thermal systems can be more suitable where higher temperature is required. Their output is intermittent, making them highly reliant on TES, especially seasonal storage, to balance supply and demand.

Geothermal energy is usually available as warm water at low- to medium temperatures in naturally occurring underground reservoirs and can be extracted for heating applications like DHNs [59]. It is well-suited for base-load heat supply in DHNs due to its stable and continuous output. Geothermal systems are commonly classified based on depth and enthalpy, ranging from shallow (low-temperature) to deep (medium- to high-temperature) resources, as well as by the method of heat extraction (e.g., hydrothermal vs. enhanced systems) [60]. The feasibility of geothermal integration depends on resource temperature, depth, and local geological conditions, as well as compatibility with network temperature requirements. In this paper, the focus is on shallow to deep geothermal systems for direct heat supply, explicitly excluding ground-source heat pumps and geothermal systems used for electricity generation.

Biomass fuel sourced from plant and animal waste can be used as a renewable energy source in DHNs. Biomass's renewability is a topic of debate in the renewable energy field, so here we want to state that its renewability depends strongly on sourcing, land-use context, and sustainability standards [61]. It can be burned directly in the boilers to produce heat energy or combined with a CHP plant to serve a DHN. Biomass-supported systems can have medium-term or seasonal storage that can help mitigate the challenge of intermittent supply [62]. Thus, making it suitable for both conventional high-temperature and modern low-temperature DHNs.

4.1.2. Electricity-to-heat

Here electricity from RES is converted into heat and is supplied to DHNs. This pathway enables the integration of intermittent renewable electricity into thermal networks. Following RES can follow this pathway.

Solar photovoltaic (PV) panels are not heat sources in the thermal sense; they convert solar energy to electricity. This renewable electricity can be converted to heat using electric boilers or large-scale heat pumps to serve the DHNs, or else can be stored in batteries for later use [63]. The performance of PV-based DHNs depends on electricity availability, conversion efficiency, and the coefficient of performance (COP) of heat pumps. They are advantageous in low-temperature DHNs, where heat pumps operate more efficiently.

Similarly, *Wind* energy is converted to electrical energy by feeding it to the wind turbines [64]. For DHN applications, this electrical energy must be converted into heat using heat pumps, electric boilers, or related power-to-heat technologies. The intermittent nature of wind causes fluctuations which is challenging for electricity grids, so energy storage is used to stabilize the power output. Electrochemical cells or batteries are most used for storage, from there energy is fed to grid or can be converted to heat for DHNs [64]. Integration into DHNs allows excess renewable electricity to be utilized effectively and reduces curtailment.

4.1.3. Energy carrier-based

In this pathway, renewable energy is first converted into intermediate energy carriers such as green hydrogen, which can be stored and later converted into heat for DHNs. This pathway is particularly relevant for long-term storage and sector coupling. Following RES can follow this pathway.

Green Hydrogen is usually produced by feeding the electricity from RES to an electrolyzer that uses it to produce hydrogen [65]. It can be stored for extended periods and is one of the potential solutions to address the challenges associated with variability in RES. Additionally, hydrogen can help alleviate issues such as grid congestion [66] by providing the necessary flexibility. Hydrogen is typically utilized in boilers and gas turbines for heat and electricity production or in fuel

cells that cogenerate both [67,68]. Its overall efficiency is relatively low due to multiple energy conversion steps. As a result, hydrogen is typically considered a system-level flexibility option rather than a primary heat source for DHNs.

4.2. Evaluation of RES for DHNs

This section examines the potential of different RES to serve DHNs. RES are reviewed based on cost, efficiency, storage potential, complexity, flexibility, and carbon footprint. A discussion is provided that intuitively highlights the benefits and limitations of each renewable energy source. This should help readers to get an overview of different RES in DHNs and to qualitatively understand the main trade-offs.

It is important to note that the available literature for RES in DHNs is highly heterogeneous in terms of energy conversion pathways, system configurations, scales, regional conditions, and underlying assumptions. As a result, direct comparison across RES on a unified basis is inherently challenging. Also, a common reference boundary is required for proper comparison, such as 1 kWh_{th} of useful heat delivered at the consumer substation. However, because the reviewed studies do not consistently report results at this boundary, the values are retained as reported and interpreted as indicative rather than directly comparable. Therefore, the reported values for cost, efficiency, and other indicators are presented here as indicative values/ranges drawn from different studies, intended to provide general insight rather than strict comparability. Also, discussions are provided in relation to their mentioned energy conversion pathway and boundary.

4.2.1. Cost

Since DHNs are designed for heat transmission, the relevant economic metric is the levelized cost of heat (LCOH). In general, it accounts for annualized capital investment, operation and maintenance (O&M) costs, fuel or electricity input costs, and auxiliary system costs (pumping, heat exchangers, wells, collectors, storage units, inverters, heat pumps, etc.) depending on the system studied. It will vary depending how the specific study has estimated it. Thus, comparing the LCOH across different RES in DHNs is challenging due to the diversity in system setups, scales, and regional conditions. Also, while the IRENA publishes annual reports on the levelized cost of electricity (LCOE) for RES [69], there is no equivalent standardized report for LCOH. However, several studies have estimated the LCOH for different RES in distinct DHNs and to provide insight into the LCOH related to RES in DHNs, a discussion is presented here. Wyrwa et al. [57] estimate an LCOH of \$0.054/kWh when flat plate solar collectors fulfill 20 % of total heat demand. Goel et al. [70] report a lower LCOH of \$0.031/kWh for a single parabolic trough collector. Saini et al. [63] find a LCOH of \$0.083/kWh for heat generated using PV systems with heat pumps.

For wind turbines, Cao et al. [71] reports the LCOH of \$0.016 to \$0.056/kWh depending upon the factors like scale of the system, use of heat pump or electric boiler, and others. Bareib et al. [64] explore power-to-heat systems utilizing surplus wind energy for space heating, reporting an LCOH of \$0.06/kWh. For a geothermal system, Romanov et al. [59] calculate an LCOH of \$0.042/kWh, while Oh et al. [72] estimate a higher LCOH of \$0.071/kWh due to the inclusion of costs associated with converting decommissioned oil and gas wells into geothermal wells. Maki et al. [73] report an LCOH of approx. \$0.037/kWh for a biomass-based boiler using wood pellets, chips, and straw. For hydrogen-based systems, Arsalis et al. [68] find a levelized cost of \$0.059/kWh in a hybrid configuration (electricity plus heat). For hydrogen only, the LCOH will be even higher because, currently, as per IEA [74] unit of cost of hydrogen produced using PV or wind energy is \$1.5-\$4/kg which is relatively high compared to other fuels. These values provide the general assessment of LCOH for RES in DHN integration.

4.2.2. Thermal efficiency

This assessment focuses on efficacy of RES-based DHNs in converting renewable energy into usable heat, which is critical for DHNs. Various solar thermal systems demonstrate distinct thermal efficiencies based on the energy conversion pathway (e.g., electrical efficiency, thermal efficiency, or COP) and other factors. For example, evacuated tube solar collectors achieve approximately 60 % [75], high vacuum solar collectors reach 52 % [76], and two-stage solar concentrators (TSSC) above 50 % [77].

PV arrays produce electricity, which can be used directly or in combination with other sources, often as part of a CHP system within DHNs. Accordingly, the reported efficiencies reflect both electrical and thermal performance. Weiler et al. [78] and Keskin et al. [79] cite PV module efficiencies of 17 % and 20.4 %, with CHP system thermal efficiencies of approx. 40 % and 50.3 %, respectively. Like PV arrays, wind turbines provide electrical output and follow a comparable integration path in DHNs. Electrical efficiency of wind turbines is claimed to be up to 50 % [80]. Arabkoohsar et al. [81] mention a wind turbine electrical efficiency of 31.4 %, though thermal system efficiency is not specified. However, a study focusing on long-distance heat transmission mentions the wind-to-heat conversion efficiency of ~ 40 % using a heat pump [82].

Geothermal systems used for direct heat supply in DHNs can achieve substantially high COP values, often around 8–10, signifying very efficient processes, because heat is supplied directly and only limited pumping electricity is required [83]. However, for complete geothermal-based DHN, Kalinci et al. [84] estimate a thermal efficiency of 40.21 % due to various heat transfer losses occurring between the geothermal well and the end users. Koch et al. [85] report a CHP plant efficiency of 43.9 % in biomass-based systems, with associated individual biomass-based boilers reaching up to efficiency of 92 %. Similarly, Sigurjonsson et al. [86] document a thermal efficiency of 44 % for a biomass-based DHN. For hydrogen, Patin et al. [87] state that fuel cell thermal efficiency ranges from 15 to 45 %, depending on load factors, while Amrouche et al. [88] estimate a thermal efficiency of ~ 30 % for hydrogen-fueled gas turbines.

4.2.3. Storage potential

Storage plays a central role in balancing supply and demand in DHNs, particularly for intermittent RES. All RES discussed in this article possess energy storage capabilities. Solar thermal and geothermal systems typically use TES, while PV and wind turbine systems rely on battery storage. Biomass can be stored via thermochemical methods [89], and hydrogen can be stored as compressed gas in tanks, underground caverns, or solid-state materials that absorb hydrogen [90]. If required, hydrogen can be converted to heat and stored in TES. Storage is not linked to a source, but to a commodity. Storage costs are commonly expressed as the levelized cost of storage (LCOS) (\$/kWh). However, key factors, such as storage duration, upfront investment, operating costs, and spatial requirements, vary significantly across these technologies and should be considered alongside LCOS.

Although, to give the reader a perspective about the storage cost related to RES. A discussion is provided hereafter. TES in DHNs exhibits a wide LCOS range, from 0.10 to 208.70 \$/kWh, depending on the storage type, such as water tank TES, UTES, BTES, ATES, phase change materials, salt hydration, or absorption systems [91]. Similarly, storage durations vary widely, from a few hours to several months. For battery storage, commercial-scale LCOS is estimated at 164 \$/kWh for an 8-hour system and 215 \$/kWh for a 2-hour system [92]. Thermochemical heat storage for biomass yields an LCOS between 0.92 and 2.37 \$/kWh, assuming one full charge and discharge per day [89]. Hydrogen storage, depending on the method, also shows varied LCOS. Patel et al. [90] report 0.732 \$/kWh for hydrogen stored in pipelines with a daily discharge cycle, while another study estimates an LCOS of 9 \$/kWh for hydrogen-fueled vehicles with a one-day cycle [93].

4.2.4. Complexity

In DHNs, system complexity influences the feasibility of integration, particularly in relation to control strategies, infrastructure requirements, and coupling between energy sectors. It is reviewed based on the number of energy conversions required for each renewable energy source to be integrated into DHNs and the number of main components involved. PV systems require the conversion of solar energy to electricity and subsequently to heat. The major components include PV panels, inverters, heat pumps or electric boilers, control systems, heat exchangers, and circulation pumps [63]. Wind turbines follow a similar conversion path, wind to electricity to heat, and share most components with PV systems, except for the turbines. Geothermal systems provide heat directly but involve more infrastructure, such as wells, wellheads, multiple heat exchangers, dedicated piping networks, and central pumping stations [59].

Biomass is combusted in boilers to generate heat, requiring components like fuel storage and handling systems, boilers, heat exchangers, pumps, control systems, and ash removal units [62]. Hydrogen can be used directly in boilers for heat generation or indirectly via fuel cells to produce electricity, which is then converted to heat. Its associated infrastructure includes production units (e.g., electrolyzer), storage tanks, boilers or fuel cells, heat exchangers, pumps, and control systems [67]. STCs convert solar energy directly into thermal energy and involve fewer components, such as collectors, heat exchangers, pumps, and controllers.

4.2.5. Flexibility

Flexibility in DHNs is closely linked to the ability of the network to absorb variable heat inputs, utilize storage, and coordinate with electricity systems. Each RES can provide flexibility by adapting its operation to changes in supply, demand, or external conditions. Depending upon the nature of RES and energy conversion, the flexibility mechanism and role vary for different RES. Solar PV [79] and wind [81] are highly weather dependent for generation but can supply electricity to flexible loads (heat pumps, EVs, electrolyzer) or charge batteries. They can provide flexibility through storage, demand-side measures, or backup generation. Geothermal [94] and biomass [85] are dispatchable; solar thermal [57] becomes flexible if paired with thermal storage. They allow the operator to adjust output according to needs within technical and resource limits. They can match output to demand directly, store heat for hours to months, and integrate well with DHNs. Hydrogen [66] is not a primary source but an enabler that connects electricity and heat systems for long-term flexibility. It can absorb surplus electricity from PV/wind, store it seasonally, and reconvert it to electricity or heat as needed. Flexibility depends on both the technology's controllability and the system context.

4.2.6. Carbon footprint

RES have significantly lower carbon footprints than fossil fuel-based systems; they are not entirely emission-free. During operation, RES typically produce near-zero CO₂ emissions; however, emissions do occur during upstream processes such as raw material extraction, manufacturing, transportation, installation, and end-of-life disposal.

For direct heat technologies, carbon emissions are expressed in per unit of heat (g CO₂/kWh_{th}). The reported carbon emissions are approximately 10 g of CO₂ equivalent per kilowatt-hour (g CO₂/kWh_{th}) for geothermal systems, 10–35 g CO₂/kWh_{th} for STCs, and 5–200 g CO₂/kWh_{th} for biomass-based systems [95]. For electricity-generating RES, emissions are typically reported in per unit of electricity (g CO₂/kWh_e). The reported emissions are 11 g CO₂/kWh_e for wind and 48 g CO₂/kWh_e for PV [96]. When these systems are used in DHNs, the effective emissions per unit of heat depend on the conversion technology (COP of heat pump or electric boiler efficiency). Similarly, for green hydrogen, total emissions depend on two main factors: the type of RES used to generate electricity for electrolysis, and the subsequent energy conversion method. For instance, a hydrogen system comprising wind turbine, fuel

cell, and electrolyzer emits around 34 g CO₂/kWh [97].

Here, the emissions reported in g CO₂/kWh_e are converted to g CO₂/kWh_{th} using a correlation ($\text{g CO}_2/\text{kWh}_{\text{th}} = \text{g CO}_2/\text{kWh}_e / (\text{COP or efficiency})$) [98] and considering heat pump with typical COP of 2.5. Thus, in terms of g CO₂/kWh_{th}, the emission values are 4.4 g CO₂/kWh_{th} for wind, 19.2 g CO₂/kWh_{th} for PV, and 13.6 g CO₂/kWh_{th} for green hydrogen. It is to be noted here that heat pump considered here has a COP of 2.5 which represents the high efficiency of 250 %. However, if electric boiler with efficiency less than 100 % was considered for electricity-to-heat conversion, the estimated emission values would be different. Also, here the emission of green hydrogen is derived from a setup with wind turbine and electrolyzer, if it is changed to other energy source like PV, the emission value will change. Thus, it can be concluded that carbon footprint comparisons across RES in DHNs are inherently challenging due to differences in system boundaries, energy carriers, and conversion pathways.

Overall, it can be inferred that due to the diversity of system configurations and assumptions in literature, the reported values for different factors like LCOH, efficiency, LCOS, etc. are all indicative and it is difficult to put them into directly comparable metrics. Also, the above evaluation of RES under various factors highlights that no single RES is universally optimal for DHNs. Their suitability depends strongly on network characteristics, integration pathways, and system objectives. Direct thermal sources offer higher efficiency but may be constrained by availability and intermittency, while electricity-based pathways provide flexibility at the cost of additional conversion losses. Energy carrier-based options, such as hydrogen, enable long-term storage and sector coupling, but they involve additional conversion losses and higher system complexity. Therefore, hybrid systems, combining multiple RES and integration pathways, look promising. They can present a more robust and flexible approach for integrating renewables into DHNs, enabling more reliable, efficient, and sustainable heat delivery. However, their performance is highly context-dependent and must be evaluated case by case rather than assumed to be superior.

5. Classification of modeling approaches for DHNs

DHNs are complex infrastructures, and RES integration increases this complexity. Given the substantial infrastructure and investment DHNs require, system modeling provides a powerful means to assess their performance across various parameters without altering the physical setup. Thus, decision-makers must also identify appropriate modeling approaches to evaluate these choices effectively. As discussed in Introduction section, while several studies have reviewed DHN modeling approaches, classifications often focus on specific aspects such as software tools, components, or optimization methods. However, there is a lack of classification based on the physics of the models. Additionally, the recent advancements in data-driven models for DHNs require more attention. This section seeks to fill these gaps. Additionally, this section also highlights the suitability of different modeling approaches for analyzing RES-based DHNs. Furthermore, a framework is proposed to relate common DHN tasks to appropriate modeling approaches.

Researchers have widely adopted modeling approaches to explore different components, configurations, and operational strategies within DHNs. Given the breadth of DHN modeling literature, classifying the modeling approaches offers a structured means to review existing research, ensuring a focused and insightful analysis. Numerous modeling approaches are available in the literature to evaluate DHN performance. This section presents and categorizes these modeling approaches while explaining their applications in DHN studies. Since no universally accepted classification method exists, a framework emphasized on technically distinct modeling aspects is proposed and is illustrated in Fig. 3.

Modeling techniques for DHNs may aim to simulate the entire system or focus on specific components. Component-level models are especially valuable for design tasks such as determining pipe diameters and pump

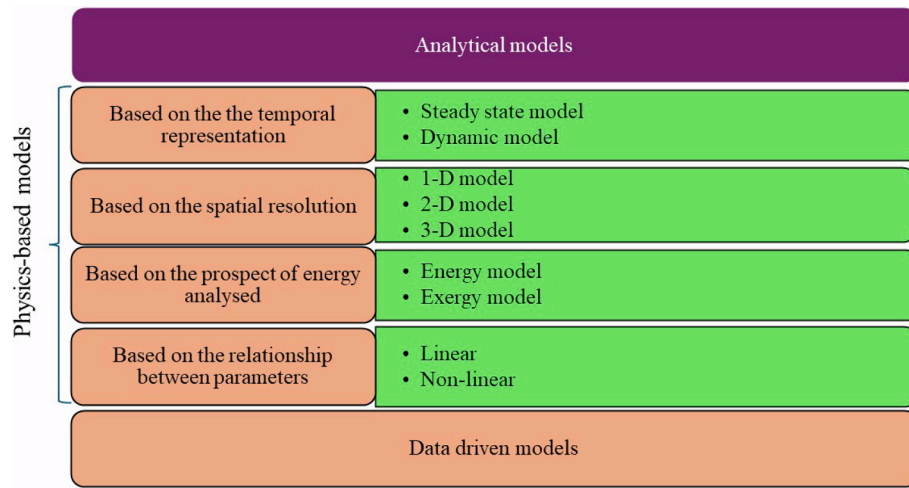


Fig. 3. Classification of modeling approaches for DHNs.

capacities, while integrated system models are better suited for scheduling and operational management. The level of detail and accuracy needed may differ between the two. While this section primarily focuses on thermal network modeling, some studies explicitly integrate electricity into their DHN models, especially when assessing integrated

energy systems (IES). This aspect is important and has been discussed accordingly.

The purpose of categorizing modeling approaches is to provide a clearer understanding of the diverse aspects of DHN modeling. It is essential to recognize that these categories are not mutually exclusive; a

Table 2

Article-wise categorical fit of the proposed modeling approaches for DHNs.

Author(s)	Steady state	Dynamic	1D	2D	3D	Energy	Exergy	Linear	Nonlinear	Data-driven
Wang et al. (2023)	✓	✓						✓		
Duquette et al. (2016)	✓	✓	✓							
Meibodi et al. (2024)	✓	✓			✓					
Yang et al. (2018)	✓									
Xiang et al. (2019)	✓									
Ma et al. (2021)		✓								
Qin et al. (2019)	✓	✓							✓	
Sartor (2017)	✓	✓				✓	✓			
Li et al. (2010)	✓	✓							✓	
Dalla Rosa et al. (2011)	✓			✓				✓		✓
Villar et al. (2013)		✓		✓						
Danielewicz et al. (2016)	✓				✓					
Hussein et al. (2021)					✓					✓
Kudela et al. (2019)	✓		✓							
Jakubek et al. (2023)	✓		✓					✓		
Ocioń et al. (2019)	✓		✓	✓				✓		
Sartor et al. (2018)		✓	✓	✓			✓			
Meibodi et al. (2023)		✓		✓	✓					✓
Allen et al. (2020)						✓				✓
Kallert et al. (2017)		✓					✓			
Li et al. (2010)	✓	✓								
Ozcan et al. (2021)	✓					✓	✓			
Keçebaş et al. (2011)	✓					✓	✓			
Ozgener et al. (2006)	✓					✓				
Quirosa et al. (2023)		✓	✓	✓		✓				
Li et al. (2023)						✓	✓			✓
Ozgener et al. (2005)	✓					✓	✓			
Li et al. (2012)						✓	✓			
Machado et al. (2022)		✓				✓			✓	
Ahmed et al. (2023)		✓							✓	
Blommaert et al. (2020)								✓	✓	
Lambert et al. (2024)								✓	✓	✓
Spirito et al. (2024)						✓		✓		✓
Lin et al. (2025)		✓	✓					✓		
Lumbreras et al. (2021)										✓
Hua et al. (2024)										✓
Idowu et al. (2014)										✓
Gianniou et al. (2018)										✓
Abghari et al. (2019)										✓
Hossain et al. (2020)										✓

Note: The ticks are marked according to the modeling approaches (Steady state, Dynamic, 1D, 2D, 3D, Energy, Exergy, Linear, Nonlinear, Data-driven) used by each reference in Table 2 and are accurate to the best of our knowledge. Also, articles are categorized based on the authors' emphasis on different technical aspects; however, the discussion in the following sections focuses solely on the primary objective of each study.

single model may fall under multiple classifications. For example, a dynamic model may also be an exergy model and take a 1-D or 3-D form. This multi-label structure overlap is evident in Table 2, illustrating how each study aligns with the proposed classification criteria.

Therefore, the proposed framework should be interpreted as a faceted or multi-label classification rather than as a mutually exclusive taxonomy. At the highest level, DHN models are distinguished by modeling paradigm, namely physics-based/analytical models and data-driven models. Physics-based models are then described through four technical dimensions: temporal representation, spatial resolution, thermodynamic perspective, and mathematical structure. These dimensions are different in nature because they describe different modeling choices made during model development. Therefore, a single model may be characterized by multiple labels, such as dynamic–1D–energy-based–nonlinear. This multi-label structure reflects the practical nature of DHN modeling, where models are typically constructed by combining several methodological choices according to the objective, required accuracy, available data, system scale, and computational constraints.

The contribution of the framework is therefore not the isolated identification of each individual attribute, but the use of these attributes to provide an organized discussion of DHN modeling literature and support model selection. This is further developed in Section 5.6, where common DHN modeling objectives are linked to these modeling approaches. Thus, making it useful for several stakeholders like researchers in this field, operators and control engineers, etc.”.

5.1. Classification based on the temporal representation (steady state, dynamic)

Steady-state models assume equilibrium conditions, while dynamic models account for time-dependent variations in the system's behavior. Both approaches are widely used in DHNs depending on the modeling objectives. Yang et al. [99] develop a steady-state integrated model for CHP-based DHNs. Their formulation solves coupled hydraulic–thermal equations for the network while incorporating power flow constraints, making it relevant for IES. Duquette et al. [100] create a steady-state physical pipe model using a variable transport delay formulation to simulate DHNs with variable flow. This approach balances accuracy and computation time, making it practical for large networks with variable speed pumping systems. Xiang et al. [101] present an improved steady-state hydraulic-thermal decoupling method, reporting approximately 35 % performance gains using a recursive search strategy.

Conversely, other researchers emphasize dynamic models for their ability to accurately reflect real-time system behavior. Wang et al. [102] observe that long-distance district heating pipelines often use pseudo-dynamic models and propose a fully dynamic model for fast and accurate analysis. Meibodi et al. [103] develop a model that combines the dynamic thermal network (DTN) method with the plug flow N-continuously stirred tanks (PFST) model, effectively capturing pipeline dynamics over short time scales. Ma et al. [104] propose a dynamic model for integrated heat–electricity systems, incorporating integrated demand response to optimize the operation of both networks simultaneously. Sartor [105] create an open-source dynamic simulation tool to support developments in DHNs. It uses a modular structure to represent pipes, substations, and heat sources, allowing flexible scenario testing.

Some studies integrate both modeling approaches to reduce computation time while capturing essential transients. Qin et al. [106] propose a quasi-dynamic model for IES that combines DHNs and power networks. The model accommodates different temporal resolutions and incorporates multiple distributed energy resources Li et al. [107] develop steady-state and dynamic models of an indirect DHN for comparative analysis, demonstrating trade-offs between accuracy and simulation time.

A recurring pattern is that hydraulics are often modelled in steady-state for efficiency, while thermal dynamics are treated with dynamic formulations to capture transport delays and demand fluctuations

[100,103,106]. However, several studies also couple hydraulics dynamically with thermal behaviour when detailed operational accuracy is required [102,104,107]. Steady-state approaches have low computational requirements, making them well-suited for design and planning tasks at both network and system levels. Dynamic models simulate transient variations in temperature, flow, and pressure over time, making them essential for analysing operational flexibility, control strategies, and system response to disturbances suited for decision making both in design and operation phase. Thus, they can be useful for RES-based DHNs, as they can capture variations in renewable generation, thermal storage behavior, and demand fluctuations.

5.2. Classification based on the spatial resolution (1D, 2D, 3D)

Modeling of DHN pipelines is strongly influenced by how temperature gradients are represented. Pipes are the dominant source of thermal losses and play a central role in system efficiency, cost, and reliability. Depending on the level of details required, variations in temperature, flow, momentum, etc. can be considered along the radial, axial, and circumferential directions, corresponding to 1D, 2D, or 3D models.

Kudela et al. [108] develop a 1D steady-state model to simulate heat transfer in aboveground heating pipes with thermal accumulation. Similarly, Jakubek et al. [109] use a 1D model with experimental validation to analyze heat losses in pre-insulated twin pipes. Dalla Rosa et al. [110] employ 2D finite element method (FEM) modeling to assess various DHN pipe configurations. Villar et al. [111] use a 2D computational fluid dynamics (CFD) model in Ansys Fluent to evaluate a DHN using waste heat from a steel plant. Danielewicz et al. [112] propose a 3D model to accurately estimate pipe heat losses for design optimization. Hussein et al. [113] introduce an automated 3D simulation platform that enables rapid and efficient design of district-level optimal pipe layouts and sizing.

Some studies compare or combine multiple modeling dimensions. Ocłoń et al. [114] evaluate heat losses in twin and pre-insulated pipes using both 1D and 2D FEM models, accounting for temperatures at varying soil depths. Sartor et al. [115] examine the feasibility of simulating heat wave propagation using 1D and 2D finite volume method (FVM) models with identical spatial resolution. Meibodi et al. [116] use a DTN model alongside 2D and 3D models to capture dynamic heat transfer in underground pipelines.

The choice of dimensionality reflects a trade-off between computational cost, accuracy, and the ability to capture local effects. 1D models are widely used because they approximate heat transfer along the pipe axis with relatively low computational burden. They are effective when the objective is to estimate overall losses or efficiency and temperature profiles. 2D models include radial–axial distributions, making them valuable for deeper analysis of underground pipes, soil–pipe interactions, etc. 3D models provide the most detailed representation of thermal behaviour. They are indispensable for design optimization, fault analysis, or cases where complex geometries (e.g., joints, bends, fittings) affect heat losses. Studies confirm that while 1D models are efficient for system-level studies, 2D and 3D models are essential for detailed pipe-level assessments [114–116]. For RES integration, spatial resolution becomes important when assessing distributed heat sources, local heat injections, and temperature variations in low-temperature DHNs. Accordingly, any of the above approaches can be chosen.

5.3. Classification based on the prospect of energy analyzed (Energy, Exergy)

Energy analysis quantifies the total energy entering and leaving a system, based on the first law of thermodynamics. In contrast, exergy analysis incorporates the second law of thermodynamics to evaluate the quality of energy, identifying how much can be converted into useful work and where losses due to irreversibility (e.g., friction or heat loss) occur in the system [117].

Some studies explicitly present their models as energy-based models. For example, Allen et al. [118] advocate for topology optimization to support DHN adoption, using energy modeling with integrated thermal and hydraulic calculations to compare the performance of “conventional” and “advanced” systems at the district level. Ozgener et al. [119] Compare two geothermal-based DHNs using energy analysis and propose a model to improve their heating performance. Quirosa et al. [120] introduce a method to control the temperatures of DHCNs by integrating coaxial borehole heat exchangers. Energy analysis examines this integration of different systems and shows the decline in costs and emissions.

Some other studies are based on exergy. For example, Kallert et al. [121] show the advantages of exergy-based evaluation for small-scale DHNs by modeling ten low-energy residential buildings. Li et al. [122] incorporate exergy efficiency into multi-objective optimization (including auxiliary equipment and carbon trading), achieving measurable performance gains. Ozcan et al. [123] conduct numerical investigations of conventional and advanced exergy performance, analyzing waste heat from four plants.

There are also studies that combine energy and exergy analyses. For example, Keçebaş et al. [124] study both for the Afyon geothermal DHN in Turkey, showing the potential of exergy analysis in system optimization. Ozgener et al. [125] further emphasizes this by modeling geothermal DHNs and evaluating performance and efficiency through both lenses using real system data. Li et al. [126] compute total energy and exergy efficiencies for a hypothetical low-temperature DHN serving thirty homes.

Both (energy and exergy) analyses are valuable; energy analysis is often preferred for its simplicity, lower computational demand, and suitability for early-stage design or when only thermal balance is needed. It typically forms the foundation of modeling studies involving heat transfer in DHNs. Exergy analysis is increasingly used for deeper efficiency assessments, especially at low supply temperatures or when integrating multiple thermal sources. Exergy-based models are especially relevant for RES integration, as they enable better assessment of low-temperature heat sources and the efficient utilization of renewable energy within DHNs.

5.4. Classification based on the relationship between parameters (linear, nonlinear)

In DHNs, thermo-hydraulic equations include nonlinear terms and pressure–flow relationships depend on velocity and temperature. Dynamic heat demands further couples thermal and hydraulic behavior. As a result, small changes in temperature, load, or mass flow can induce disproportionate responses elsewhere in the network, making DHN behavior fundamentally nonlinear. A nonlinear transient model is often essential for designing effective controllers for such systems, as it captures complex and dynamic behavior. Consequently, nonlinear modeling approaches have been explored in DHN research. Ahmed et al. [127] use a nonlinear model to describe temperature dynamics in DHNs, demonstrating its utility in controller design. Their approach employs a scalable graph-theoretic framework to represent temperature behavior of the network. Machado et al. [128] investigate a nonlinear thermo-hydraulic model of DHN comprising multiple producers, consumers, and sinks, assuming a fully meshed and interconnected topology. Blommaert et al. [129] introduce an automated method for DHN topology design based on a nonlinear model of flow and heat transfer. Lambert et al. [130] implement a two-stage optimization: initially, pipe diameters and routing are optimized using MILP, results from first phase are fed to sequential quadratic programming to solve a nonlinear thermo-hydraulic flow model.

In contrast, linear models are generally not applied to full-scale DHNs or their core components, as these systems typically operate under conditions that defy linear approximation. However, linearization techniques or simplified linear models are employed for specific tasks

such as system optimization and control. This includes linear and MILP formulations, which are widely used in DHN planning and operation studies. Linearized DHN representations are also common in model predictive control (MPC) applications. Spirito et al. [131], for instance, utilize a linear programming model to assess the potential for widespread adoption of renewable-based DHNs, identifying regions where such systems are more cost-effective and environmentally advantageous than individual heating. Lin et al. [132] apply linearization and iterative optimization to simplify a dynamic hydraulic-thermal model for optimizing single-pipe operational balance.

Linear models assume proportional relationships between system variables, making them simpler to solve but less accurate for systems with strong nonlinear behaviors. Hence, in DHNs, they are generally used in suboptimization (like determining optimal pipe layouts in complex RES-based DHNs) or approximate analysis of a subsystem. Nonlinear models provide high accuracy and physical realism, making them essential for RES-based DHNs as they can capture the dynamic interaction between renewable heat sources, storage systems, and network operation.

5.5. Data-driven models

All the classifications discussed so far relate to physical models. Here, we discuss data-driven models and machine learning (ML) approaches that have been applied to DHNs. Unlike physical models, these methods leverage large datasets, often from smart meters, supervisory control and data acquisition (SCADA) systems, or sensors, to identify patterns, forecast performance, and support real-time decision-making. This paper focuses primarily on networks, while the application of data-driven models focuses on demand-oriented aspects or operation and control, so, to provide the reader with a glimpse of these, a brief discussion in terms of their applications in DHNs is presented here.

Data-driven approaches are applied to different applications in DHNs such as heat demand forecasting, which is crucial for optimizing heat production and reducing fuel costs. Short and long-term heat load predictions are conducted using methods such as linear regression, decision trees, artificial neural networks (ANNs), [133] and support vector machines (SVMs) [134]. Similarly, demand-side management for DHNs requires accurate load predictions from cities and buildings. Adjusting or shifting demand profiles to match generation availability can improve efficiency and help to integrate RES. In this line, Lumbreras et al. [135] introduce a novel data-driven model based on a Q-algorithm to estimate and describe heating demand in buildings connected to DHNs. Hua et al. [136] analyze the hourly load patterns for a city and compare the prediction accuracy of black-box ANN model with multiple linear regression (MLR) model, finding that MLR methods provide better insights into load patterns.

Another important application includes customer segmentation and consumption pattern analysis, which are studied to optimize heat distribution. Clustering methods like k-shape [137] and k-means [138] are used to group consumers by typical daily heating profiles for targeted control strategies. Further, detecting anomalies in district heating substations can prevent inefficiencies and system failures. Abghari et al. [139] develop an advanced mining approach that combines clustering and sequential pattern mining to identify faulty substations. Xue et al. [140] use data mining techniques to detect operational faults, while Li et al. [141] introduce a two-level fault detection framework that employs convolutional neural networks (CNNs). In addition, leak detection in underground district heating pipelines is crucial for preventing water and energy loss. Hossain et al. [142] implement deep learning-based CNN models alongside traditional machine learning classifiers, such as logistic regression (LR), random forests (RF), and SVM, to classify leakage faults in infrared images captured by drones.

With the increasing integration of artificial intelligence (AI) across all sectors, these methods are becoming more critical for DHNs. Integrating various RES, which are inherently variable, combined with

increasing fluctuations in consumer loads, will require extensive data processing and management [143]. As a result, data-driven approaches are expected to play a greater role in their real-time control and optimization.

5.6. Analysis of modeling approaches and selection strategies

In terms of classification, various modeling approaches have been discussed so far. This section aims to provide a decision tree to guide the selection of an appropriate model for DHN-related applications.

Before moving to a decision tree that lays out the path for selecting a possible modeling approach, it is important to clarify the relationship between modeling objectives and modeling approaches. Table 3 provides a selection-oriented overview linking common DHN modeling objectives to appropriate modeling approaches and representative studies.

Further, to provide an illustrative link between the RES integration pathways discussed in Section 4 with the modeling approaches reviewed in Section 5, Table 4 is formulated. Different RES introduces distinctive physical characteristics like slow subsurface dynamics for geothermal, intermittent electricity generation for PV and wind, conversion-chain losses for hydrogen, time-varying availability and storage cycles for solar, and these characteristics narrow the set of modeling approaches that can capture the relevant behavior. The table does not imply that each pathway-model combination has been directly tested in the cited literature. Rather, it summarizes examples of modeling approaches that may be suitable based on the technical characteristics of each pathway.

Table 4 shows that the selection of a modeling approach depends not

Table 3

Selection-oriented overview of modeling approaches for common DHN analysis tasks.

Modeling objectives	Modeling approaches with representative references
<i>Thermal analysis</i> (temperature profiles, heat-loss assessment)	Steady state for thermal performance [100]; 1D/2D FEM based for heat loss calculations [114]; Fully dynamic DTN/thermo-hydraulic for transient transport [102,103]; 2D/3D FEM/CFD for local detail [110,112].
<i>Hydraulic analysis</i> (pump sizing, pressure, flow balance)	Steady-state hydraulic solvers for pump sizing [100]; hydraulic-thermal decoupling to solve steady-state DHN model [101]; Fully dynamic thermo-hydraulics for long-distance DHN [102].
<i>Pipe performance</i> (insulation, materials, local gradients)	1D for transients in pipe with thermal accumulation [108]; 2D FEM for twin pipes [109]; DTN + PFST for analysis of buried pipelines [103].
<i>Layout optimisation/network planning</i> (routing, diameters, expansion)	Steady-state model for expansion planning [99]; 3D for pipe routing and optimization [113]; 2D CFD for layout optimization [111]. Nonlinear for optimal topology and pipe diameter [129,130].
<i>Integrated operation/planning</i> (RES, storage, electricity coupling)	Quasi-dynamic for optimization and planning of IES [106]; Dynamic for energy flow study, control, and flexibility improvement of IES [104]; Steady state for optimal heat-power flow analysis [99];
<i>Energy & exergy performance benchmarking</i>	Energy analysis for system-level balances [118–120]; Exergy analysis for efficiency/irreversibility [121–123]; Combined energy-exergy [124–126].
<i>Controller design</i>	Nonlinear dynamic for controller design [127,128]
<i>Demand forecasting</i>	Heat demand forecasting with regression/ANN/SVM [135,136]; Dynamic model for demand response [104].

Note: Linear models are generally employed as approximations in optimization subproblems (as discussed in Section 5.4). Also, Table 3 tabulates some of the important and relevant activities, it can be extended further by including other activities like leak detection, customer segmentation, and many others.

Table 4

Illustrative linkage between RES integration pathways and DHN modeling approaches.

RES integration pathway	Potentially suitable modeling approaches
Solar thermal with TES (Direct thermal)	Dynamic models to capture solar variability and TES charge/discharge behaviour, combined energy and exergy analysis for low-temperature DHN performance, 1D network models for temperature propagation and heat-loss assessment, 2D/3D models for detailed collector/pipe, heat-transfer studies when local gradients are important, linear optimization for storage sizing.
Geothermal (Direct thermal)	2D FEM and 3D models for detailed pipe and borehole heat-transfer analysis, energy and exergy for heat utilization, steady-state thermo-hydraulic models for base-load assessment, dynamic thermo-hydraulic models for network response, 1D models for well/network temperature propagation, nonlinear models for coupled flow-pressure-temperature behaviour.
Biomass boiler or biomass CHP (Direct thermal)	Steady-state models for sizing and planning; dynamic operational models for boiler response, linear/MILP optimization for dispatch scheduling in multi-source systems; nonlinear models for part-load boiler/CHP behaviour.
Solar PV or wind with heat pump/electric boiler (Electricity-to-heat)	Dynamic models for integrated heat-electricity systems with demand response, nonlinear models for temperature dynamics and controller design, data-driven models for renewable-generation and heat-demand forecasting, linear optimization for operational scheduling under electricity-price or availability constraints.
Green hydrogen (Energy carrier-based)	Energy/exergy analysis for conversion-loss assessment across electrolysis, storage, and reconversion, dynamic models for electricity-hydrogen-heat coupling and long-duration storage, nonlinear models for electrolyzer, fuel-cell, gas-turbine, or CHP performance.

only on the modeling objective, but also on the characteristics of the RES pathway being integrated. Additionally, the distinction between new and existing DHNs is also important for RES integration. In new DHNs, the network temperature level, pipe sizing, storage capacity, and source location can be co-designed with the selected RES pathway. This creates opportunities for low-temperature operation, efficient heat-pump integration, and optimized placement of storage or distributed heat sources. In existing DHNs, RES integration is usually constrained by the installed pipe network, existing substations, consumer-side temperature requirements, available land, and legacy heat sources. Consequently, retrofit cases often require more detailed thermo-hydraulic modeling, dynamic analysis of supply and return temperatures, and evaluation of auxiliary technologies such as heat pumps, boosters, or backup boilers.

5.7. Decision tree for selection of modeling approach(s)

Fig. 4 presents a structured decision tree to guide the selection of appropriate modeling approaches for DHNs. The decision process begins with identifying the modeling objective, followed by the RES integration pathway and the network context, namely whether the system is a new DHN or an existing DHN undergoing retrofit or expansion. These factors determine the required temporal resolution, spatial detail, coupling with electricity or storage systems, and acceptable computational complexity.

Fig. 4 presents a structured decision tree to guide the selection of appropriate modeling approaches for DHNs. The decision process begins with identifying the modeling objective ensuring that the practical applications discussed in the text can be directly translated into the decision process. The decision tree is intended as a qualitative screening tool rather than a quantitative standard. It guides the user through objective-

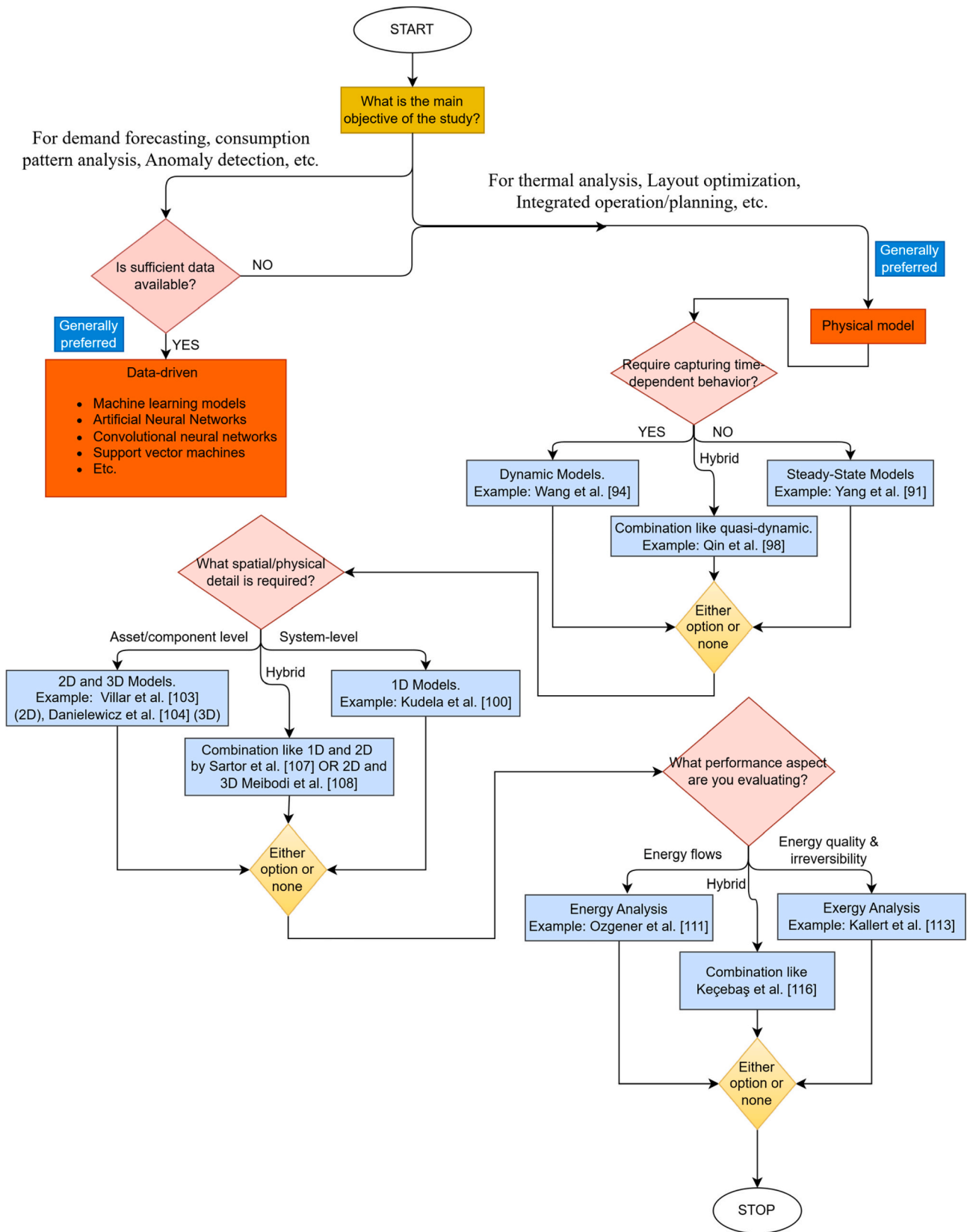


Fig. 4. Decision Tree for Modeling Approach Selection.

oriented questions, such as whether transient behaviour, spatial detail, or data-driven forecasting is required. The final choice should then be refined using task-specific performance requirements, data availability, computational resources, and the representative studies summarized in Table 3. Because acceptable accuracy, temporal resolution, and computational burden vary strongly with the application, network scale, and available measurements, universal numerical thresholds are not prescribed here. For example, the temporal resolution required for annual planning, daily scheduling, real-time control, and pipe-level transient analysis can differ substantially; therefore, these thresholds should be defined by the user according to the intended application.

It should be noted that the selection is not exclusive; in many cases, hybrid approaches combining multiple modeling paradigms may be required. One can think of a task related to DHNs and can choose from the suggested models in Table 3 or can use the decision tree in Fig. 4 that provides a structured pathway from task to model type.

By following this structured process and related discussions (Section 5.1 to 5.5), users can select a modeling approach or a combination of them that aligns with their objectives, required accuracy, and available resources. Depending on the modeling goal, these approaches can be applied at different scales and scopes, from detailed component-level thermohydraulic simulation to system-level models integrating sources, storages, and even electrical networks.

6. Conclusions

This review provides an examination of renewable energy source (RES) integration and modeling approaches in district heating networks (DHNs), emphasizing their importance in achieving NZE by 2050. Through bibliographic analysis and literature review, the historical development and current adoption of RES in DHNs, specifically solar, wind, geothermal, biomass, and hydrogen, are analyzed. The study highlights that although the use of RES in DHNs dates back centuries, their integration has become important and feasible in recent decades due to technological advancements, cost reductions, and the global decarbonization agenda.

On the modeling side, the paper proposes a novel classification framework for DHN modeling approaches. Models are evaluated by temporal representation (steady-state vs. dynamic), spatial resolution (1D–3D), thermodynamic basis (energy vs. exergy), mathematical relationship (linear vs. nonlinear), and computational paradigm (physical vs. data-driven). This classification helps researchers and decision-makers identify appropriate modeling approaches based on accuracy, complexity, and modeling objectives. A decision tree is also presented to support informed selection of a modeling approach. For RES, it is observed that the selection of an appropriate modeling approach depends not only on the modeling objective but also on the characteristics of the RES being integrated.

On RES integration in DHNs, the paper presents a structured overview of integration pathways, organized by the way RES supply usable heat to the network. Furthermore, the review assesses each RES across six key performance dimensions: cost, efficiency, storage potential, complexity, flexibility, and carbon footprint. A qualitative synthesis of trade-offs shows why no single RES is universally superior for DHNs. Consequently, it is recommended that hybrid systems, which leverage the complementary strengths of multiple RES, can become feasible and scalable approach for future DHNs. Nevertheless, the hybrid configurations can have different local resource availability, temperature level and storage potential. Therefore, hybrid systems should be viewed as context-dependent options rather than universally superior solutions.

Despite its broad scope, this review has some limitations. First, while it covers five major RES types selected through bibliometric analysis, other relevant options such as industrial and data-center waste heat, aqua thermal, hydrothermal, etc. are not explored. They are referenced where relevant in the paper, and dedicated reviews of these sources are identified as a direction for future work. Second, comparative analysis

across performance metrics like LCOH or efficiency is based on data from varied experimental and modeling contexts. These comparisons, while helpful, are inherently constrained by assumptions and may not capture real-world variability or local conditions. In terms of modeling, while the review proposes a broad classification framework, the complexity and hybrid nature of many models may lead to overlaps that are difficult to fully disentangle. Additionally, although data-driven and AI-based models are acknowledged, their integration with physics-based models is still an emerging area that requires more focused research.

Future research should address these gaps by developing more integrated, hybrid modeling approaches that combine physical laws with data-driven techniques to improve prediction, optimization, and control. Additionally, the variability of RES, such as solar and wind, necessitates advanced storage solutions and predictive control systems. More work is needed to model and evaluate TES, hydrogen storage, and sector coupling options like power-to-heat in the context of DHNs.

Finally, supportive policy frameworks and regulatory measures are vital for enabling widespread adoption. Future studies should also consider multi-commodity modeling (heat and electricity) and market modeling. Regulatory innovations such as green tariffs, carbon pricing, and renewable heat mandates, when combined with integrated heat–electricity market modeling, can more effectively complement technical and economic efforts to accelerate RES integration in DHNs.

CRedit authorship contribution statement

Anubhav Goel: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Yashar Ghiassi-Farrokhfal:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Pejman Shoeibi Omrani:** Writing – review & editing, Methodology, Investigation. **Femke Janssen:** Writing – review & editing, Investigation, Formal analysis.

Declaration of competing interest

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

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Data availability

Data as and where used is credited with references.

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