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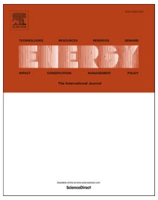

Decarbonizing a Polish district heating network using ambient and waste heat: a techno-economic analysis considering uncertainties in future energy prices and availability

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ABSTRACT

District heating (DH) systems can contribute substantially to the decarbonization of the heating sector by enabling the implementation of sustainable heating solutions such as ambient heat (AH) and waste heat (WH). However, these sources are subject to economic risks arising from uncertainties in future energy prices and availability. This paper presents a techno-economic analysis for a decarbonized DH network for a city in Poland, using a simulation model that evaluates levelized cost of heat (LCOH) across a wide range of heat supply portfolios including AH and WH sources. It considers uncertainties related to energy price and WH cessation scenarios as well as sensitivities related to WH prices, heat demand, and biomass availability. Results show that the DH system configuration plays a key role in determining the average cost, due to the relatively large share of CAPEX in the LCOH calculations, underscoring the importance of accurate investment cost assumptions. Further important factors are the development of the heat demand and the availability of biomass. The presence of low-cost industrial WH is beneficial. In general, there is a trade-off: minimizing average cost results in a higher economic risk.

1. Introduction

1.1. Motivation

Heating demand constitutes a significant share of final energy demand but remains predominantly reliant on fossil fuels, making its decarbonization central to achieving European climate objectives [1,2]. District heating (DH) networks can contribute substantially to heat decarbonization as they enable implementation of sustainable heating solutions on a large scale and the use of heat sources that are difficult to integrate on a small scale. This includes ambient heat (AH) and waste heat (WH), often facilitated by heat pumps (HPs) [3,4].

The decarbonization of DH systems using AH and WH requires large investments in sustainable heat supply technologies such as heat exchangers and HPs, but factors such as energy prices or WH availability also affect system costs. The uncertainty in the future development of these factors results in economic risks in the form of variations in the expected cost of the system, with the relevance of different factors varying per heat source. For example, future availability of AH sources is relatively certain, but they have low temperatures, requiring coupling with HPs to supply heat to DH. This leads to higher investment costs and increased vulnerability to electricity prices [5]. However, HPs can also provide greater flexibility by increasing coupling of the electricity and heat sectors [6–8]. In contrast, high temperature WH sources have relatively low investment and operation costs as no HP is necessary, but there is greater uncertainty regarding future availability as industrial activities may change or be discontinued [9]. Thus, in analyzing the decarbonization of DH using AH and WH, it is not only important to consider technical performance and overall cost but also the system's resilience in the face of uncertainty.

Given these challenges, the central aim of this study is the techno-economic analysis and comparison of future fully renewable DH

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system configurations for the case study of a small town in northwestern Poland. The paper focusses on AH and WH in the resilient decarbonization of the network, considering various uncertainties related to the future development of energy prices, WH availability, heat demand, and biomass availability.

1.2. State of the art

The following sections discuss existing works on the applied modeling approach – techno-economic analysis – as well as the integration of uncertainty modeling into it.

1.2.1. Techno-economic analyses of ambient and waste heat

1.2.1.1. Ambient heat with large-scale heat pumps. AH refers to heat found in the atmosphere, ground, and water bodies, which needs to be combined with large-scale HPs[1] to supply heat at temperatures high enough for DH [10]. Studies analyzing AH with large-scale HPs often focus on optimal operation strategies. Abokersh et al. found HP control strategies significantly influence economic performance, with one strategy consistently resulting in a lower levelized cost of heat (LCOH) [11]. Bach et al. studied the integration of drinking water, sewage water and sea water HPs in Copenhagen's DH and highlighted the importance of the COP in HP modelling [6]. Others focus on the flexibility HPs provide in increasing the interconnection between the electricity and heat sector. Fambri et al. showed that flexibility provision improved the balance of the electricity distribution system and had greater profitability when doing so [7]. Seawater HPs increased renewable energy integration compared to a biomass-based DH system but were less attractive from a business economic perspective [4]. Comparing decentralized and centralized heating systems with HPs, centralized systems were more cost effective and robust across carbon constraint scenarios [2]. In optimizing a system with a biomass generator, HP, and heat storage, results indicated that a seasonal storage was necessary in scenarios with limited biomass availability and that for optimal operation, the HP was used during low electricity prices and the heat storage during high electricity prices [12]. Kontu et al. found that competition with combined heat and power (CHP) plants reduces HP viability in medium- to large-scale DH systems with heat only boilers (HOBs) and CHPs compared to small-scale systems with HOBs, highlighting the importance of the configuration and size of the system analyzed. However, the inclusion of a HP reduced variable costs across all system sizes, especially in low electricity price scenarios [13]. Yang et al. emphasized that the LCOH and environmental benefits of HPs depend on system configuration, electricity prices, and the electricity mix considered [14].

1.2.1.2. Waste heat and its competition to ambient heat. WH is heat generated as a byproduct, which may require coupling with HPs for integration in DH networks [15,16]. Overall, techno-economic analyses indicate WH is cost-effective. For example, across various industrial sectors, WH was generally less expensive than solar DH and the average Danish DH cost [17], WH from a petrochemical cluster in Sweden proved profitable currently and with reduced future availability due to increased internal heat recovery [3], and systems with WH recovery from a waste water treatment plant (WWTP) and deep cooling of flue gases had a lower LCOH than a reference scenario without WH [18]. Higher investment costs were reported for greater steelwork and WWTP WH integration due to necessary investments in HPs, however these configurations performed best economically when accounting for the monetized cost of climate change [19]. Both Bühler et al. [17] and Pakere et al. [18] highlight that the temporal mismatch between WH availability and DH demand hampers WH's potential to replace fossil fuels, but that coupling with storage can reduce this and ensure peak demand is met. Several studies analyzed the techno-economic performance of DH systems incorporating both HPs and WH. Gonzalez Salazar et al. analyzed paths for replacing coal in Berlin's DH and found that costs largely depend on fuel prices and regulatory frameworks [20]. Specht et al. compared decarbonization options for Leipzig, finding systems with WH, solar, and biomass or electric heating had lower LCOH and were more robust than systems reliant on hydrogen or natural gas with carbon capture and storage (CCS) [21]. Su et al. analyzed Helsinki's DH decarbonization, determining that overall heat production costs are expected to triple due to investments in new low-carbon technologies, but WH from datacenters remains profitable [22]. Yuan et al. argue a tradeoff exists between WH and HPs since greater WH hinders renewable energy penetration while increased HPs lead to higher investment costs, and that therefore a combination of both technologies is optimal [5].

1.2.2. Uncertainty modeling for heat supply technologies and systems

Uncertainties in future energy prices and availability in techno-economic analyses of DH systems with AH and WH are usually addressed through scenario or sensitivity analysis. However, these methods fail to consider the expected probability of future developments. Furthermore, sensitivity analysis measures the isolated effect of single variables rather than the combined effect of simultaneous changes in multiple variables.

To address these limitations, one quantitative risk assessment method used is Monte Carlo simulation (MCS). However, studies using MCS to analyze economic risk of individual heat supply technologies primarily focus on CHP plants. Most focus on natural gas CHPs [23–26], but other fuels like biomass [27,28], municipal solid waste [28] and coal [29] are also considered. Other heat supply technologies considered are biomass boilers [30], wastewater HPs [31], and WH from data centers [32]. Most studies vary economic variables like electricity prices, fuel prices, O&M costs, and investment costs but some also vary technical parameters like lifetime, efficiency, heat demand, and availability. Approaches to modelling uncertainty in future heat source availability include modelling scheduled and unscheduled shutdowns in the MCS simulation [29] or varying plant lifetime [26]. Key findings differ across studies. A coal CHP with CCS was found to have higher risks than one without due to higher investment costs and lower electricity generation efficiency, but was more robust in the face of uncertainty in future greenhouse gas emission allowances [29]. Decentralized HPs generally performed better than DH with CHP, but outcomes were largely dependent on input parameters, indicating that results are case specific and modelling must account for local conditions [28]. Research has also shown that uncertainty significantly influenced the optimal size and cost of a CHP, and not accounting for it led to an overestimation of size and of cost savings [24]. Additionally, it has been highlighted that deterministic models fail to account for the flexibility CHPs provide in responding to volatile electricity prices, making them more attractive when this is considered [25]. MCS has also been applied to assess the flexibility of energy hubs integrating various heat supply technologies, storage options, and/or demand side management (DSM) under volatile market prices, allowing for a valuation of investments which accounts for strategic and operational flexibility [33,34]. The inclusion of heat storage and DSM in an energy hub increased investment costs but also reduced economic risk, reflecting their ability to provide greater flexibility and robustness in the face of volatile energy prices [33].

While MCS is a widely used quantitative risk assessment method, other approaches have also been applied in energy system analyses. These include stochastic optimization methods, mean-variance portfolio (MVP) theory, and real options analysis (ROA) [35]. Stochastic optimization accounts for uncertainty by optimizing decisions under multiple probabilistic scenarios, MVP theory balances risk and return in investment decisions, and ROA evaluates investment decisions under

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[1] The term 'large-scale' is used to refer to HPs in the MW range at a scale large enough to provide heat to a DH system (in contrast to HPs at an individual household level).

uncertainty by allowing flexibility in timing, such as deferring or expanding projects as new information becomes available. [35]. Volodina et al. used stochastic ordering to compare a DH system with WH from a datacenter coupled with a HP, a CHP, and both accounting for uncertainty in heat demand and energy prices. Results indicated that coupling the datacenter WH with a HP to supply both baseload and seasonal demand was the most robust solution [36]. Zhang et al. employed a combination of uncertainty analysis methods to analyze individual heating systems and different types of thermal networks under uncertainty in demand, equipment efficiency, equipment cost and electricity prices. They found DH systems were most sensitive to heat demand and electricity prices while individual heating systems were more sensitive to equipment efficiency and investment costs [37]. However, the application of quantitative uncertainty modelling methods to analyze DH systems with AH and/or WH remains limited.

1.3. *Contribution*

Papers analyzing the techno-economic performance of DH systems with AH and/or WH sources mostly focus on DH systems with AH coupled with large-scale HPs. Only a limited number of studies consider DH systems with WH or both AH and WH, illustrating the urgency for further research on this aspect. Moreover, within these studies, if considered at all, future uncertainty is generally reflected only in the consideration of future scenarios or through sensitivity analysis. These approaches disregard the expected probability of the distribution of uncertain inputs, i.e., quantifying the uncertainty, and the combined effect of multiple uncertainties on the outcome. However, these aspects are crucial for assessing the effect of uncertainty in real-world situations, thus this represents a significant gap in the state of the art.

Uncertainty modeling plays a key role in capturing the inherent variability of future conditions, enabling its consideration in assessment of decarbonized DH systems and the quantification of risks associated with it. Furthermore, by explicitly quantifying uncertainty, rather than relying solely on scenario or sensitivity analysis, it is possible for decision makers to better understand the risks associated with different investment decisions. This leads to more robust planning and enhances the ability to balance trade-offs between system flexibility and cost-effectiveness. Despite its recognized importance, comprehensive uncertainty modeling remains largely absent in techno-economic analyses on DH systems with AH and WH.

To bridge these critical research gaps, this study presents an approach which integrates uncertainty quantification for external parameters that are outside the control of the decision makers (i.e. the future development of energy prices and WH availability), together with sensitivity analysis for parameters that can be influenced or that are too complex to represent with a probability density function (i.e. WH price, future heat demand and biomass availability) into the techno-economic analysis. Furthermore, a novelty of this study is its application to a real-world DH network using real operational data, made possible through collaboration with the DH network operator as part of the HeatMineDH project (see “funding information”). This partnership allowed for detailed modeling based on actual system characteristics and decarbonization considerations, enhancing the practical relevance of the findings. Moreover, while DH decarbonization has been widely studied in Western Europe and Scandinavia, this study is one of the first to conduct such an analysis for Poland, where research on AH and WH integration in DH systems remains scarce. By combining uncertainty quantification with a real-world case study in an underexplored geographical context, this work provides new insights into the feasibility and risks of integrating AH and WH in the resilient decarbonization of DH networks.

The paper is structured as follows: Section 2 outlines the applied methodology, case study and uncertainties considered, Section 3 presents results, Section 4 discusses results and concludes.

2. Method

A model was developed to simulate a future fully renewable DH system for the case study. The model evaluates configurations with and without AH and WH sources, using LCOH as an indicator of techno-economic performance. Variations in stochastic external factors were modelled through deterministic sampling of energy price scenarios and WH cessation scenarios (reflecting the possibility that a WH source is no longer available i.e., due to bankruptcy or relocation), and the calculation of the probability of each scenario occurring. In contrast to the MCS approaches described above, the deterministic sampling method boosted computational speed while still considering the full range of energy price and WH cessation scenarios to be modelled, enabling multiple heat supply configurations to be calculated. For each system configuration analyzed, the simulation model was run for all possible combinations of energy price and WH cessation scenarios, with the resulting weighted average LCOH and standard deviation providing a measure of average cost and associated economic risk, respectively. Sensitivities in the future WH price, WH cessation probability, heat demand, and biomass availability were also considered. Fig. 1 presents an overview of the methodology.

The following sections are structured as follows: Section 2.1 introduces the concept of LCOH, the key performance indicator used in this paper, Section 2.2 showcases the design of the simulation algorithm, and Section 2.3 describes the case study. Finally, Section 2.4. outlines the different system configurations, scenarios, and uncertainties considered.

2.1. *Key performance indicator: levelized cost of heat*

As key performance indicator, the LCOH was used to assess the performance of all system configurations and scenarios. The LCOH measures the average cost of heat production over the study period, accounting for all capital (CAPEX), operational (OPEX), and residual costs and evenly distributing these across the heat produced over the duration of the study period (costs for constructing and maintaining the DH network are not considered).

As a future greenfield scenario was modelled, it was assumed that the full investment cost is paid for each heat supply technology at the start of the study period, since the currently existing assets are assumed to reach the end of their lifetime and re-investments would be required. Annual costs and heat output were determined by the simulation model (refer to Section 2.2). If the expected lifetime of a new technology was shorter than the study period, it was assumed a replacement of the same size was built, resulting in new CAPEX costs. Residual value refers to the estimated monetary value of each technology at the end of the study period. It was estimated as the discounted portion of the initial investment corresponding to the proportion of the remaining useful lifetime at the end of the study period relative to expected lifetime. When a WH source ceased operation (see Section 2.4.2), no residual value was accounted for as it was assumed to be a stranded investment.

Base LCOH. Specifically, residual value was calculated as follows:

$$RV_{T,i} = \frac{\frac{L_i - T}{L_i} \cdot CAPEX_{0,i}}{(1+r)^T} \tag{1}$$

Where.

$RV_{T,i}$ = residual value of technology i the end of the study period T
L_i = expected lifetime of technology i [years]
T = study period [years]
$CAPEX_{0,i}$ = initial investment cost for technology i [€]
r = interest rate

The LCOH was calculated as follows:

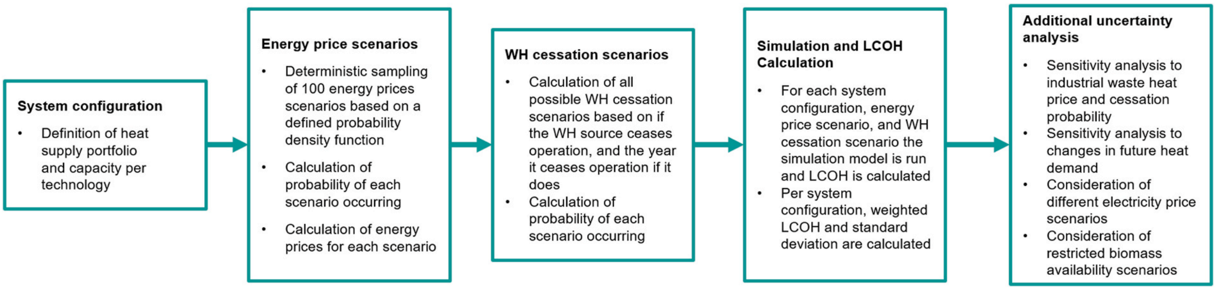

Fig. 1. Overview of methodology.

$$LCOH = \frac{CAPEX_0 + \sum_{t=1}^{T} \frac{OPEX_t + CAPEX_t}{(1+r)^t} - \frac{RV_T}{(1+r)^T}}{\sum_{t=1}^{T} \frac{E_t}{(1+r)^t}} \tag{2}$$

Where.

$LCOH$ = levelized cost of heat [€/MWh]
$CAPEX_0$ = initial investment cost [€]
$OPEX_t$ = operational costs in year t (fixed and variable) [€]
$CAPEX_t$ = investment costs in year t (occurs if a new heat supply technology is built) [€]
RV_T = residual value at the end of the study period
E_t = heat supplied in year t [MWh]
t = year
r = interest rate
T = study period [years]

2.2. Simulation approach

To calculate the LCOH, a simulation model was run to determine annual cashflows and heat output per heat supply technology over a 20-year study period.

The simulation model was implemented using a python-based simulation tool (TESCA) [38]. TESCA has an object-oriented programming approach and represents different technologies (i.e. HPs) as component classes with specific attributes and methods. The model runs through a stepwise simulation of the study period determining component behavior based on a predefined operation strategy.

Model inputs are the heat supply technologies in the system and their capacities, annual residential heat demand, electricity, biomass, biomethane, and WH prices, and temperatures of AH and WH sources. The model steps through hourly timesteps and determines the amount of heat supplied by each heat supply technology based on an economic ranking where the full capacity of the lowest cost source is used until demand is fully met. The model output is the hourly production from each heat source, based on which annual cashflows are calculated. These consist of fixed O&M costs, electricity and fuel costs, and electricity revenues for the CHP. DH distribution costs and revenue from heat supplied by the DH system is not considered. These outputs are combined with investment costs to calculate LCOH over the 20-year study period. Fig. 2 provides an overview of the TESCA simulation model, highlighting model components and their defining attributes, input timeseries data, operation simulation, and outputs.

2.3. Case study

The TESCA model was applied to a case study of a city in north-western Poland with a population of around 13,000 and a DH network covering a large portion of the city. The DH network supplies an annual heat demand of approximately 21.5 GWh with a peak demand of around 10 MW. The current heat supply portfolio consists of two coal fired boilers with a combined capacity of 13.8 MW and a natural gas CHP with a capacity of 0.877 MW.

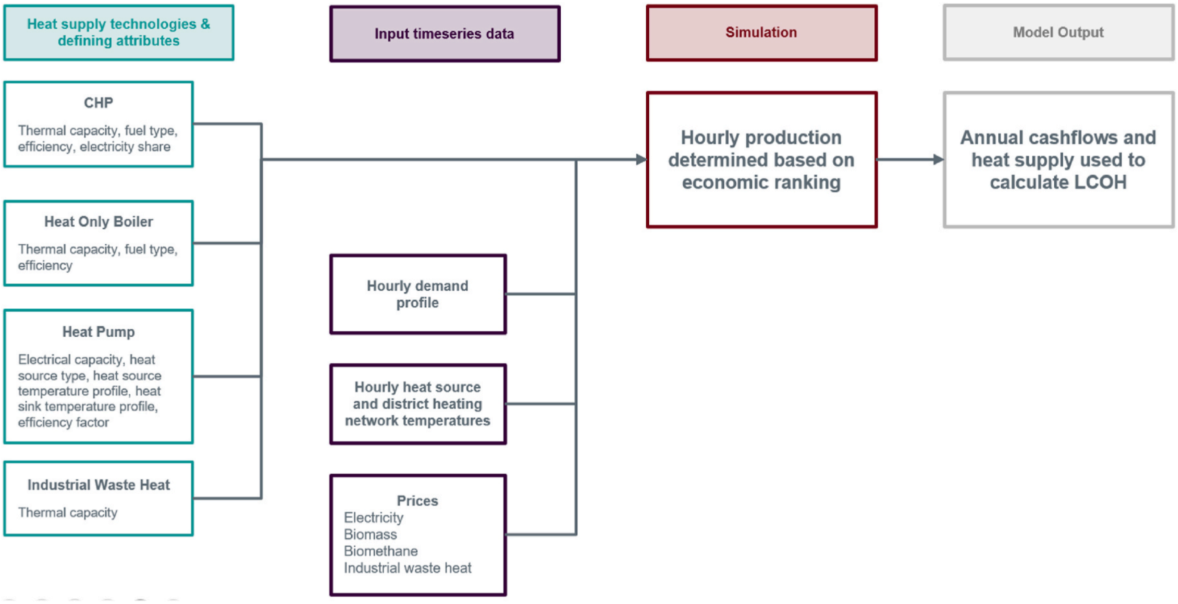

Fig. 2. Overview of TESCA simulation model, accounting for technology configurations, time series data, and deriving model outputs from hourly dispatch simulations.

Two potential AH and WH sources identified by the DH network provider are an iron foundry located around 2 km outside the city and a WWTP located between the iron foundry and the city. Additionally, an air-source HP was considered. As a future greenfield scenario was modelled, it was assumed a biomass boiler and new CHP replace the coal boilers and the existing CHP (see Section 2.4). Fig. 3 shows the system configuration considered. The DH network supply temperature, ranging between 62 and 95 °C depending on outdoor air temperature, was assumed to be the output temperature of all heat supply technologies. Heat pump performance was estimated using the Carnot COP and an efficiency factor of 0.5, with the DH supply temperature as the sink temperature and hourly outdoor temperatures (−13.2 °C–34 °C) and monthly average effluent temperatures (10 °C–19 °C) as source temperatures. This resulted in average COPs of 3.10 and 3.21 for the air and wastewater HP respectively. The DH return temperatures was not explicitly modelled. More details on the case study, like cost assumptions or technical parameters, are provided in the supplementary material.

2.4. System configurations, scenarios, and uncertainties

To properly study the effects of different system configurations and future uncertainties related to energy prices and WH availability on techno-economic performance, a total of 8800 scenarios were pre-generated to be evaluated. Uncertain future parameters such as WH price, heat demand and biomass availability, that do not form any obvious assumptions of future distributions are not included in these scenarios and were investigated based on sensitivity analysis on top of the given simulation approach.

2.4.1. System configurations

Two base configurations formed the foundation of the analysis: (B1) a configuration consisting of a biomass HOB and biomethane CHP and (B2) a configuration incorporating a biomass HOB, biomethane CHP, and WH from the iron foundry nearby. The capacities considered for each base configuration were defined by the DH operator. Variations of these base configurations included the integration of an air-source HP, wastewater HP, or both, resulting in a total of eight system configurations (see Table 1).

2.4.2. Uncertainties

In addition to system configurations, the study addressed key uncertainties in the future development of energy prices and WH availability. Energy price scenarios were modelled through deterministic sampling of 100 energy price scenarios weighted based on a defined probability density function. WH availability was modelled by considering the chance that WH from the iron foundry is no longer available. WH cessation scenarios were defined by whether the WH ceases to be available and the year it does if yes, resulting in 21 possible WH cessation scenarios.

For each system configuration analyzed, the simulation model was run and the LCOH was calculated for all possible combinations of energy price and WH cessation scenarios. Table 2 shows an overview of all system configuration and uncertainty scenarios modelled. The resulting weighted average LCOH and standard deviation provide a measure of average cost and economic risk, respectively, adequately reflecting the techno-economic performance of each system configuration accounting for uncertainty in future energy prices and WH availability.

As discussed in Section 1.2.2, the uncertainties associated with different relevant input data are important to consider. Since doing so inherently increases the model's complexity – and therefore reduces its computational performance – the wide range of possible factors are here reduced to the most crucial ones: (1) energy prices and (2) the possible timing of WH cessation.

Energy prices. The considered energy price scenarios reflect uncertainty in future price developments for key energy sources – directly and heavily influencing resulting cost of heat. The following three energy carriers were selected as most relevant to the investigated use-case: biomethane, biomass, and electricity – for details see the supplementary material.

As done in Ref. [9], energy price scenarios were represented by a price lambda (λ), a variable ranging from 0 (minimum price P_{min} scenario) to 1 (maximum price P_{max} scenario). A probability density function (PDF) for the likelihood of different price scenarios was defined by a Beta (2,2) distribution. The beta distribution represents the assumptions that an average price scenario is expected to be most probable, minimum, and maximum price scenarios are equally probable, and that values below the minimum or above the maximum scenario are irrelevant.

As described in Section 2.2, deterministic sampling was used to obtain a weighted sample of 100 energy price scenarios based on the PDF defined. Specifically, 100 price lambda values equally spaced between 0 and 1 were sampled and assigned a weight equal to the probability of that price lambda occurring as defined by the PDF.

The price lambda was combined with minimum and maximum prices for each energy source to calculate energy prices in that scenario: $P_{\lambda} = (1 - \lambda) \cdot P_{min} + \lambda \cdot P_{max}$. The use of a single (shared) price lambda per energy price scenario applied to electricity, biomethane and biomass prices accounted for correlations between energy prices, reflecting their interdependence due to shared market dynamics, such as the substitution of biomethane for natural gas and the linkage of electricity prices to gas prices.

It is important to remark, that due to missing data, electricity prices are based on two historic years. The main analysis was done for the year 2022 due to its large variability. To test the effect of a different electricity price profiles, the model was also run for the year 2024.

Waste heat cessation. As discussed in Section 1, WH can play an important role as future heat source for DH. However, its availability cannot be guaranteed – and influencing it (from a DH operator's point of view) may not be as viable as with conventional assets. The WH cessation scenarios therefore consider uncertainty in the future availability of WH from the iron foundry, reflecting the risk that the WH ceases to be available for the DH i.e., due to bankruptcy, relocation, or increased internal heat recovery. The WH cessation scenario is defined by whether the iron foundry WH ceases to be available and, if yes, in what year. As a twenty-year study period was analyzed, there were 21 possible WH cessation scenarios: twenty scenarios for each year the iron foundry could cease operation, and one scenario where it does not cease operation at all. If the iron foundry is not included in the initial system configuration (as is the case for all B1 configurations), there is only a single scenario possible.

To quantify the risk of WH sources ceasing to be available, the probability of a company going bankrupt in Poland was used as a proxy for annual WH cessation probability. This was calculated by dividing the annual number of company bankruptcy court orders by the number of companies[2] in Poland for the period of 2016–2022, resulting an average probability of 0.7 % ([39,40]). However, WH cessation probabilities may differ across industries and regions due to factors such as economic conditions and policy changes. As a consequence, this approach may underestimate the risk. Therefore, the model was also run with a 2, 4, 6, 8, and 10 factor increase in the WH cessation probability.

Weighted LCOH. To reflect the combined probability of the energy price scenario and WH cessation scenario being analyzed, each LCOH is assigned a weight equal to the product of the probability of the energy price scenario and the probability of the WH cessation scenario:

$$w(\lambda, X) = w(\lambda) \cdot w(X) \tag{3}$$

Where.

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[2] Defined as non-financial companies with more than 10 employees.

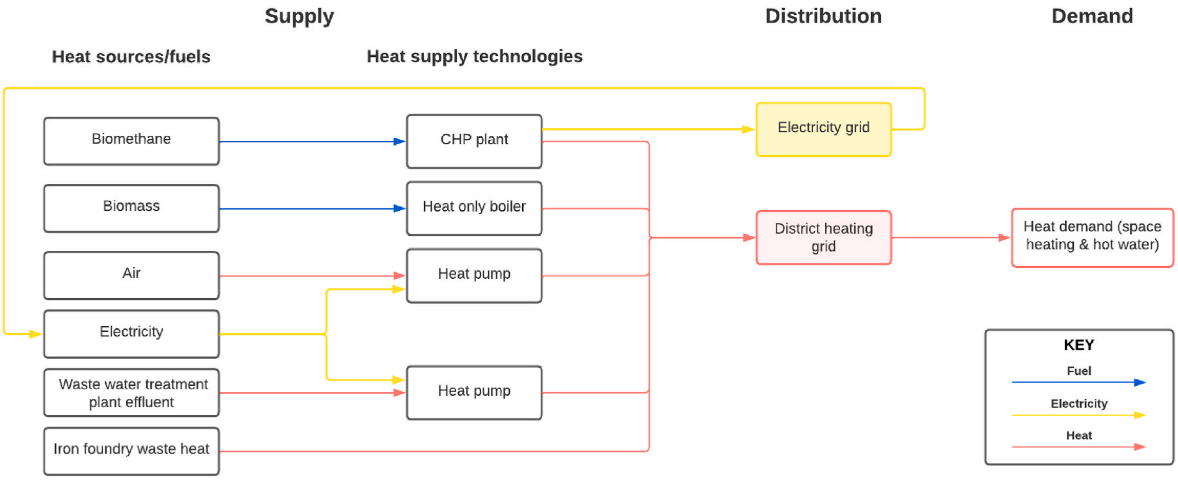

Fig. 3. Case study system configuration.

Table 1
Installed capacity per technology per system configuration considered.

	Installed capacity [MW_{th}]					
	Biomass HOB	Biomethane CHP	Iron foundry WH	Air HP	Waste-water (WW) HP	Total
Base configuration 1 (B1): Biomass HOB & Biomethane CHP						
B1	12.31	3.92	–	–	–	16.23
B1+ Air HP	12.31	3.92	–	1	–	17.23[a]
B1 + WW HP	12.31	3.92	–	–	1	17.23[a]
B1 + Air HP + WW HP	12.31	3.92	–	1	1	18.23[a]
Base configuration 2 (B2): Biomass HOB, Biomethane CHP, and iron foundry WH						
B2	14.87	1.36	1.9	–	–	18.13[b]
B2+ Air HP	14.87	1.36	1.9	1	–	19.13[b]
B2 + WW HP	14.87	1.36	1.9	–	1	19.13[b]
B2 + Air HP + WW HP	14.87	1.36	1.9	1	1	20.13[b]

[a] 16.23 without air HP or WW HP.
[b] 16.23 without iron foundry WH, air HP, or WW HP.

Table 2
Overview of system configurations and uncertainty scenarios modelled. Refer to the supplementary materials for technical parameters of the assets and their detailed configuration.

System configuration		Number of energy price scenarios	Number of WH cessation scenarios	Number of scenarios per system configuration
Base configuration	Additional AH sources			
B1: Biomass HOB + biomethane CHP	None	100	N/A	100
	Air HP	100	N/A	100
	Wastewater HP	100	N/A	100
	Air HP + Wastewater HP	100	N/A	100
B2: Biomass HOB + biomethane CHP + iron foundry WH	None	100	21	2100
	Air HP	100	21	2100
	Wastewater HP	100	21	2100
	Air HP + Wastewater HP	100	21	2100
Total number of scenarios				8800

$w(\lambda, X)$ = weight of energy price scenario λ and WH cessation scenario X
$w(\lambda)$ = weight of energy price scenario λ
$w(X)$ = weight of WH cessation scenario X

This resulted in a weighted sample of LCOHs for every system configuration considered, which reflected the effect of uncertainty in future energy prices and WH availability. For each weighted sample, the weighted sample mean and standard deviation were calculated to reflect the average cost and economic risk across energy price and WH cessation scenarios for each system configuration.

2.4.3. Sensitivity analysis

Sensitivity analysis plays a critical role in assessing the robustness of LCOH estimations by examining the impact of key uncertain parameters on system performance. This study focuses on three sensitivities: WH pricing, future heat demand, and biomass availability. These factors are integral to the overall cost structure, yet their future values are uncertain due to external influences such as market competition, technological advancements, and local agreements. Exploring these uncertainties enhances the understanding of potential risks and supports more informed decision-making in the design and optimization of DH systems.

WH price. The price for WH is influenced by local conditions and parties involved and can be agreed on bilaterally between the DH operator and the WH provider [18]. Thus, it was assumed to be constant over the study period at 20 €/MWh. However, as its exact value in the future is uncertain and it influences total costs and the attractiveness of utilizing WH, a sensitivity analysis was conducted varying the WH price between 0 and 60 €/MWh in 20 € increments.

Future heat demand. The magnitude of future DH demand is subject to uncertainty in various factors including the impact of climate change on winter temperatures, changes in the number of connected users, and improvements in building energy efficiency through retrofitting. Since these factors would be too complex to represent them with a probability density function, a sensitivity analysis was conducted to assess the impact of a 10, 20, or 30 % increase or decrease in space heating demand. Domestic hot water demand was assumed to remain constant.

Biomass availability. The base model assumes unlimited biomass availability, relatively low biomass costs, and a large installed capacity

Table 3
Summary of uncertain parameters considered.

	Range	Probability
Deterministic sampling		
Energy price scenario (price lambda)	0–1	Beta(2,2) distribution
Electricity price	Electricity price profile from 2022±30 % of hourly price, and additional model run with the electricity price profile of 2024± 30 % of hourly prices	Beta(2,2) distribution
Biomass price	20-35 €/MWh	Beta(2,2) distribution
Biomethane price	80-120 €/MWh	Beta(2,2) distribution
WH cessation	0: WH does not cease operation 1-20: year WH ceases operation	0.7 % annual cessation probability, and additional variations of 1.4, 2.8, 4.2, 5.6, and 7 % annual cessation probability
Sensitivity analysis		
WH price	0, 20, 40, 60 and €/MWh	N/A
Space heating demand	±10, 20 or 30 % of base scenario	N/A
Biomass restriction	Low, medium, high, very high, and maximum	N/A

of the biomass HOB in both B1 and B2, making biomass an attractive heat source. However, realistic utilization of biomass in DH systems faces the uncertainty of potential supply limitations. On one hand, biomass can be used as a carbon neutral alternative for a wide range of applications [41]. Thus, competition with other sectors or within the heating sector may limit the future availability of biomass. On the other hand, societal or regulatory reservations might apply against "burning wood just for heat". Especially in light of RED III, the availability of biomass as fuel for heat generation using biomass HOBs needs to be critically discussed. In turn the effect of such supply limitations on the overall LCOH was studied in more detail. Therefore, five scenarios with increasing levels of limitation on biomass availability were modelled (low, medium, high, very high, and maximum) in addition to the base scenario with no limitation. This was achieved by considering the effect of scarcity on market prices, in the form of a "virtual" price multiplier. Assuming that an essential need like heating would be (partially) government supported, this "virtual" price was only used to disincentivize biomass usage in the model – the resulting LCOH are still based on the assumed fixed base price.

2.4.4. Summary

Table 3 provides a summary of the uncertain parameters varied.

3. Results

3.1. Overview

For the chosen configurations and uncertainties, the weighted average LCOH ranges between around 81–95 €/MWh for B1 configurations, and 79–92 €/MWh for B2 configurations, while the standard deviation across all configurations is close to 2.35 €/MWh and relatively equal between them (Fig. 4 and Table 4). Across configurations, the relatively low standard deviation (2.38–2.92 % of LCOH) indicates minimal economic risk. For both B1 and B2 configurations, the addition of a HP increases LCOH but slightly decreases standard deviation, highlighting the risk-reducing benefits of diversified heat sources and the flexibility they offer. Furthermore, though differences are small, B2 configurations perform better than their counterpart B1 configuration, having a lower LCOH and standard deviation. This is largely because the iron foundry WH is relatively inexpensive, and its cost does not vary across price scenarios. The slightly lower standard deviation of B2 configurations compared to B1 configurations—despite the additional uncertainty in WH availability present in base scenario B2 due to the inclusion of WH iron foundry— suggests that this uncertainty does not lead to significantly greater economic risk. This is because the economic benefits of the low and stable cost of WH outweigh the potential risks associated with its uncertain availability.

The biomass HOB dominates heat production, supplying over 80 % in B1 configurations and 65 % in B2 configurations (see supplementary material, Figure SM2). This is due to its large installed capacity, low cost, and unlimited biomass supply. The CHP can supply heat at a competitive price when electricity prices are high enough to offset biomethane costs, while HPs perform competitively at low electricity prices. In B2 configurations, over 20 % of heat comes from iron foundry WH due to its low cost. Reduced CHP contribution in B2 configurations reflects its reduced capacity and displacement by the industrial WH.

Due to its large capacity and heat production, the biomass HOB constitutes the largest portion of LCOH across all configurations (Fig. 5). In B2 configurations, its larger capacity results in a higher CAPEX, but reduced production due to the availability of low-cost WH leads to lower OPEX. CHP costs are lower in B2 configurations compared to B1 configurations due to reduced capacity and production. Heat provided by the iron foundry comes at a low cost, both in terms of OPEX and CAPEX. Introducing HPs increases LCOH due to the additional CAPEX and their relatively high fixed OPEX, despite the reductions in variable OPEX which HPs provide at low electricity prices.

3.2. Variation across energy price and wh cessation scenarios

Fig. 6 shows average LCOH across energy price scenarios and WH cessation scenarios exemplary for configuration "B2 + Air HP + Wastewater HP" (for other configurations, see supplementary material, Figure SM3). As the price scenario increases, the LCOH increases due to greater OPEX costs from higher biomass, biomethane, and electricity prices. Similarly, earlier WH cessation scenarios have a higher LCOH. The WH cessation results in a stranded investment and higher OPEX costs for the remainder of the study period as the relatively low-cost WH is no longer available, and the earlier this occurs, the more prominent these effects are in the LCOH.

As can be seen, increasing the price scenario, largely impacts the difference in LCOH across WH cessation scenarios. This is due to an even greater increase in OPEX costs once the WH ceases operation due to higher energy prices. This highlights the importance of the assumption that the industrial WH price is agreed on bilaterally between the WH provider and DH system operator and does not change with energy price scenarios.

3.3. Sensitivity to waste heat price and cessation probability

At WH prices between 0 and 30 €/MWh (base case is 20 €/MWh), the iron foundry WH is one of the cheapest heat sources in the system, meaning LCOH is directly linked to WH OPEX costs (Fig. 7). However, at a WH price of 40 €/MWh, heat from the biomass HOB is less expensive in most energy price scenarios and will be used instead, meaning the LCOH is less affected by the increase in WH price. A greater number of HPs reduces the sensitivity of LCOH to changes in WH prices, demonstrating their role in enhancing system flexibility and robustness against future WH price uncertainties.

Higher WH cessation probabilities lead to a higher weight for scenarios where the iron foundry ceases operation, which are more expensive than those where it does not cease operation. This results in a higher LCOH and standard deviation with increasing WH cessation probability (Fig. 8).

3.4. Changes in future heating demand

As space heating demand increases, LCOH decreases and vice-versa (Fig. 9). This is because investment costs constitute a significant

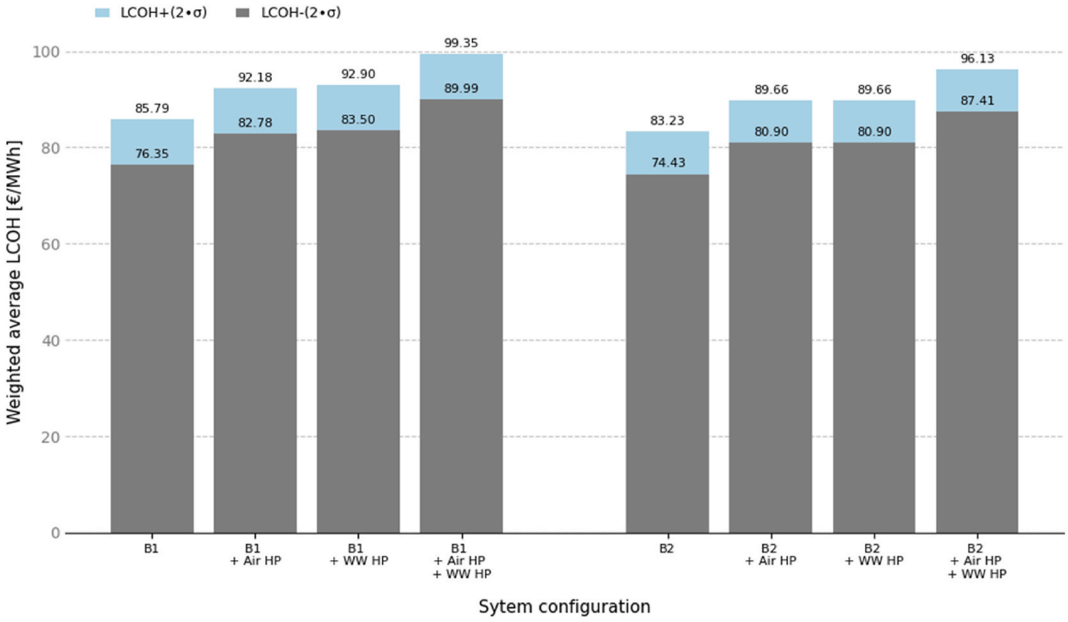

Fig. 4. Weighted average levelized cost of heat (LCOH) plus and minus twice the standard deviation per system configuration to showcase an "expected lower and upper boundary" for the LCOH value.

Table 4
Weighted average levelized cost of heat (LCOH) and standard deviation (SD) per system configuration in the case study.

	LCOH [€/MWh]	SD [€/MWh]	SD [% of LCOH]
Base scenario 1 (B1): Biomass HOB & CHP			
B1	81.07	2.36	2.92 %
B1+ Air HP	87.48	2.35	2.69 %
B1 + Wastewater HP	88.20	2.35	2.67 %
B1 + Air HP + Wastewater HP	94.67	2.34	2.47 %
Base scenario 2 (B2): Biomass HOB, CHP, and iron foundry WH			
B2	78.83	2.20	2.79 %
B2+ Air HP	85.28	2.19	2.56 %
B2 + Wastewater HP	85.28	2.19	2.56 %
B2 + Air HP + Wastewater HP	91.77	2.18	2.38 %

portion of LCOH and are distributed over a greater amount of heat supplied. The LCOH of configurations with more technologies (i.e., B2 + Air HP + WW HP) varies less with changes in heat demand than that of configurations with less technologies (i.e., B2) due to overall higher investment costs. However, standard deviation increases with greater heat demand. This is because uncertainty in future energy prices and availability impact operational costs rather than investment costs. Therefore, the greater the heat demand, the more LCOH is impacted by the uncertainty factors considered.

3.5. Effect of different electricity price profiles

Compared to electricity prices in 2022, those in 2024 had lower peaks which occurred less often (see supplementary material, Figure SM4), this results in a significant reduction in heat supplied by the CHP as potential revenues from selling electricity are lower. The 2024 electricity prices were also lower than in 2022, and even negative in some timesteps. This resulted in the increased operation of the HPs. As

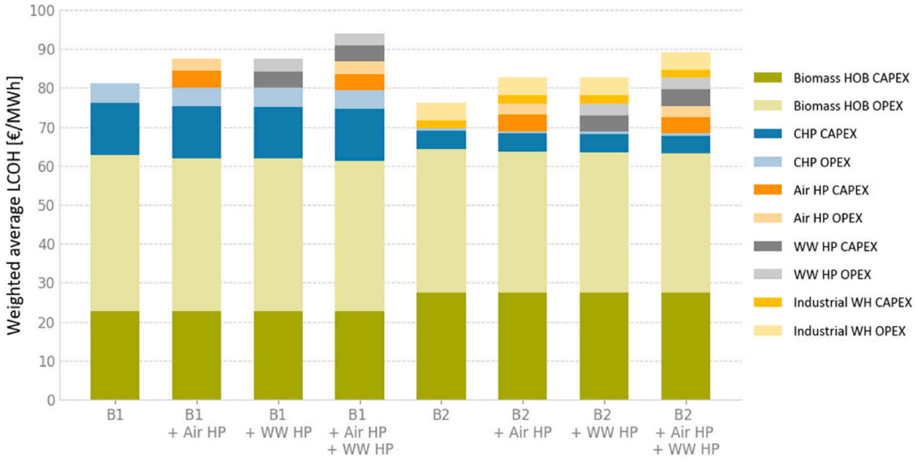

Fig. 5. Weighted average LCOH per system configuration broken down into CAPEX and OPEX per heat supply technology. OPEX costs for the CHP show net cost, accounting for electricity revenues and fuel costs.

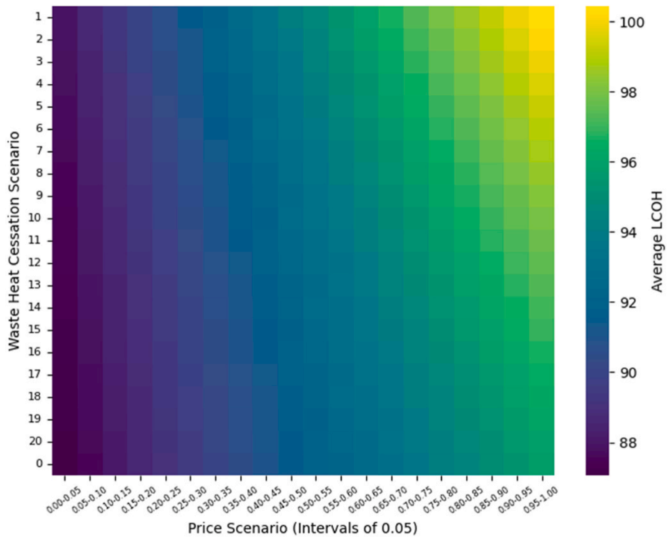

Fig. 6. Variation in average levelized cost of heat (LCOH) across energy price and WH cessation scenarios for configuration B2 + Air HP + Wastewater HP.

shown in Fig. 10, across all configurations, the LCOH was higher for 2024 prices, largely due to reduced revenues from the CHP despite reduced operational costs for the HPs. Standard deviation was also higher across all configurations, and especially for B1 configurations without WH from the iron foundry. The CHP's reduced potential to make revenues from high electricity peaks, results in a reduction in the dampening effect this has in high energy price scenarios, and weighted average LCOH experiences greater variation across energy price scenarios. It is also notable that configurations with additional HPs or with the iron foundry WH experienced a lower increase in LCOH and standard deviation compared to configurations with neither. This highlights the benefits of diversified system configurations in the face of future uncertainty.

3.6. Impact of biomass restrictions

To only capture the effect of the actual limitation, and not that of an associated (potential) occurrence of rising[3] fuel prices, the simulation was de-incentivized to use biomass in increasing degrees, and the resulting LCOH and allowed biomass share were recorded. The latter is hereby defined as percentage of total annual heat demand that can be covered using the biomass HOB under the applied limitation.

No system configuration resulted in a feasible operation with less than 19 % overall biomass share, due to limits in the installed capacity of technologies other than the biomass HOB. As can be seen in Fig. 11, "B1 + Air HP + Wastewater HP", the only configuration achieving feasible operation with 19 % biomass share, is however least favorable for biomass shares exceeding 60 %, where it results in considerably higher LCOH than all other designs. It can further be derived that system configurations belonging to "B2", while consistently performing better from an LCOH point of view (see also Section 3.1) require much higher biomass shares to operate feasibly.

Assuming a system operator (or planner) might not be willing to rely on a configuration that consistently requires it to cover more than three quarters of the total heat demand only using biomass it can derived that.

- System configuration "B1 + X", with either an Air HP or Wastewater HP (but not both) as additional heat sources, performs well over a wide range of biomass shares.
- If a reliance on at least 40 % biomass share is acceptable, the corresponding "B2 + X" (again either, but not both additional sources) result in roughly 5–10 % reduced overall LCOH compared to the former.

All other configurations are either too expensive, without offering an adequate improvement in biomass-independence, or result in lower LCOH while relying on biomass shares that are out of proportions (e.g., configuration "B2").

4. Discussion and conclusions

DH networks have a strong potential to contribute to decarbonizing the heating sector, since they enable the implementation of sustainable heating solutions on a large scale and the use of heat sources that are difficult to integrate on a small scale. This includes the largely untapped potential of AH and WH sources.

This study aimed to conduct a techno-economic comparative analysis of future decarbonization options for the case study of the DH network of a town in northwestern Poland, focussing on AH and WH and the consideration of uncertainties in future energy prices, WH availability, heat demand, and biomass availability. The analysis was carried out in the context of future fully renewable energy systems, comparing alternative configurations under uncertainty rather than estimating the performance of a single system under fixed conditions.

This was achieved by developing a model to simulate DH systems with and without AH and WH sources and evaluate their LCOH. For each system configuration analyzed, the DH system was simulated for all possible WH cessation scenarios for each of the one hundred energy price scenarios considered. Each LCOH was assigned a weight based on the probability of the WH cessation and energy price scenarios occurring. The weighted average LCOH and standard deviation for each system configuration were used to measure the central tendency and magnitude of the variation in LCOH due to uncertainty in future energy prices and WH availability, providing an indication of average cost and associated economic risk. Additionally, sensitivities regarding WH prices, future heat demand, and biomass availability were analyzed.

A main conclusion is that the **DH system configuration plays a key role in determining the average cost of the DH system**, as has been shown also by e.g. Kontu et al. [13] and Yang et al. [14]. This is because in the investigated system, CAPEX constitutes a large share of the LCOH.

A large fraction of the CAPEX is determined by the DH network operators' suggestions for the heat supply portfolio (B1 and B2 configurations), designed for maximum peak load coverage. Although the investigated HPs were able to reduce the OPEX in this study (especially in the biomass limitation scenarios), they did not change the base configuration, thus adding investment costs and increasing the overall LCOH.

Consequently, a **realistic estimation of the CAPEX** is very important. Although having a close cooperation with the DH network operator, more precise cost data would require detailed feasibility studies. Further on, very limited experience exists in Poland for some of the analyzed technologies. Consequently, for some technologies generic catalogue data has been used for estimating the CAPEX, not sufficiently considering the local situation (area available, integration works etc.). Additionally, a conservative approach was adopted by using upper bounds of CAPEX ranges provided by the DH operator and assuming a relatively short 15-year lifetime for most technologies (agreed on with the DH operator to align with their amortization period). These two assumptions may result in an overestimation of CAPEX costs, amplifying the CAPEX share of the LCOH which in turn reduces the impact of OPEX-related uncertainties on LCOH.

Since the CAPEX constitutes a large portion of the LCOH, **heat**

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[3] On the one hand, a limited supply of biomass could be expected to be linked to increased prices. However, it is unclear whether "district heating" (as essential societal need) may be subject to subsidies. Furthermore, such a shortage may consequently increase demand for other substitutes (fuels or technologies), leading to correlations between uncertainties. Together this makes it hard to consistently project effects on prices and other parameters.

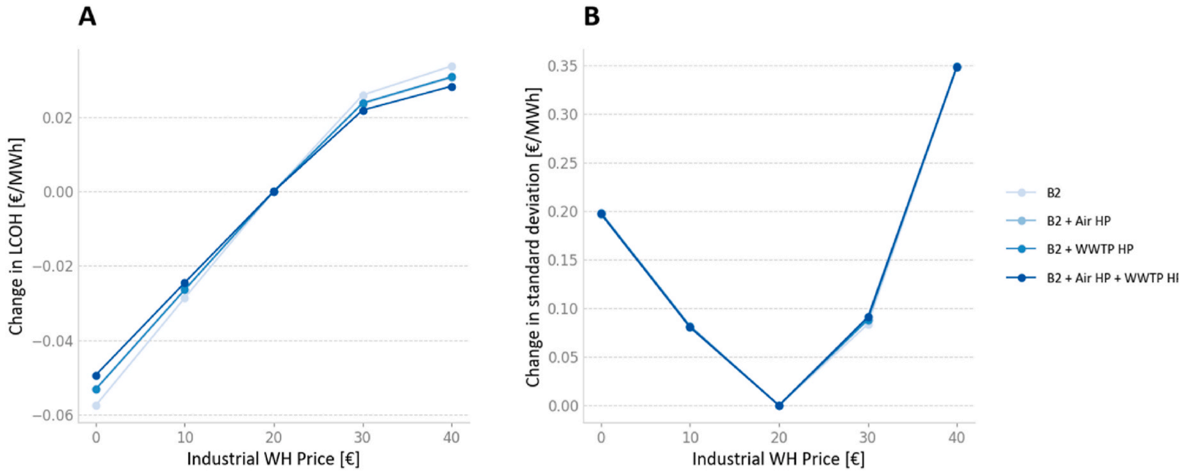

Fig. 7. Percent change in (A) weighted average levelized cost of heat (LCOH) and (B) standard deviation with increasing WH prices for each B2 system configuration.

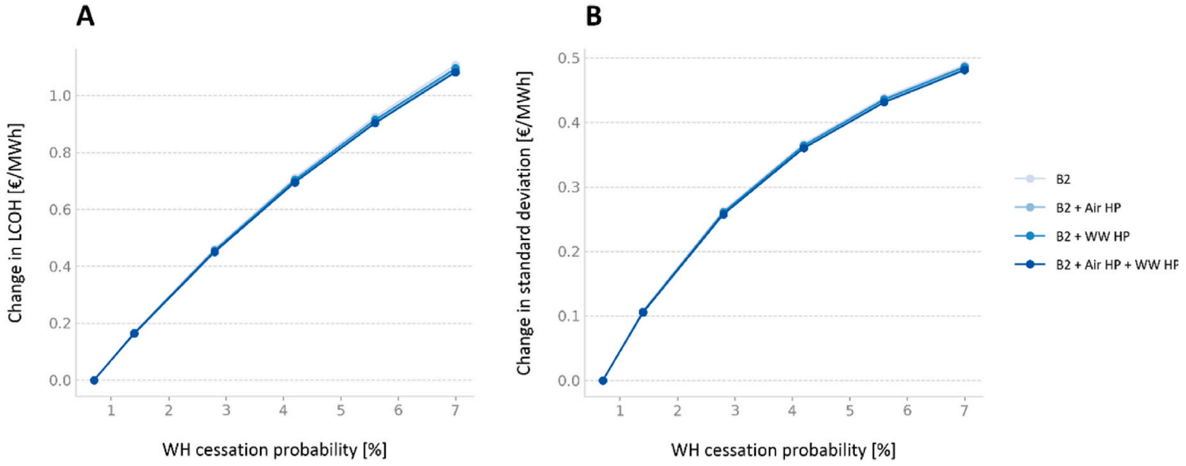

Fig. 8. Change in (A) weighted average levelized cost of heat (LCOH) and (B) standard deviation with increasing WH cessation probability for each B2 system configuration.

demand is an important factor for the LCOH. Although OPEX decreases with decreasing heat demand, CAPEX stays constant, and consequently LCOH increases with decreasing heat demand (and vice-versa); i.e. a 30 % reduction of heat demand results in a 15 to 20 €/MWh increase in mean LCOH. This effect can also be seen in the literature, e.g. Zhang et al. [37]. Consequently, a realistic heat demand estimation is important but couldn't be performed within this study due to missing data. However, it is important to note that this sensitivity is influenced by the relatively high CAPEX and short lifetimes assumed, which result in high CAPEX costs. Alternative assumptions would likely moderate this effect.

Furthermore, the study showed a heavy reliance on biomass across all configurations due to the large biomass HOB capacity, assumed unlimited fuel availability, and relatively low fuel cost. Only in scenarios where the use of biomass is restricted to below 60–65 %, systems with AH sources become competitive compared to systems without AH, having a lower mean LCOH. However, biomass use has been artificially limited in this approach by a "virtual" price increase, not considering optimized utilization of the scarce resource.

Under the assumptions that WH has a relatively low price, the price does not vary across energy price scenarios, and there is a low annual WH cessation probability, **the presence of industrial WH proved to be beneficial** to the techno-economic performance of the DH system. This is leading to reductions in mean LCOH of up to 3 €/MWh and often also a reduction in economic risk. All B2 configurations, which have WH from the iron foundry, have a lower LCOH and standard deviation compared to their counterpart configuration under B1. However, this is largely due to the assumptions concerning the modelling of industrial WH, with the sensitivity analysis showing that above a WH price of 40 €/MWh, biomass is less expensive than the WH and used instead. The reduction in standard deviation despite the presence of industrial WH and the associated uncertainty in its future availability, also indicates that the WH cessation scenarios have a smaller influence compared to energy price scenarios.

This cost effectiveness of WH is widely present in the literature, e.g. Bühler et al., Pakere et al., Morandin et al., and Su et al. all found WH sources in DH systems to be profitable [3,17,18,22]. However, Spirito et al., found that DH systems with steelwork WH had higher investment costs due to the investment in the HPs that needed to be coupled to the steelwork [19].

In general, the results also indicated a tradeoff between minimizing average cost and minimizing economic risk in the face of future uncertainties. The least expensive configuration had a 17 % lower mean LCOH relative to the most expensive configuration involving AH and WH sources (with absolute values from max. 94.67 to min. 78.83 €/MWh). Similarly, the configuration with the lowest economic risk has an 8 % lower standard deviation than the configuration with the highest risk (with absolute values from a standard deviation of max. 2.36 to min. 2.18 €/MWh). Increased supply side flexibility through a greater variety of heat sources leads to (slightly) lower

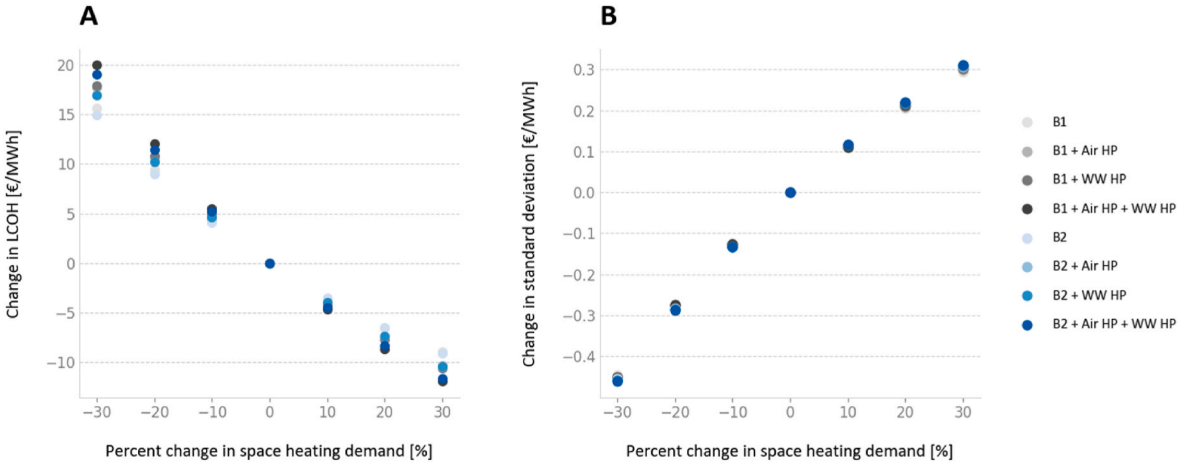

Fig. 9. Change in (A) weighted average levelized cost of heat (LCOH) and (B)standard deviation with changes in space heating demand.

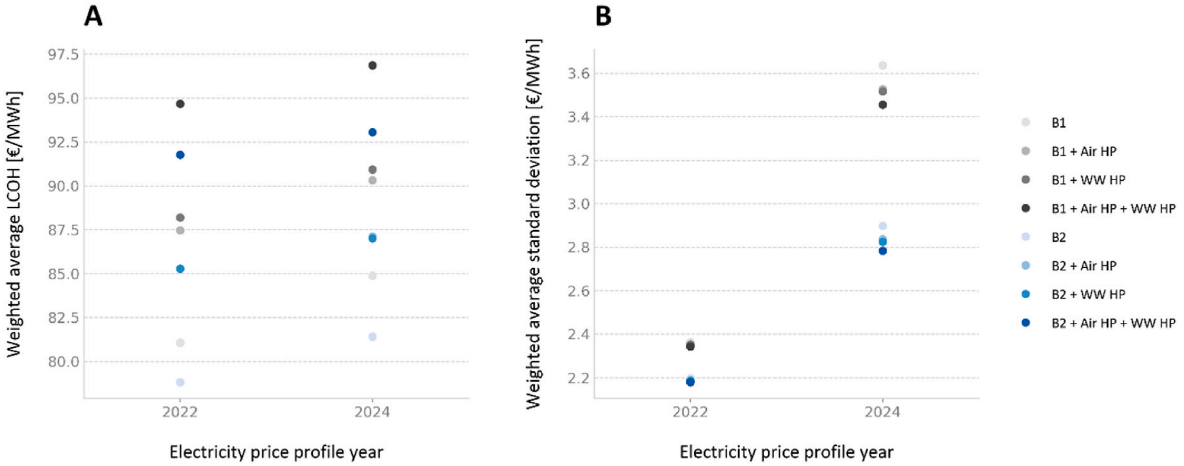

Fig. 10. Change in (A) weighted average levelized cost of heat (LCOH) and (B) standard deviation with changes in electricity price profile year.

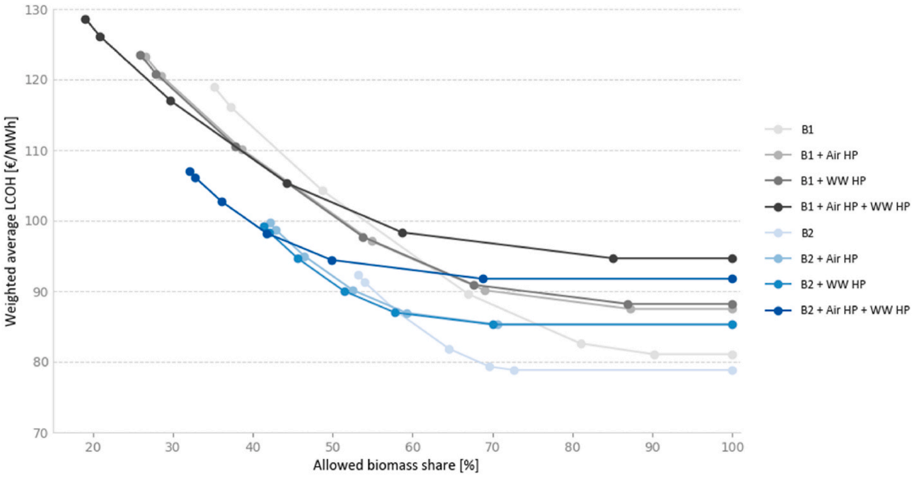

Fig. 11. Weighted average levelized cost of heat (LCOH) across different levels of allowed biomass share (share of heat which is allowed to be produced from the biomass HOB as a percent of total heat production) across all system configurations.

economic risks, but higher average LCOH, evident in both B1 and B2 configurations as more HPs are added to the system. Between these two variables, there is a tradeoff between minimizing average system costs and minimizing system risks. The configurations with high costs and low risks are generally those with more technologies and greater installed capacity. However, configurations with low cost and high risk may still perform better than the those with high cost and low risk even when the economic risk is accounted for.

This is mirrored in the results of Kienzle et al. [33] and can be attributed to the fact, that energy prices only affect the OPEX, that has a relatively low impact on the overall LCOE (see above). Further on, the historic electricity price profiles used in this study did not have many hours with very low electricity prices.

4.1. Limitations and future work

Despite the greatest possible care in the design of the study, some limitations related to the input data, model, and general factors arose:

This study considers a **green field approach using fixed system configurations** that determine the overall CAPEX.

- To reduce this CAPEX, it should be investigated, **if existing assets might be re-used in the future scenario**, e.g. by switching to renewable fuels. This includes concrete decarbonization pathways from the present fossil-based portfolio to a fully renewable future configuration, i.e. following requirements on minimum shares of renewable heat sources foreseen in the Energy Efficiency Directive, article 26. Furthermore, as conservative estimates were used, further research is needed to refine CAPEX estimates, e.g, through detailed feasibility studies.
- The **realistic technical lifetime** of the units should be investigated more in detail. On one hand this includes a transition from a technical lifetime in calendar years to a technical lifetime in operational hours, i.e. running with fewer full load hours (e.g. the CHP might only run for peak load times) can extend the overall lifetime and therefore reduce the annualized CAPEX. On the other hand, a higher number of ramp-up and ramp-down processes due to increased volatility in the electricity market may reduce the technical lifetime, increasing the annualized CAPEX.
- Further on, **modifications of the base heat supply configurations**, like geothermal energy could enhance the performance of the DH network. In this context, a more detailed analyses of the peak load coverage would be required regarding different peak load supply technologies (gas-heater, electric boiler).
- **Storages** have not been considered in this study but will also play a key role to a) decrease peak loads, b) reduce the number of ramp-up- and ramp-down processes and c) enable the system to use high electricity prices (in the case of CHP) or low electricity prices (in the case of HP), if heat demand is low. This could also include DSM measures as a “virtual” storage. Large scale storages might also shift the potential summer surplus heat from HPs to contribute to the winter demand.
- Further on, a **more detailed modelling** of heat supply technologies including flexible CHP electricity shares and ramp-up and ramp-down rates could be promising areas for future research. Also, important parameters, such as investment costs for the HP installations, need to be investigated in more detail, e.g. via detailed feasibility studies.
- Further on a **reduction of the DH network temperatures** could be considered to allow a higher COPs of the heat pumps and therefore a higher economic efficiency. However, the reduction in network temperatures in general relates to additional costs due to the required investments in optimization measures, which needs to be evaluated against the savings due to lower electricity costs for the HPs (and possible other positive effects).

A key limitation of this study is the use of **historical data as a basis for predicting future trends**, such as electricity prices and heat demand. Historical data may not fully capture the complexities and uncertainties associated with the ongoing energy transition. Furthermore, static profiles for the 20-year study period were assumed, which did not account for interannual variations or trends. Although future projections could offer a more accurate basis for modeling these factors, the methodology presented in this study remains valuable in providing insights into how systems compare under different future scenarios. Moreover, the use of a scenario-based approach ensures the methodology remains generalizable and applicable to a wide range of future timeframes where similar uncertainties in energy prices and availability will persist. In future work, future projections could be utilized and more accurate uncertainties considered related to.

- a more detailed analysis of the uncertainties in the **heat demand** development, considering factors like the number of consumers newly connected or disconnected to the DH network, future thermal retrofitting activities of buildings and by trend increasing future outdoor temperatures due to climate change. However, since very cold weeks cannot be ruled out in climate change scenarios, peak load coverage and related investments might be unaffected (see above).
- a wider range of **electricity prices**, e.g. including future scenarios for the European energy system, showing very low prices especially in summer times, but also for some hours in the winter, due to increasing PV and wind installations, but also with very high prices due to cold dark doldrums.

In this context it is important to consider, that retrofitting activities also depends on the energy costs and climate conditions, which influence customer behaviour and decisions towards energy efficiency measures. Also, correlations between weather and energy prices could be considered, i.e. the future appearance of cold dark doldrums. Also, coupling of the biomass price to electricity prices could be a future option.

Albeit considered through the sensitivity analysis conducted, the chosen **WH cessation probability** did not account for sector-specific differences nor accurately reflect the probability of the iron foundry ceasing operation. Detailed modeling of industrial WH—accounting for temporal mismatches, future changes in availability and quality – could improve understanding of its potential as a DH heat source. Also, research on the correlation between energy prices and WH availability and/or WH prices could be beneficial.

Finally, in this study, simulation methods were chosen to enable a fast computation of the different configurations and scenarios. However, this approach doesn’t properly consider the limited availability of biomass as a fuel for heat generation. In the future **optimization-based approaches** could be prioritized to allocate the biomass (e.g. for covering peak loads, see above). Also, optimization is important for suitable operation strategies for (seasonal) thermal storages. Further on, optimization could be used to identify optimal system configurations. However, calculation times will most likely increase significantly, so model simplifications might be required.

CRediT authorship contribution statement

Nyasha Grecu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefan Strömer:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Ralf-Roman Schmidt:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation, Conceptualization. **Klara Maggauer:** Methodology, Conceptualization. **Nicolas Marx:** Methodology, Conceptualization. **Bernhard Mayr:** Methodology, Conceptualization. **Wen Liu:** Writing – review & editing, Supervision, Conceptualization.

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

During the preparation of this work the author(s) used ChatGPT to assist with concise and grammatically refined expressions. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2025.136641.

Data availability

Data will be made available on request.

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