

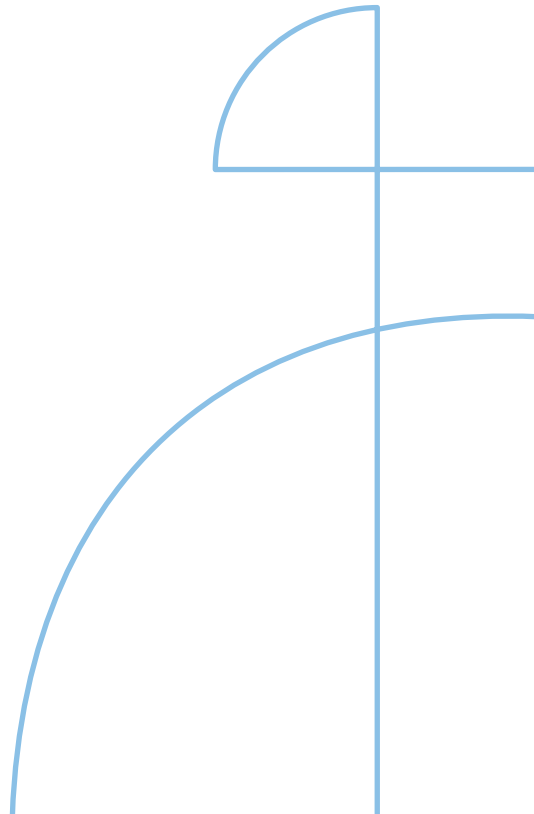


Doctoral Thesis in Energy Technology

Unlocking the Potential of Excess Heat Recovery: A Multi-model Framework for Analysing Resilient and Low-Carbon District Heating

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Abstract

Heating and cooling account for a substantial share of final energy use and greenhouse gas emissions in Europe. District heating systems play a central role in decarbonising heat supply by enabling the integration of centralised, low-carbon heat sources. However, as fossil fuels and waste incineration are phased out and biomass availability becomes increasingly constrained, district heating systems face growing challenges related to cost, resource availability, and long-term resilience. In this context, industrial and urban excess heat and cold could support a low-carbon, flexible heat supply. Despite significant documented technical potential, excess heat remains poorly integrated into district heating systems due to spatial constraints, temperature mismatches, operational variability, and fragmented decision-making among industrial actors, network operators, and policymakers.

Energy system optimisation models are widely used to support long-term energy planning and policy analysis. However, when applied to excess heat recovery, existing modelling approaches struggle to capture several critical dimensions for decision-making, including spatial feasibility, heat quality, operational behaviour, and uncertainty. At the same time, empirical evidence on how excess heat performs within real district heating systems under different technical and market conditions remains limited. This thesis addresses these gaps by combining real-world case studies with the development of methodological models to support strategic planning for excess-heat recovery in district-heating systems.

The overall aim of this thesis is to develop and apply modelling approaches that enable a comprehensive and robust assessment of the integration of excess heat into district heating systems. The work is structured around three research questions, each addressing a distinct but interconnected aspect of the problem.

The first research question examines how well existing energy system optimisation models meet the analytical needs of decision-makers involved in excess heat recovery planning. Through a structured review of modelling tools and an assessment of stakeholder requirements, the thesis shows that while current models provide robust representations of technology costs, energy balances, and long-term investment dynamics, they fall short in representing spatial variation, heat quality, and operational constraints. These limitations are particularly problematic for excess heat recovery, where feasibility and value depend strongly on distance to demand, temperature levels, and temporal stability of supply. The analysis further highlights that limited flexibility and transparency in many models reduce their usefulness for stakeholder engagement. This research question establishes the need for modelling approaches that go beyond single-model optimisation and motivates the development of a multi-model framework.

The second research question investigates how a multi-model framework can improve the analysis of excess heat integration into district heating systems. To address this question, the thesis develops a modular multi-model framework that links exergy analysis, spatial least-cost network optimisation, long-term techno-economic optimisation, and high-resolution operational validation. The framework is implemented using iterative soft linking between

models, ensuring that spatial feasibility, heat quality, and operational constraints are consistently reflected in long-term investment planning. The framework is applied to both a new district heating system and a large existing system. The results show that spatial proximity and source temperature strongly influence early investment decisions, while electricity prices and competition with existing technologies shape excess heat uptake in mature systems. Operational validation reveals differences between long-term investment pathways and short-term utilisation patterns, highlighting the importance of thermal storage and flexible operation in aligning planning and operation.

The third research question explores how district heating systems can be planned and adapted to remain resilient amid long-term uncertainty, systemic risks, and external shocks. To address this question, the thesis develops a stochastic–clustering–resilience framework that combines uncertainty sampling with long-term optimisation and post-processing analysis. This approach enables the identification of representative investment pathways and the evaluation of their performance across a wide range of future conditions. The results show that systems with diversified, flexible technology portfolios that combine excess heat recovery with electrification options such as heat pumps, electric boilers, and thermal storage perform best in terms of cost, emissions, and robustness. In contrast, systems that rely heavily on combustion-based technologies are more sensitive to fuel price volatility, policy changes, and supply disruptions.

Across all research questions and case studies, the modelling results demonstrate that excess heat can contribute significantly to cost-effective, low-carbon district heating systems, but only when spatial, thermal, operational, and uncertainty-related factors are jointly considered. Excess heat delivers the greatest system value when evaluated as part of a flexible and diversified technology portfolio rather than as a stand-alone resource.

The contributions of this thesis are twofold. First, it provides insights from multiple real-world district heating case studies, clarifying when and how industrial and urban excess heat can be effectively integrated under varying spatial, technical, and policy conditions. Second, it advances methodological approaches to excess heat modelling by developing a coherent multi-model framework that links industrial-, network-, and system-level perspectives. By integrating spatial, exergy, techno-economic, operational, and uncertainty analyses within a transparent and extensible workflow, the thesis provides improved decision support for planners, district heating operators, and policymakers. It contributes to a deeper understanding of how flexibility and adaptability, rather than single-technology optimisation, underpin resilient and sustainable transitions in district heating systems.

Keywords

District Heating, Excess heat, energy system modelling, geospatial analysis, uncertainty analysis

Sammanfattning

Uppvärmning och kylning står för en betydande andel av den slutliga energianvändningen och utsläppen av växthusgaser i Europa. Fjärrvärmesystem spelar en central roll i utfasningen av fossila bränslen i värmeförsörjningen genom att möjliggöra integration av centraliserade värmekällor med låga koldioxidutsläpp. I takt med att fossila bränslen och avfallsförbränning fasas ut och tillgången på biomassa blir alltmer begränsad, står fjärrvärmesystem inför ökande utmaningar kopplade till kostnader, resurstillgångar och långsiktig resiliens. I detta sammanhang kan industriell och urban överskottsvärme och -kyla bidra till en koldioxidsnål och flexibel värmeförsörjning. Trots en betydande dokumenterad teknisk potential är integrationen av överskottsvärme i fjärrvärmesystem fortfarande begränsad på grund av rumsliga begränsningar, temperaturskillnader, driftmässig variation samt fragmenterat beslutsfattande mellan industriella aktörer, nätoperatörer och beslutsfattare.

Optimeringsmodeller för energisystem används i stor utsträckning för att stödja långsiktig energiplanering och policyanalys. När de tillämpas på återvinning av överskottsvärme har befintliga modelleringsmetoder dock begränsad förmåga att fånga upp flera dimensioner centrala för beslutsfattande, såsom rumslig genomförbarhet, värmekvalitet, driftsbeteende och osäkerhet. Samtidigt är den empiriska kunskapen begränsad gällande hur överskottsvärme fungerar inom verkliga fjärrvärmesystem under olika tekniska och marknadsmässiga förhållanden. Denna avhandling adresserar dessa kunskapsluckor genom att kombinera fallstudier från verkliga system med metodutveckling inom modellering för att stödja strategisk planering av återvinning av överskottsvärme i fjärrvärmesystem.

Det övergripande syftet med denna avhandling är att utveckla och tillämpa modelleringsmetoder som möjliggör en omfattande och robust analys av integrationen av överskottsvärme i fjärrvärmesystem. Arbetet är strukturerat kring tre forskningsfrågor som var och en behandlar en distinkt men sammanlänkad aspekt av problemområdet.

Den första forskningsfrågan undersöker i vilken mån befintliga energisystemmodeller svarar mot de analytiska behov som beslutsfattare har vid planering av återvinning av överskottsvärme. Genom en strukturerad genomgång av modelleringsverktyg och en analys av intressenters behov visar avhandlingen att befintliga modeller ger robusta beskrivningar av teknikkostnader, energibalanser och långsiktiga investeringsdynamiker, men att deras förmåga att representera rumslig variation, värmekvalitet och driftmässiga begränsningar är begränsad. Dessa begränsningar är särskilt problematiska för återvinning av överskottsvärme, där genomförbarhet och värde i hög grad beror på avståndet till efterfrågan, temperaturnivåer och stabiliteten i värmetillförseln över tid. Analysen visar också att begränsad flexibilitet och transparens i många modeller minskar deras användbarhet i dialog med intressenter. Denna forskningsfråga etablerar därmed behovet av modelleringsmetoder som går bortom enskilda optimeringsmodeller och motiverar utvecklingen av ett multimodellramverk.

Den andra forskningsfrågan undersöker hur ett multimodellramverk kan stärka analysen av hur överskottsvärme integreras i fjärrvärmesystem. För att besvara denna fråga utvecklar avhandlingen ett modulärt multimodellramverk som kopplar samman exergianalys, rumslig

kostnadsoptimering av nät, långsiktig teknoekonomisk optimering samt högupplöst operativ validering. Ramverket implementeras genom iterativ mjuk koppling mellan modeller, vilket gör det möjligt att konsekvent integrera rumslig genomförbarhet, värmekvalitet och driftmässiga begränsningar i långsiktig investeringsplanering. Ramverket tillämpas både på ett nytt fjärrvärmesystem och på ett befintligt system. Resultaten visar att rumslig närhet och källtemperatur starkt påverkar tidiga investeringsbeslut, medan elpriser och konkurrens med befintliga tekniker påverkar upptaget av överskottsvärme i mer mogna system. Operativ validering visar också skillnader mellan långsiktiga investeringsbanor och kortsiktiga utnyttjandemönster, vilket understryker betydelsen av termisk lagring och flexibel drift för att anpassa planering och drift.

Den tredje forskningsfrågan undersöker hur fjärrvärmesystem kan planeras och anpassas för att upprätthålla sin resiliens under långsiktig osäkerhet, systemriskor och externa störningar. För att besvara denna fråga utvecklar avhandlingen ett ramverk som kombinerar stokastisk analys, klustring och resiliensanalys genom att integrera osäkerhetssampling, långsiktig optimering och efterföljande resultatanalys. Detta tillvägagångssätt gör det möjligt att identifiera representativa investeringsbanor och utvärdera deras prestanda under ett brett spektrum av framtida förutsättningar. Resultaten visar att system baserade på diversifierade och flexibla teknikportföljer, där återvinning av överskottsvärme kombineras med elektrifieringsalternativ såsom värmepumpar, elpannor och termisk lagring, presterar bäst när det gäller kostnader, utsläpp och robusthet. System som i hög grad är beroende av förbränningsbaserade tekniker är däremot mer känsliga för volatilitet i bränslepriser, policyförändringar och störningar i energitillförseln.

Sammanfattningsvis visar avhandlingens resultat att överskottsvärme kan bidra väsentligt till kostnadseffektiva och koldioxidsnåla fjärrvärmesystem, men endast om rumsliga, termiska, driftrelaterade och osäkerhetsrelaterade faktorer beaktas samlat. Överskottsvärme skapar störst systemvärde när den betraktas som en del av en flexibel och diversifierad teknikportfölj snarare än som en fristående resurs.

Avhandlingens bidrag är tvådelat. För det första ger den empiriska insikter från flera verkliga fjärrvärmesystem och belyser därigenom när och hur industriell och urban överskottsvärme kan integreras effektivt under olika rumsliga, tekniska och policyrelaterade förutsättningar. För det andra utvecklar avhandlingen metodologiska angreppssätt för modellering av överskottsvärme genom ett sammanhängande multimodellramverk som kopplar samman industriella, nätbaserade och systemövergripande perspektiv. Genom att integrera rumsliga analyser, exergianalys, teknoekonomisk modellering, operativ analys och osäkerhetsanalys i ett transparent och utbyggbart arbetsflöde stärker avhandlingen beslutsstöd för planerare, fjärrvärmeoperatörer och beslutsfattare. Den bidrar därmed till en djupare förståelse för hur flexibilitet och anpassningsförmåga, snarare än optimering av enskilda tekniker, utgör grunden för resilienta och hållbara omställningar av fjärrvärmesystem.

Nyckelord

Fjärrvärme, överskottsvärme, energisystemmodellering, geospatial analys, osäkerhetsanalys

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List of Appended Papers

Paper I

S. Kumar, J. Thakur, and F. Gardumi “Techno-economic modelling and optimisation of EHC recovery for industries: A review”, Renewable and Sustainable Energy Reviews, Volume 168, 2022, <https://doi.org/10.1016/j.rser.2022.112811>.

Paper II

S. Kumar, J. Thakur, J.M. Cunha, F. Gardumi, A. Kök, A. Lisboa and V. Martin “Techno-economic optimization of the integration of industrial EH into DHS with high spatial and temporal resolution,” Energy Conversion and Management, Volume 287, 2023, <https://doi.org/10.1016/j.enconman.2023.117109>.

Paper III

M. Silva, S. Kumar, A. Kök, A. Cardoso, M. Hummel, P.S. Nielsen, B.S. Khan, A.S. Faria, M. Jensterle, C. Marques, “EMB3Rs: A game-changer tool to support waste heat recovery and reuse”, Energy Conversion and Management, Volume 309, 2024, <https://doi.org/10.1016/j.enconman.2024.118408>.

Paper IV

S. Kumar, A. Kök, J. Dalgren, J. Thakur, V. Martin, F. Gardumi, “Strategic Integration of Urban Excess Heat Sources in DH: A Spatio-Temporal Optimisation Methodology”, Applied Energy, Volume 396, 2025, <https://doi.org/10.1016/j.apenergy.2025.126236>

Paper V

S. Kumar, F. Gardumi, V. Martin, J. Thakur “Resilient District Heating Transitions under Uncertainty: Insights from Stochastic Optimisation and Pathway Clustering” [Under review]

Nomenclature

AI	Artificial Intelligence
BALMOREL	Baltic Model of Regional Electricity Liberalisation
CHP	Combined Heat and Power
COP	Coefficient of Performance
DCHP	Data Centre Heat Pump
DH	District Heating
DHCS	District Heating and Cooling Systems
DHN	District Heating Network
DHS	District Heating System
DST	Decision Support Tool
DTW	Dynamic Time Warping
EH	Excess Heat
EHC	Excess Heat and Cold
ESOM	Energy System Optimisation Model
EU	European Union
GAMS	General Algebraic Modelling System
GHG	Greenhouse Gas
GIS	Geographic Information System
HP	Heat Pump
HTHE	High Temperature High Electricity
HTLE	High Temperature Low Electricity
IEH	Industrial Excess Heat
IPCC	Intergovernmental Panel on Climate Change
KPI	Key Performance Indicator
LCOH	Levelised Cost of Heat
LHS	Latin Hypercube Sampling
LTHE	Low Temperature High Electricity
LTLE	Low Temperature Low Electricity

MILP	Mixed-Integer Linear Programming
MSW	Municipal Solid Waste
NECP	National Energy and Climate Plan
NG	Natural Gas
OEMOF	Open Energy Modelling Framework
OSM	Open Street Maps
PETA	Pan European Thermal Atlas
RDM	Robust Decision Making
RED	Renewable Energy Directive
RES	Renewable Energy Source
RSD	Relative Standard Deviation
STHP	Sewage Treatment Heat Pump
SWHP	Sea Water Heat Pump
TES	Thermal Energy Storage
TIMES	The Integrated MARKAL–EFOM System
UEH	Urban Excess Heat

Terminology

This thesis employs a range of modelling concepts used throughout the analysis, which therefore require clear and consistent interpretation. To avoid ambiguity, this section introduces the key terms and concepts used in the thesis. Each concept is defined in detail in the following subsections, providing an everyday basis for the methodological discussions that follow.

The terms are introduced in a bottom-up, meaning-based order rather than alphabetically. In this way, their understanding is intended to be established in a connected and constructive manner.

Excess heat: In this thesis, excess heat refers to thermal energy generated as an unavoidable by-product of industrial, commercial, or urban activities, remaining after internal heat recovery within the primary process and otherwise rejected to the environment.

Long-term investment model: A long-term investment model is an optimisation or simulation model used to analyse the evolution of an energy system over extended time horizons, typically spanning multiple years or decades. It represents investment decisions in energy technologies and infrastructure and evaluates their long-term cost, performance, and system impacts under given assumptions and constraints. Such models are commonly used to assess strategic planning questions, technology deployment pathways, and long-term decarbonisation options.

Dispatch model: A dispatch model represents the short-term operation of an energy system by determining how available technologies are operated over a given time period to meet demand. It typically operates at high temporal resolution, such as hourly or sub-hourly, and focuses on operational feasibility, resource availability, and variable costs. Dispatch models generally assume fixed system capacities and do not make long-term investment decisions.

Modelling framework: A modelling framework is the overarching methodological structure that defines how models, data inputs, and analytical steps are combined to address a specific research question. It specifies the role of each model, the flow of information between them, and the assumptions governing their interaction. A framework is conceptual and not tied to a specific software implementation.

Workflow: A workflow describes the ordered sequence of modelling steps and data exchanges carried out within a modelling framework. It outlines how models are executed, how outputs from one step serve as inputs to the next, and how the overall analysis progresses from inputs to results for a given application or case study.

Platform: A platform is the software-based implementation of a modelling framework that provides a user interface for configuring inputs, executing the underlying models, and visualising results. It enables interaction with the framework through a front-end that supports scenario management, data handling, and result exploration, thereby facilitating practical application.

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1 Introduction

A major global challenge today is reducing greenhouse gas (GHG) emissions to limit the rise in global temperatures. The industrial sector is a significant contributor, accounting for 21% of global energy-related GHG emissions in 2019, according to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) [1]. It accounts for a larger share of global emissions than the buildings sector and is nearly comparable to the transport sector, as shown in Figure 1.

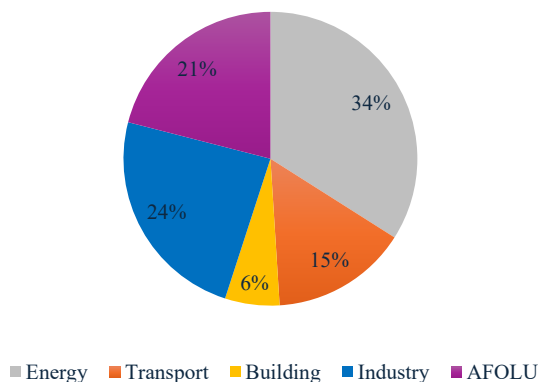


Figure 1: Contribution of major sectors to global greenhouse gas emissions, showing the relative shares of energy (34%), industry (24%), AFOLU (21%), transport (15%), and buildings (6%). [1]

Energy-intensive industrial processes rely heavily on fossil fuels and generate substantial thermal energy as a byproduct. However, many of the long-term options required to decarbonise these processes, such as hydrogen-based steelmaking, are still under development [2] and are unlikely to reach wide deployment in the near future [3]. In the short term, however, mature measures such as energy-efficiency improvements and the recovery of Excess Heat and Cold (EHC) offer valuable, holistic opportunities to reduce system-wide emissions. Industries such as iron and steel, cement, and fertiliser production release large amounts of excess thermal energy at temperatures and exergy levels suitable for recovery and reuse. Although recovering this Excess Heat (EH) does not directly reduce emissions from industrial production itself, it can support wider decarbonisation by supplying low-carbon heat to other sectors or by returning it to the industrial process through internal recovery. When redirected to residential or commercial heating systems, recovered EH can replace fossil-fuel-based heating, thereby reducing emissions across the broader heating and cooling supply, which accounts for a large share of global final energy use.

The heating and cooling supply accounts for nearly 50% of global final energy use and remains a significant source of greenhouse gas emissions in 2023 [4]. Here, the heating and cooling supply refers to the total final energy demand for thermal purposes across residential, commercial, public service, and industrial sectors, including both space conditioning and process heating and cooling. In the European Union (EU), this sector accounts for half of final

energy use, with approximately 79% still supplied by fossil fuels as of 2023, as illustrated in Figure 2 [5]. Oil and natural gas dominate, with gas alone accounting for 46% of heating and cooling use [6], highlighting the urgent need to transition to more sustainable supply options across both centralised and decentralised systems. District Heating and Cooling Systems (DHCS) have long served as efficient infrastructures for delivering thermal energy for space heating and cooling [6]. Large-scale District Heating Systems (DHS) offer considerable potential for reducing emissions by integrating renewable and fossil-free energy sources [7]. As Werner et al. observe, the fundamental idea of DHS is to utilise local or residual heat that would otherwise be wasted and distribute it through thermal networks to meet local demand [8]. Recent advancements in fourth- and fifth-generation DHS (Table 1) focus on enhanced efficiency and system integration, with an increasing emphasis on incorporating EH, geothermal energy, and solar thermal technologies, which typically operate at supply temperatures of 60°C to 70°C [8].

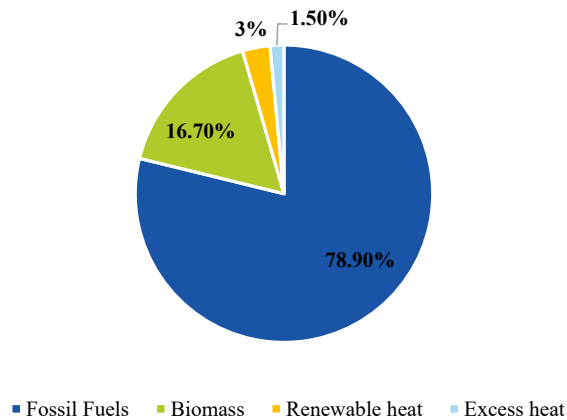


Figure 2: Share of fuels used in heating and cooling supply in the European Union in 2023, showing contributions from fossil fuels (78.9%), biomass (16.7%), renewable heat (3%), and EH (1.5%) [4].

Building on these EU-wide directives, Sweden has already achieved substantial progress in decarbonising its heat supply. In Sweden, DH is well developed and provides over half of the space- and water-heating needs in homes and service buildings [9]. These systems are widely used in cities and have long relied on Combined Heat and Power (CHP), Municipal Solid Waste (MSW) incineration, and biomass [10]. Biomass, accounting for around 60% of the heat supply in 2024, has benefited from Sweden's abundant domestic resources and established supply chains [11]. However, its long-term viability is increasingly uncertain due to ecological constraints, tightening sustainability criteria, and competing demand across sectors. Intensive harvesting may compromise biodiversity and soil carbon retention. At the same time, EU policies such as the Renewable Energy Directive II (RED II) are expected to prioritise biomass for harder-to-electrify applications [12], [13]. Simultaneously, biomass prices have shown considerable volatility, especially since 2021, raising operational costs for DH operators and, hence, end users [14], [15]. MSW availability is also declining as recycling and circular-economy policies reduce MSW volume and alter its composition [16]. In particular, removing plastic fractions lowers the carbon content and can reduce the overall energy yield of waste

streams. Together, these developments are affecting the reliability of combustion-based heat supply, which highlights the need to accelerate the integration of low-carbon alternatives, particularly EH and large-scale Heat Pumps (HPs).

Table 1: *Generations of District Heating (DH)* [17]

Generation of DH (GDH)	Definition	Supply Temperature Range
1GDH	Early systems used steam from a central plant to supply buildings through basic pipe networks.	Steam (typically > 100 °C).
2GDH	Systems using pressurised hot water instead of steam to improve efficiency and reliability.	Pressurised hot water above ~100 °C.
3GDH	Systems with supply temperatures below ~100 °C use pre-insulated pipes to reduce losses.	Supply between ~100 °C and ~80 °C.
4GDH	Low-temperature systems are designed for high efficiency and easy integration of renewable and EH sources.	Maximum forward-flow temperature around ~70 °C (and below, with low return temperatures targeted).
5GDH	Ultra-low-temperature networks that use bidirectional heat flows and local heat pumps to exchange heat between buildings.	Supply temperatures typically range from ~10-25 °C (near ambient) to ~50 °C in some cases.

Numerous studies have estimated EH availability in the industrial sector across different regions. As a first step, exergy-based process models have been used to determine the technical potential for heat recovery. Miró et al. compiled national estimates of Industrial Excess Heat (IEH) potential across Europe, North America, and Japan [18]. In the EU, IEH alone could account for between 9% and 22% of final energy demand. This represents significant potential, particularly when combined with energy-efficiency and decarbonisation measures. Pili et al. estimated the EHC potential in the German industrial sector to be approximately 200 TWh per year in 2020 [19], while Albert et al. reported a potential of 46 TWh per year in the United Kingdom in 2018 [20]. These exergy-based assessments have been further refined using a Geographic Information System (GIS) to identify industrial EHC sources and the locations of space-heating demand. A GIS-based analysis of 1608 industrial sites in Europe found that 42 TWh of EH could be recovered and used in DHS by 2020, representing around 8 % of the DH supply in the EU28 in energy terms [21]. A spatial mapping of georeferenced industrial sites within 10 km of DH areas indicates that approximately 230 PJ (64 TWh) per year of IEH could be recovered from 752 sites, meeting up to 17% of the DH demand for residential and service buildings in 2024 [22].

In Sweden, approximately 4.7 TWh of EH is recovered in 2024, which accounts for around 12 % of the total estimated EH (39 TWh per year) and 9 % of the DH supply [21], [23]. In contrast, a 2013 study by the Swedish Energy Agency projects an increase in EH potential from 22 TWh

in 2015 to 33 TWh per year by 2050 [24]. The projected increase reflects the estimated technical availability of EH under future industrial development scenarios, rather than a guaranteed or cost-optimal deployment level. Another study commissioned by the Swedish Energy Markets Inspectorate, drawing on underlying assessments from the Swedish Energy Agency, concludes that Sweden has a theoretical excess-heat potential of 110–170 TWh per year, expected to become available after the industrial transition around 2045. However, the realisation of this potential is constrained by technical, economic and regulatory barriers, distance to existing DHNs, required infrastructure investments and conditions for third-party access [25].

The most significant opportunity lies in recovering low-temperature heat sources, particularly from UEH. Lund et al. projected that the total EH potential could increase further with the expansion of DHSs and the broader use of such low-grade sources [26]. These urban sources include surplus thermal energy from data centres, hospitals, metro tunnels, and water streams such as sewage and seawater. The ReUseHeat project estimates that UEH in the EU28 amounts to about 512 TWh per year. This could supply up to 10 % of the total heating demand in buildings [26], [27]. While wastewater treatment plants and service-sector buildings make the largest contributions, smaller sources, such as metro stations, still represent valuable energy assets [38]. Despite this potential, the uptake of UEH has remained limited, primarily due to its low temperature, which makes it less economically competitive than fuels such as biomass and natural gas [28]. The integration of these sources into DHS is a crucial step towards advancing fourth- and fifth-generation networks [29].

Although the technical potential for EH recovery is well established, its use in DHS remains limited. Several barriers still hinder large-scale, resilient implementation. Here, “Resilience” is defined as the ability of a system to continue operating amid many uncertain futures, withstand unexpected shocks, and avoid significant or long-lasting price impacts.

1.1 Rationale and Aim

DHS across Europe is undergoing structural transitions driven by climate targets, ecological constraints, and changing policy frameworks. While EH represents a technically viable and increasingly policy-relevant energy source, its integration into DHS remains limited. This is due to a range of factors, including spatial and thermal mismatches, economic competitiveness, and infrastructural dependencies [30], [31]. Empirical studies further indicate that institutional and coordination challenges between industrial actors and DH operators, including timing misalignments and broader socio-strategic barriers, often constitute the most critical obstacles to implementation [32]. In parallel, systemic uncertainties related to electricity markets, biomass availability, geopolitical tensions, and climate uncertainties are complicating investment and operational decisions within DHS. This highlights the need for a strategic integration plan that connects technical feasibility with practical implementation.

There is growing recognition that robust and adaptive planning tools are necessary to guide the integration of EH and the development of DHS under conditions of long-term uncertainty [33], [34], [35], [36], [37]. While existing modelling approaches can capture spatial, exergy, stakeholder, and risk dimensions, they often treat these aspects in isolation, rather than within

a unified framework. Treating these aspects separately can result in plans that perform well in one respect but fail in others, leading to solutions that are less practical, more costly, and less reliable to handle future changes. Moreover, most tools rely on deterministic inputs for key parameters, such as electricity prices, biomass and MSW availability, and energy potential, which limits their ability to account for operational and investment risks. This thesis addresses these methodological gaps by developing an integrated multi-model framework that combines long and short-term energy system modelling, exergy and spatial analysis, stakeholder-informed framing, and stochastic optimisation to support resilient decision-making in DHS planning.

In this regard, this thesis aims to:

‘Advance modelling approaches for integrating EH into DHS by capturing long-term investment planning together with spatial, exergy and operational aspects, while accounting for uncertainties in future system development.’

To address this aim, the thesis develops a coherent line of inquiry that leads to three overarching modelling challenges. These are examined through the methodological developments and model applications presented in the appended papers. The thesis adopts a two-pronged approach, generating insights that support strategic EH integration and DHS planning, while also offering methodological insights that highlight the key modelling advances achieved in this work and the practical considerations that emerged during implementation. These methodological reflections are included to clarify how the integrated multi-model framework addresses known modelling challenges and the main shortcomings identified in the modelling process, and to inform future model development and applications.

The broader challenges that guide the thesis are:

1. The limited ability of current optimisation tools to support strategic EH planning, as they often lack the modelling capabilities needed to reflect both industrial and DH stakeholder needs.
2. The absence of integrated modelling approaches, since most existing tools treat spatial, techno-economic and exergy aspects separately rather than within a unified framework.
3. The long-term uncertainties and systemic risks require planning approaches that can support resilient DHS development and assess how systems perform under unexpected shocks.

The following section presents how the literature has addressed these challenges and identifies the remaining scientific gaps, leading to the Research Questions of this thesis.

1.2 Literature Gaps and Research Questions

Although EH recovery offers substantial technical and economic potential, its integration into DHS remains constrained by several barriers [38]. Albert et al. reported low industrial engagement with EHC initiatives and emphasised the importance of financial incentives to

encourage participation [20]. Viklund et al. and Wahlroos et al. observed that many industrial actors lack the technical expertise and internal capacity needed to implement recovery projects, making them dependent on DHS operators for planning support [39], [40]. Transparent contracting was identified as a key condition for effective collaboration, while data limitations further constrain project development [41]. Even when EHC investments show positive net present values, successful implementation often depends on stakeholder cooperation [38]. Thollander et al. found that contract structure and duration can act as key enablers. At the same time, risk aversion, information asymmetries, and lack of trust between industrial stakeholders and DHS operators remain significant barriers [42]. In later studies, Lygnerud et al. and Thollander et al. identified regulatory uncertainty, limited awareness, and cost-sharing challenges as significant barriers to stakeholder collaboration in UEH recovery [42], [43]. Forming partnerships is often slow and prone to organisational disruptions, and integration may require strategic and operational adjustments within DH companies. Additional constraints, such as regulatory gaps, limited market access, and weak financial incentives, further limit the commercial viability of these projects [44]. Evidence from Swedish EH–DHS partnerships shows that non-technical barriers, such as cultural distance between actors, lack of trust, and difficulties in forming long-term contracts, can obstruct projects even when the techno-economics are favourable [32]. Although these barriers cannot be explicitly captured within techno-economic modelling, they shape investment timing, risk perception, and stakeholder coordination, which are approximated through scenario-based uncertainty analysis and constraint formulation. Together, these studies show that non-technical factors are as important as technical and economic ones in enabling large-scale EH integration.

Policy instruments such as investment support, green certification, and third-party access to DH networks can encourage investment, but dependence on DHS operators and institutional inertia continue to limit their impact [39]. Energy policy analysis and long-term strategic planning increasingly rely on models to represent the complex flows and interdependencies within energy systems. These models capture environmental, economic, and social dimensions and are widely used to analyse policy impacts and support integrated decision-making across sectors [45].

Within energy modelling, techno-economic optimisation provides a structured approach to assessing technical and economic implications and system-wide effects. Optimisation is preferred over other modelling approaches because it can compare many design and investment options simultaneously, quantify trade-offs among cost, performance, and emissions, and identify configurations that best meet long-term planning goals [46]. By providing transparent and comparable data, modelling can help bridge interconnected gaps in regulation, coordination, and capability that constrain collaboration and investment. Such assessments can help address barriers, including limited technical expertise, incomplete information on recovery options, and uncertainty over the economic viability of investments [33]. A wide range of modelling studies demonstrate the value of these tools, for example, reviews of DH modelling and optimisation approaches [37], [46] dynamic and operational analyses of DHS [47], spatial and thermal network simulations [48], long-term scenario modelling and excess-heat

integration assessments at the national scale [54], and sector-coupling or multi-energy optimisation studies [52], [53].

However, the effective implementation of EH recovery strategies requires collaboration between industrial stakeholders, network operators, and policymakers [31]. The decision-making criteria vary among stakeholders, depending on their roles, incentives, and objectives within the energy system. An industrial stakeholder's evaluation typically focuses on the techno-economic feasibility of recovery systems, including projected revenue from EH sales and overall investment profitability. Modelling can support such evaluations by quantifying recovery potential and investment performance [54]. Industrial operators often use advanced tools such as computational fluid dynamics, pinch analysis, or thermodynamic optimisation to improve process efficiency and equipment sizing. However, these methods focus on plant-level performance and do not address system-level integration into DHS [30]. In principle, such methods could be embedded within wider modelling frameworks. Still, in practice, they remain process-optimisation tools and do not account for network expansion, market conditions, or strategic coordination across actors. Integration into DHS requires planning at a much larger spatial scale and consideration of long-term strategic objectives that extend beyond conventional single-plant optimisation [50], [55].

At the system level, DH network operators focus on minimising investment and operational costs associated with network expansion and operation. Their decision-making depends on the spatial distribution of future heat demand and the costs of integrating EH sources. Key challenges include the distance between heat sources and demand centres, high network extension costs, and uncertainty in securing long-term supply contracts. These long-term planning requirements are closely linked to broader energy system considerations and the policy environment in which DHS operates.

From a broader energy system perspective, decisions are guided by socio-economic and policy considerations, including infrastructure compatibility, alignment with decarbonisation targets in the heating and cooling sector, sector-coupling initiatives, and complementarity with decentralised options such as individual HPs.

While these objectives differ across industrial actors, DH operators, and system-level planners, they are all shaped by a set of cross-cutting barriers shown in Figure 3. These include limited information and analytical capacity, coordination challenges in securing long-term supply and investment agreements, and regulatory or market conditions that do not fully support excess-heat integration [39], [40], [41]. These barriers affect stakeholders differently: industries face uncertainty about long-term profitability, network operators face risks to supply reliability and infrastructure investment, and system-level planners confront policy and compatibility constraints [42], [43]. Together, these barriers frame the conditions under which stakeholders pursue their objectives and highlight the need for integrated planning tools.

To address this complexity, modelling should integrate techno-economic dimensions and align with different stakeholder roles and planning scales [56], [57]. At the same time, it should also

include technical improvements such as high spatial and temporal resolution, links to exergy analysis, and the addition of thermal storage to enable system-level integration [30]. Doing so can help overcome institutional and policy barriers, improve coordination among actors, and align actions with long-term decarbonisation strategies. This calls for integrated analytical frameworks that consider technical, institutional, and stakeholder dimensions, enabling models to serve as decision-support tools that reflect the diverse decision-making criteria of the actors involved.

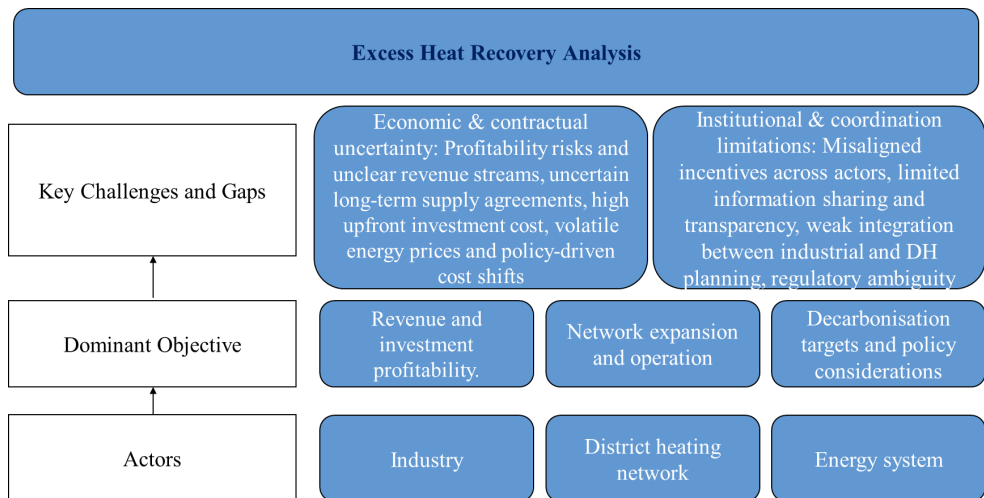


Figure 3: Conceptual framework illustrating the levels of decision-making involved in integrating EH into DHS, highlighting the perspectives of industry, DH network operators, and the wider energy system, along with key economic, institutional, and policy considerations influencing investment, network expansion, and decarbonisation objectives.

However, most existing energy system models still fall short of capturing these multi-dimensional requirements in practice. While several studies have reviewed Energy System Optimisation Models (ESOMs) [58], [59], [60], none have done so from the joint perspectives of industrial and DH stakeholders, particularly in the context of EH recovery and DHS development. Limited attention has been given to how well existing models reflect the specific needs of these systems and actors as integral parts of broader energy systems. This gap underscores the need to critically evaluate whether current modelling tools can effectively address the diverse needs of industrial actors, network operators, and system planners. This leads to the first research question:

RQ1: *What modelling capabilities do energy system optimisation tools need to support the strategic planning of excess heat recovery in DHSs, and how well do current tools meet the needs of different stakeholders?*

ESOMs capture both long-term planning horizons (Capacity expansion models) and short-term operational configurations (Operation optimisation/dispatch models). They identify the least-cost investment pathways under resource and budget constraints to evaluate EH integration.

Their structured outputs make them useful for strategic decision-making. However, assessing EH recovery has traditionally relied on manual calculations and context-specific data, limiting the identification of viable integration solutions due to the scarcity of specialised tools [61].

EH integration depends on the location of heat sources, transport costs, demand characteristics, and the heat quality. The temperature and scale of the source determine the feasible transmission distance and potential for recovery. Spatial optimisation is needed to identify suitable recovery sites, capacity expansion modelling to evaluate financial viability, and dispatch optimisation to assess operational performance and flexibility [62]. Given the complex interactions between spatial distribution, techno-economic feasibility, and system operation, a more integrated approach is required to support strategic planning. However, most existing approaches prioritise techno-economic factors while often neglecting spatial and operational constraints [63].

Spatial aspects have been used previously to assess EH potential by geospatially mapping IEH sources and heat demand. For example, Manz et al. mapped 1,608 IEH sites across Europe and estimated that recovered heat could meet up to 17 % of the EU's hot water demand in 2021 [21]. Another geospatial analysis by Manz et al. showed that economic feasibility was typically achieved for EH sources within a two-kilometre radius of existing DHS infrastructure, highlighting the importance of spatial proximity [64]. Although internal reuse remains an option, mapping analyses suggest that significant EH volumes would still be available for DH after covering on-site needs [22], [65]. Within the EU's Heat Roadmap Europe project, several versions of a Pan-European Thermal Atlas (PETA) have been developed to locate strategic regions for DHS expansion based on regional balances of heat supply and demand [66]. These analyses, dating back to 2014 (with the latest update, PETA v5.2, in 2023), showed that 46% of IEH and 31% of heat demand in the EU27 are co-located within such regions. Möller et al. enhanced this approach by estimating the techno-economic potential within the atlas framework [67]. At the same time, Grundahl et al. used it to evaluate the cost-effectiveness of expanding DH into nearby towns in Denmark [68].

In addition to spatial considerations, the temporal variability of EH availability presents a significant barrier to the adoption of EH recovery solutions [69]. Heat demand in DHS also fluctuates over time, making high temporal-resolution analysis essential for accurately assessing integration potential [70]. Chambers et al. developed a spatiotemporal method for integrating IEH into DHS, linking the spatial mapping of supply and demand with a monthly energy balance to assess the feasibility of network extension and seasonal storage potential [71]. Other studies have linked spatial analysis tools with ESOMs to conduct spatiotemporal assessments. In this approach, a heat atlas is used to estimate network extension costs, which are then input to an ESOM to optimise the integration of IEH. Petrovic et al. implemented this for Denmark [72].

A more detailed temporal analysis of the EH has been carried out using ESOMs in previous studies. Different types of ESOMs have been used to analyse EH recovery and DHS planning. Sandvall et al. used a capacity expansion model to investigate the integration of EH in DHS.

The results demonstrated cost savings and improved competitiveness for DHS when various EH sources were integrated [73]. Further analysis by Sandvall et al. indicated that EH could displace natural gas, with profitability increasing under a carbon tax [50]. Monsalves et al. used another capacity expansion model to evaluate flexible cooling and EH recovery from data centres in Denmark. The study indicated reduced emissions and costs, with summer baseload demand met through enhanced recovery rates [74].

Several other studies have used a capacity expansion model to examine the integration of specific UEH sources. Davies et al. modelled heat recovery from London's underground tunnels, showing cost savings and emission reductions when used for social housing [75]. A study on data centre heat recovery in London indicated potential savings of £1 million annually and carbon reductions exceeding 4,000 tonnes [76]. Lund et al. used an operational optimisation model to analyse the integration of four UEH sources: data centres, wastewater treatment plants, metro ventilation, and building cooling systems across Germany, Romania, France, and Spain by 2050 [26]. The findings indicated potential annual savings of up to 1 billion euros and a reduction of 50 TWh in biomass use. UEH integration was also found to enhance DHS competitiveness relative to individual heating solutions and to support DHN expansion, particularly in cities with limited coverage. However, the feasibility of using HPs is constrained by factors such as the temporal variability of heat availability and the need to ensure baseload supply in DHS, highlighting the importance of high-resolution analysis of UEH sources and DHS operations. Although UEH sources offer significant potential, they generally supply low-temperature heat. In addition to spatial and temporal factors, the exergy content of EH is crucial in determining its recoverability for DHS. Such low-temperature sources require temperature boosting, which often reduces system efficiency and creates technical and economic challenges [60].

To address the challenges associated with low-temperature EH, an exergy analysis can be used to evaluate heat quality and recovery potential at the process level. It supports component and system design by accounting for temperature and fluid properties [77]. Unlike conventional energy analysis, which focuses on energy flows between nodes, exergy analysis prioritises high-temperature sources to enhance overall system efficiency [78]. Cunha et al. developed a characterisation algorithm incorporating exergy-related parameters, including temperature, mass flow rates, and fluid properties, to support technology selection for IEH integration [77]. Zuberi et al. combined spatial mapping with exergy analysis to evaluate the techno-economic feasibility of EHC recovery in the Swiss industrial sector [79]. Although incorporating exergy into ESOMs improves accuracy by accounting for temperature compatibility across technologies, it introduces computational complexity due to the non-linear interactions between temperature and mass-flow variables. A practical compromise is to incorporate exergy feasibility assessments into energy-based optimisation frameworks, thereby enabling the evaluation of both the quantity and quality of EH. While this approach is well-established in process and power plant optimisation, it is not commonly applied in DHS planning, where whole-system analyses integrating exergy, spatial, and techno-economic considerations remain limited [80].

These three dimensions — spatial distribution, temporal variability, and heat quality — must be jointly considered when evaluating the integration of EH into DHS. However, most modelling studies analyse the integration of EH into DHS from isolated perspectives, treating the spatial, temporal, and heat-quality dimensions separately. This fragmented approach reduces the practical relevance of results, as these factors are closely interdependent in determining recovery potential. While ESOMs evaluate techno-economic performance, they often overlook the spatial expansion of networks required for integration. Network extension costs are typically represented through one-way soft links, excluding technical details such as pipe sizing and thermal losses that strongly influence cost-effectiveness [30], [72]. Since the pipe diameter accounts for a significant share of the investment cost, and the transmission distance affects the feasibility of IEH utilisation, neglecting these factors limits the practical use of the model output [81], [82]. If pipeline distance and diameter are not represented, the model may underestimate infrastructure costs or propose connections that are not economically viable. Likewise, insufficient temporal detail can average out fluctuations in UEH availability, potentially leading to sub-optimal sizing of HPs, storage, or backup units in the DHS. Table 2 summarises how existing modelling studies capture spatial, techno-economic, exergy, and operational dimensions, showing that few adopt an integrated approach. Then it indicates that the present work intends to include all of them.

Together, these limitations highlight the need for integrated modelling approaches that capture the spatial, temporal, and exergy characteristics of EH sources alongside techno-economic and operational considerations. Such frameworks are essential for realistic, system-level assessment and long-term planning of DHS development. To evaluate EH integration effectively, long-term investment planning must therefore be complemented with spatial and operational modelling frameworks. Although some studies have attempted to link these elements [79], [80], spatial analysis often relies on heuristic cost assumptions, while operational optimisation remains decoupled from investment planning.

Table 2: Representation of Key Dimensions Across Existing Modelling Studies.

Study	Spatial	Capacity Investment	Exergy	Operational	Approach
[21], [64], [22], [65], [66]	✓	–	–	–	GIS (cost estimation and not optimisation)
[67], [68], [30], [72]	✓	–	–	✓	Linked Operational optimisation + GIS (cost estimation) through a one-way soft link
[71]	✓	✓	–	–	Linked Capacity expansion optimisation + GIS (cost estimation) through a one-way soft link
[73], [50], [74], [75], [76]	–	✓	–	–	Capacity expansion optimisation
[26]	–	–	–	✓	Operational optimisation
[77], [78]	–	–	✓	–	Exergy analysis
[79]	✓	–	✓	–	Linking spatial (cost estimation) with exergy analysis
This Thesis	✓	✓	✓	✓	Integrated multi-model framework

Against this background, the second research question is:

RQ2: *How can a multi-model framework coherently integrate spatial, techno-economic, and exergy dimensions to develop technically feasible and cost-optimal strategies for EH integration into DHS?*

Building on the need for integrated spatial, capacity investment, and operational optimisation, as well as exergy analysis, an additional challenge lies in the long-term uncertainties and systemic risks associated with integrating EH into DHS. As resource constraints and uncertainty over the availability of combustible fuels grow, DHS are increasingly turning to non-combustion-based sources, such as large-scale HPs powered by EH. While this shift is not yet uniform across Europe, long-term energy transition scenarios and policy roadmaps anticipate an expanding role for large-scale HPs and other non-combustion technologies in future DHS

[17], [83], [84]. However, incorporating significant shares of EH, particularly from urban sources, adds complexity to system planning and operation. Unlike combustion-based sources, which provide a stable baseload, EH availability depends on industrial and service-sector activities and can fluctuate with changes in occupancy, cooling demand, or operational disruptions. In addition, reliance on third-party EH suppliers introduces contractual and institutional risks, as long-term delivery agreements are often uncertain or difficult to enforce [43]. This variability further amplifies existing uncertainties in DHS planning, including electricity price volatility impacting HP operation, climatic variations influencing heat demand, and shifting policy frameworks on emissions and resource availability. These evolving policy and resource conditions similarly undermine the long-term viability of combustion-based heat sources such as biomass and MSW.

As discussed in Section 1.1, the long-term viability of biomass and MSW is increasingly constrained by ecological, policy, and resource competition factors [85], [86], [87], [88]. These limitations, alongside declining MSW availability and evolving sustainability criteria, reduce the feasibility of combustion-based baseload options and reinforce the need to diversify DHS supply through non-combustion sources such as EH.

In addition to uncertainties in resource availability, DHS are increasingly exposed to regulatory risks. Under the EU's revised Fluorinated Greenhouse Gas Regulation, high-global-warming-potential refrigerants, such as R134a, will face servicing restrictions starting in 2025 and a ban on new installations starting in 2028. A near-complete phase-out of hydrofluorocarbons is expected by 2030 [89]. This shift requires adopting lower-impact alternatives, including hydrofluoroolefins (e.g., R1234yf, R515B), low-impact hydrofluorocarbons (e.g., R152a), and natural refrigerants such as CO₂ (R744), ammonia (R717), and propane (R290) [90], [91]. These options differ in efficiency, safety, and flammability, often demanding costly system modifications to comply with new standards [92]. As a result, the evolving regulatory landscape adds further uncertainty to the cost-effectiveness of HP technologies in DHS.

Beyond continuous variability, DHS planning must also account for low-frequency, high-impact extreme events that can impact system performance. First, EH supply can be permanently withdrawn through industrial restructuring or plant closure, resulting in the decommissioning or withdrawal of connected EH capacity [93], [94], [95], [96]. Second, short-term EH outages, caused by maintenance, operational disruptions, or process changes, create temporary zero-output periods followed by recovery, with reliability implications for DH dispatch [97], [98]. Third, electricity price spikes, observed during the 2021–2022 European energy crisis and in subsequent periods of market stress, raise operating costs for electricity-based supply and should be treated as shock processes in system planning [99], [100]. Together, these discrete events introduce a distinct layer of uncertainty beyond scenario-based variability and should be incorporated into the stochastic framework used for investment and operational planning.

Scenario analysis has been widely used to explore uncertainty in DH planning, focusing on future energy mixes, technology transitions, and system competitiveness under changing policy

or resource conditions. For example, Lund et al. and Mathiesen et al. investigated how 100% renewable energy systems and sector coupling influence the role of DH in national transitions [55], [101] while Persson et al. evaluated how urban density and heat demand affect DH competitiveness [102]. David et al. assessed large-scale HP integration in future DH configurations across Europe, and Sifnaios et al. analysed scenarios with and without large-scale thermal energy storage to determine their effect on system flexibility and emissions [103], [104]. Together, these studies demonstrate that DH costs, competitiveness, and system roles are susceptible to future assumptions.

In Sweden, a growing number of studies have begun to address these limitations by incorporating uncertainty through sensitivity testing and stochastic modelling. Åberg examined how reductions in heat demand and variations in electricity prices affect DH system operation, highlighting the strong dependence of outcomes on input assumptions [105], [106]. Romanchenko et al. analysed the operation of Göteborg's DHS under fluctuating electricity prices, showing notable shifts in costs and dispatch patterns across price scenarios [107]. Similarly, Sandvall explored the impacts of electrification and building renovations on the evolution of DH through extensive scenario analysis [49]. Vilén et al. applied a scenario-based analysis using six DH configurations, exploring different combinations of fuel availability, EH use, and grid temperature, to assess uncertainty. Results show that EH integration and lower DH temperatures are robust strategies for cost competitiveness under changing future conditions [108]. Policy-oriented scenario analysis further illustrates how Swedish DH pathways respond to alternative policy frameworks and bioeconomy developments, reinforcing the need for uncertainty-aware planning [109], [110]. Recent guidance from the Swedish Energy Agency reinforces this need, calling for integrated planning tools to address emerging uncertainties in urban heat systems [111]. In response, a few studies have moved beyond deterministic, scenario-based approaches by explicitly representing uncertainty in DHS operations and planning through stochastic optimisation.

Malmgren performed a stochastic optimisation of investment and operational decisions under uncertainty in electricity prices and heat demand, demonstrating the system's sensitivity to these factors and the value of exploring uncertainty for robust planning [112]. Guericke et al. formulated a stochastic network-based model for DH generation under uncertain prices and variable heat generation [34], while Siddique et al. developed a multistage stochastic framework for large-scale HP dispatch under uncertain electricity market conditions [113]. Lambert et al. extended this approach to multi-stage stochastic investment phasing for DH network expansion [114]. Other studies have explored two-stage stochastic optimisation of district energy systems with investment and operational recourse [115], [116]. However, these studies primarily address operational uncertainty or incremental capacity decisions rather than long-term investment planning. While no existing work explicitly applies stochastic optimisation to DHS investment planning in the presence of structural shocks such as EH source shutdowns, outages, or electricity price spikes, similar methodological advances are emerging in broader energy-systems research.

The broader energy-systems literature increasingly emphasises the need for stochastic frameworks that capture complex interactions, external shocks, and long-term uncertainties. Liu et al. [117] and Zhong et al. [118] emphasise the value of probabilistic and resilience-based modelling, while Kazempour et al. and others call for robust planning approaches that account for parameter variability and external shocks [119].

The review highlights that while existing studies have advanced DHS planning through scenario, sensitivity, and stochastic analyses, most remain limited to ‘short to medium-term’ or deterministic frameworks. Current models seldom account for the combined effects of market volatility or discrete shocks such as EH source shutdowns, outages, and electricity price spikes. As DHS increasingly depend on electrified, decentralised, and EH sources, these uncertainties become critical for long-term investment and operational planning. Although long-term stochastic approaches are well established in broader energy system modelling, their application to DHS remains sparse and largely operational in scope. There is thus a clear need for integrated, stochastic investment frameworks that can capture systemic risks and spatial–temporal complexity, supporting resilient and cost-effective pathways for future DHS development. Against this background, the third research question is:

RQ3: How can DHS be planned and adapted to integrate EH while remaining resilient to long-term uncertainties, systemic risks, and external shocks?

To summarise, the above-mentioned research questions inform the overall aim of this thesis:

Advance modelling approaches for integrating EH into DHS by capturing long-term investment planning, spatial, exergy, and operational aspects, while accounting for uncertainties in future system development.

1.3 Thesis organisation

This thesis consists of two parts. The first is a cover essay (Kappa), and the second is a compilation of research articles. The Kappa is organised into six chapters. Following this introductory chapter, the second chapter outlines the qualitative methods and the choice of the modelling tools. This corresponds to RQ1. The third chapter describes the stagewise development and application of the integrated multi-model framework for analysis of EH recovery and use in DHS. This chapter corresponds to RQ2. The fourth chapter presents the development and application of the methodology for incorporating uncertainty into the framework. This chapter corresponds to RQ3. The fifth chapter summarises the overall methodological insights from the development of the multi-model framework. The sixth chapter concludes by summarising the responses to the research questions and by stating the thesis’s main contributions. Figure 4 summarises the structure adopted in this thesis.

1.3.1 Appended publications

The RQs are answered through five publications appended to this thesis. Their content and connections to each RQ are expanded on below. Following the papers, Table 3 summarises the relations between each paper and RQ.

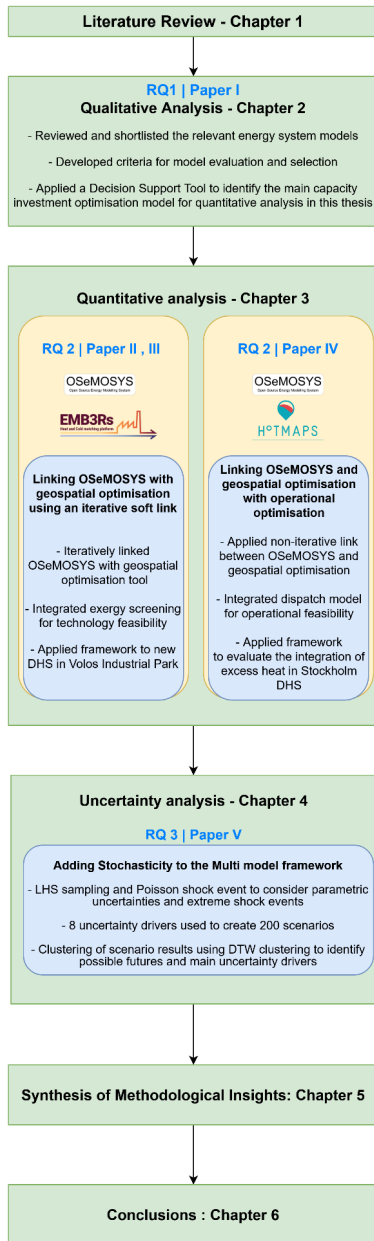


Figure 4: Overview of the structure of the thesis, showing the progression from the literature review and qualitative model assessment, to quantitative multi-model analyses of EH integration, followed by uncertainty analysis using stochastic scenarios, and concluding with the synthesis of methodological insights and conclusions.¹

¹ LHS stands for Latin Hypercube Sampling, and DTW stands for Dynamic Time Warping. These concepts are explained in detail in Section 4.2

Paper I [P1]

S. Kumar, J. Thakur, and F. Gardumi “Techno-economic modelling and optimisation of EHC recovery for industries: A review”, *Renewable and Sustainable Energy Reviews*, Volume 168, 2022, <https://doi.org/10.1016/j.rser.2022.112811>.

This paper develops a review-based methodology to evaluate energy system optimisation tools for industrial EHC recovery, focusing on stakeholder-specific decision-making needs. Seven tools are assessed against spatial, temporal, and techno-economic criteria, and a decision-support tool is proposed to help stakeholders identify suitable models. The study finds no tool meets all requirements, underscoring the need for interoperability and stakeholder-informed development. ***RQ1 was addressed by evaluating how well current tools meet stakeholder needs and by highlighting limitations in usability, openness, and comprehensiveness, thereby emphasising the need for more interoperable, stakeholder-informed modelling frameworks.***

Author contributions: Conceptualisation, methodology, data curation & processing, analysis, visualisation, and write-up of the original draft were conducted by the thesis author under the supervision of F. Gardumi and J. Thakur. All authors participated in the review of the manuscript.

Paper II [P2]

S. Kumar, J. Thakur, J.M. Cunha, F. Gardumi, A. Kök, A. Lisboa and V. Martin “Techno-economic optimization of the integration of industrial EH into DHS with high spatial and temporal resolution,” *Energy Conversion and Management*, Volume 287, 2023, <https://doi.org/10.1016/j.enconman.2023.117109>.

This paper develops a multi-model framework integrating spatial, techno-economic, and exergy analyses to assess IEH recovery. An energy system optimisation model is combined with spatial and exergy tools and applied to an industrial park in Greece, revealing how spatial constraints and exergy efficiency affect the cost-optimal development of DH. Building on insights from Papers I to III, this study addresses ***RQ2 by illustrating how integrating spatial, techno-economic, and exergy analyses within a multi-model framework can inform decision-making for EH recovery and DH system planning.***

Author Contribution: The author of this thesis led the Conceptualisation, Methodology, further development of OSeMOSYS, the development of the links between the different tools, analysis, Validation, and wrote the original draft. Co-authors J. Thakur, F. Gardumi, J.M. Cunha, A. Kök, and A. Lisboa supported the Conceptualisation and development of the methodology. Co-author V. Martin supported the conceptualisation and, along with F. Gardumi and J. Thakur, provided supervision during the writing process. All authors participated in the review of the manuscript.

Paper III [P3]

M. Silva, **S. Kumar**, A. Kök, A. Cardoso, M. Hummel, P.S. Nielsen, B.S. Khan, A.S. Faria, M. Jensterle, C. Marques, “EMB3Rs: A game-changer tool to support waste heat recovery and reuse”, *Energy Conversion and Management*, Volume 309, 2024, <https://doi.org/10.1016/j.enconman.2024.118408>.

In this study, the EMB3Rs platform is introduced as an open-source online tool designed to support the assessment and integration of various types of EH into DHSs. The platform builds on key methodological elements developed in this thesis, in particular the modelling requirements identified in [P1] and the multi-model framework linking spatial analysis, techno-economic optimisation, and system-level assessment established in [P2]. While the primary objective of this thesis is not to develop or demonstrate the EMB3Rs platform as a software product, the platform serves as a vital implementation context for the methods developed in this work, applied in a web-based environment. The platform allows users to explore spatial, techno-economic, and system-integration dimensions of EH recovery through an intuitive interface, demonstrating how the concepts developed in [P1] and [P2] can support early-stage planning and screening. Its application to multiple case studies provided additional practical insights, which in turn informed further methodological refinements developed later in the thesis, particularly in [P4] and [P5]. ***RQ2 was addressed by demonstrating the application of the integrated approach to a range of case studies. It showed the framework's flexibility and provided methodological insights for further model development.***

Author Contribution: The author of this thesis co-led the Conceptualisation, Methodology, development of software, analysis, along with A. Kök, B., Khan, A.S., Faria, and C. Marques contributed significantly to the review and editing of the draft. First Author M. Silva led the writing of the draft and project administration. All authors participated in the review of the manuscript.

Paper IV [P4]

S. Kumar, A. Kök, J. Dalgren, J. Thakur, V. Martin, F. Gardumi, “Strategic Integration of Urban Excess Heat Sources in DH: A Spatio-Temporal Optimisation Methodology”, *Applied Energy*, Volume 396, 2025, <https://doi.org/10.1016/j.apenergy.2025.126236>

Content: This paper develops a spatio-temporal optimisation methodology to integrate UEH sources into DHS, combining spatial planning, long-term techno-economic analysis, and short-term operational evaluation. Applied to the Stockholm DHS, the study shows how spatial, exergy and techno-economic aspects can be coherently combined to inform cost-effective integration strategies. ***RQ2 was addressed by illustrating the practical application of a multi-model framework that combines spatial analysis, techno-economic optimisation, and operational analysis to inform decision-making in EH integration. The scenario analysis and modelling assumptions address parametric uncertainties and system dependencies in RQ3.***

Author Contribution: The author of this thesis led the Conceptualisation, data collection and curation, Methodology, further development of OSeMOSYS, development of links between the different tools, analysis, Validation, and Visualisation, and wrote the original draft. Co-Authors J. Thakur, F. Gardumi, and V. Martin supported the Conceptualisation and provided supervision during the writing process. Co-author A. Kök participated in developing links between the tools. Co-author J. Dalgren participated in data collection, case study setup, and validation. All co-authors engaged in reviewing the manuscript.

Paper V [P5]

S. Kumar, J. Thakur, V. Martin, F. Gardumi, “Resilient District Heating Transitions under Uncertainty: Insights from Stochastic Optimisation and Pathway Clustering” [Under review]

Content: This paper develops a stochastic optimisation framework for long-term planning of a Swedish DH system, focusing on non-combustion heat sources such as EH and large-scale HPs. Uncertainties in resource availability, electricity prices and operational dependencies were modelled through scenario analysis, with post-processing using clustering to identify robust strategies. *RQ3 was addressed by demonstrating how DHS planning can be adapted to remain resilient to long-term uncertainties, systemic risks, and external shocks through stochastic modelling and resilience assessment. The findings provided actionable insights to reduce reliance on fossil fuels and enhance DHS's adaptive capacity in an uncertain energy transition landscape.*

Author Contribution: The author of this thesis led the Conceptualisation, data collection and curation, Methodology, further development of OSeMOSYS, development of stochastic optimisation, analysis, Validation, and Visualisation, and wrote the original draft. Co-Authors J. Thakur, F. Gardumi, and V. Martin supported the Conceptualisation and provided supervision during the writing process.

Table 3: Relation between each research question and the appended papers

Research Question	I	II	III	IV	V
RQ1: What modelling capabilities should energy system optimisation tools possess to support the strategic planning of excess heat recovery in DHSs, and to what degree do current tools fulfil these requirements across industrial and district heating stakeholder perspectives?					
RQ2: How can a multi-model framework coherently integrate spatial, techno-economic, and exergy dimensions to develop technically feasible and cost-optimal strategies for EH integration into DHS?					
RQ3: How can DHS be planned and adapted to integrate EH while remaining resilient to long-term uncertainties, systemic risks, and external shocks?					

1.3.2 Additional publications and contributions

While the research presented in this thesis primarily draws on the five appended publications, insights are also derived from other projects, publications, and capacity-development efforts in which the author has been involved. These efforts are listed below.

First-authored peer-reviewed journal articles

1. **S. Kumar**, V. Somanna, J. Thakur, S.N. Gunasekara, “Exploring EH Recovery in Proton Exchange Membrane Electrolysis: Technical and Economic Dimensions” Volume 342, 2025, <https://doi.org/10.1016/j.enconman.2025.120118>
2. **S. Kumar**, J. Thakur, D. Meha, “Evaluating District Cooling Potential for India using GIS-based Top-Down Approach” Energy, Volume 335, <https://doi.org/10.1016/j.energy.2025.137935>

Co-authored peer-reviewed journal articles

3. D. Groppi, **S. Kumar**, F. Gardumi, D.A. Garcia, “Optimal planning of energy and water systems of a small island with an hourly OSeMOSYS model”, Energy Conversion and Management, Volume 276, 2023, <https://doi.org/10.1016/j.enconman.2022.116541>.
4. R.H. Fonseca, **S. Kumar**, S. Ghosh, J. Thakur, A. Bhattacharya, “Modeling a 100% renewable energy pathway in developing Countries: A case study of State of Goa, India”, Energy Conversion and Management, Volume 315, 2024, <https://doi.org/10.1016/j.enconman.2024.118800>
5. R.C. Garcia, J.M.M. Arcos, **S. Kumar**, S.N. Gunasekara, J. Thakur, “Techno-economic analysis of Flexible Sector Coupling between Electrical and Thermal Sectors,” Energy Conversion and Management: X, Volume 27, 2025, <https://doi.org/10.1016/j.ecmx.2025.101145>
6. D. Timmons, L. Gnam, **S. Kumar**, J. Krail, G. Piringer, D. Rixrath, E. Wiener. “Optimizing District Heating in a Fully Renewable Energy System: An Austrian Case Study”, Renewable Energy, Volume 259, 2026, <https://doi.org/10.1016/j.renene.2025.125134>

Book chapters

1. **S. Kumar**, J. Thakur, V. Martin, 2025, “Waste heat recovery for DH” in: Waste Heat Recovery, Its Utilization and Performance Assessment. Elsevier Pub. [[in press](#)] <https://doi.org/10.1016/B978-0-443-31576-3.00014-2>
2. J. Thakur, **S. Kumar**, D. Meha, 2025, “Industrial Waste Heat Recovery: Opportunity and Challenges” in: Waste Heat Recovery, Its Utilization and Performance Assessment. Elsevier Pub. [[in press](#)] <https://doi.org/10.1016/B978-0-443-31576-3.00017-8>

Reports

1. D3.4 – The EMB3Rs Techno-Economic Optimization Module, https://www.emb3rs.eu/wp-content/uploads/2022/11/D3.4_M38_submitted.pdf
2. D6.8 – Training Materials for the EMB3RS platform, https://www.emb3rs.eu/wp-content/uploads/2023/06/D6.8-Training-materials_submitted.pdf
3. Nordic Energy Outlooks – Final report WP6: Energy efficiency and conservation, <https://www.nordicenergy.org/wordpress/wp-content/uploads/2023/02/WP6-report-Energy-efficiency-and-conservation.pdf>
4. The Celestial Earth, KTH Sweden, PTC India. (2023). Clean Energy Roadmap for the State of Goa. Indo-German Energy Programme- Access to Energy in Rural Areas II, GIZ India. https://geda.goa.gov.in/wp-content/uploads/2023/09/Clean-Energy-Roadmap-for-the-state-of-Goa-Final_compressed.pdf²

Platforms

1. **The EMB3RS Platform.** The EMB3RS platform is an open-source, web-based decision-support tool developed within the EU Horizon 2020 EMB3RS project. It enables users to assess, map and optimise the recovery and utilisation of excess heat and cold across industrial sites and urban energy systems. The author of this thesis contributed to platform development by designing and integrating methodological components derived from [P1] and [P2], including the spatial techno-economic assessment workflow and elements of the integrated planning framework. The author of this thesis determined the modelling tools to be used for the techno-economic optimisation module of the EMB3RS platform based on insights from [P1] of this thesis. The author of this thesis also developed the techno-economic optimisation module and the links to other modules based on the work done in [P2] and [P3] of this thesis. The platform extends the methods developed in this thesis and supports wider uptake through an accessible online interface.

Declaration of the use of AI

During the preparation of this doctoral dissertation, the author used ChatGPT (OpenAI) and Grammarly AI (Grammarly) to improve the text's language and clarity. ChatGPT was also used to assist in generating and refining scripts for data handling and visualisation, and in producing figures included in this thesis. All generated content, code, analyses, and figures were carefully reviewed, validated, and, where necessary, modified by the author. The author takes full responsibility for the accuracy, integrity, and originality of the dissertation.

² Note. In this report, I contribute to the methodology to a considerable extent.

2 Modelling Needs, Criteria, and Tool Assessment

This chapter presents the response to RQ1:

‘What modelling capabilities do energy system optimisation tools need to support the strategic planning of excess heat recovery in DHSs, and how well do current tools meet the needs of different stakeholders?’

To answer the above RQ, the first stage of the research applied qualitative methods to identify, assess, and compare ESOMs suitable for analysing EH recovery. Although numerous ESOMs exist, their ability to represent the multi-scale and multidimensional aspects of EH integration in DHSs has not been systematically assessed from an applied research perspective. Stakeholder perspectives discussed in Section 1.2 were central to this assessment, as they define what the models must capture. These perspectives reveal differing priorities: industrial stakeholders focus on techno-economic feasibility, network operators emphasise cost-efficient and reliable integration, and policy actors concentrate on socio-economic and regulatory alignment. Despite these differences, there is strong convergence on key modelling requirements, including representing long-term investment and operational decisions, incorporating spatially explicit network costs, capturing multiple supply-and-demand configurations, and addressing variability across temporal scales. These converging requirements served as the basis for reviewing available ESOMs and selecting the tools to be adapted for the quantitative analyses.

A comprehensive literature review of peer-reviewed research articles, technical reports, and model documentation was undertaken, drawing on the SCOPUS database and relevant grey literature. The review was guided by keyword searches including “Energy System Optimisation,” “District Heating,” “Excess Heat Recovery”, and “Techno-Economic Modelling”. The inclusion criteria required that each tool (i) be capable of modelling the heating supply, either fully or partially; and (ii) have sufficient publicly available documentation and user resources to allow adaptation for new case studies. This process yielded an initial set of 16 candidate models. Additional methodological details and a complete discussion of the analytical steps are provided in [P1] of this thesis.

2.1 From Modelling Needs to Comparison Criteria and Tool Selection

The comparison criteria were developed in three main steps. First, practical modelling needs for EH recovery at different decision-making levels were collected from the EU Horizon 2020 project EMB3RS [120]. These needs were not newly elicited within this thesis but are based on documented interactions with industrial partners and project stakeholders in EMB3RS. They describe what industrial actors, network operators and system planners require from models that support EH recovery decisions.

Second, these stakeholder-oriented needs were combined with insights from the literature on DHS planning, EH integration and existing reviews of energy system tools, following the framework introduced in [P1] of this thesis. In this step, the decision-making levels described in Chapter 1 (from industrial sites to broader energy systems; see Figure 3) were used to map

the functions required at each level and identify gaps in existing tools. Third, this thesis synthesised these sources into a structured set of comparison criteria and applied them consistently to the 16 candidate models. The final criteria were grouped into the following categories:

- Access and openness – availability of the model, solver, and shell. Critical for transparency, reproducibility, and collaborative development.
- Spatial and temporal resolution – capacity to represent spatial layouts (e.g., pipe networks, source–sink distances) and temporal variability (e.g., hourly to monthly resolution).
- Representation of techno-economic parameters – inclusion of capital, fixed, and variable costs, efficiencies, fuel-switching, and operational constraints for diverse technologies, including EH sources.
- Flexibility, modularity, and interoperability – ease of modifying the modelling tool to add new functionalities and linking with other tools.
- Policy and market representation – ability to model regulatory instruments, e.g., emissions accounting, carbon pricing, and market dynamics (e.g., price elasticity).
- Thermal Energy Storage (TES) representation – capacity to model short- and long-term storage, including physical and economic constraints.
- Representation of EH sources in the model – predefined modules or user-defined structures to represent EH sources with associated costs, emissions, and temporal availability.
- Modelling method and objective function – Specifies the mathematical structure of the optimisation model (linear, non-linear, or mixed-integer) and the primary optimisation goal(s), such as minimising system cost, reducing emissions, or solving multi-objective problems.

Some criteria, such as access, solver, or objective function type, are binary and serve as inclusion or exclusion thresholds. Others, including temporal resolution, spatial resolution, flexibility, and interoperability, offer multiple levels for the user to select from, such as “high,” “medium,” or “low.” For example, the temporal resolution criterion can be “high” when the modelling tool has been used to analyse a fine-grained resolution, such as hourly time steps. The ranges and definitions of all criteria are detailed in Table 4.

Table 4: *Interpretation of criteria ranges*

Criterion	Range	Interpretation
Temporal Resolution	Low / Low to medium/ Medium/ Medium to high/ High / No preference	Low: Monthly (12-time steps).
		Medium: Daily or representative days, 288 or 576 TimeSlices.
		High: Hourly or bi-hourly (4380 or 8760 timesteps) sufficient to capture electricity price and EH availability fluctuations.
Spatial resolution	Low / High/ No preference	Low: No spatial representation.
		Medium: Zonal aggregation or representative nodes.
		High: Explicit source–sink mapping and cost-optimal network routing.
Flexibility	Low / Low to medium / Medium / Medium to high / High / No preference	Low – The tool modification is not documented, limiting adaptability.
		Medium – Zonal aggregation or representative nodes
		High – The tool has been modified extensively with several enhancements and additions made in a reproducible manner.
Interoperability	Low / Low to medium / Medium / Medium to high / High / No preference	Low – Not linked with other tools in previous studies, and only standalone use.
		Medium – Data exchange using files to transfer data with manual interventions
		High – Linked with other tools using dynamic and automated links through both soft/complex linking methods in one or more modelling studies.

The categorisation in Table 4 follows the principle that a model should be as detailed as necessary but as simple as possible. “High” resolution or flexibility is defined as the level required to meaningfully represent temporal, spatial, and systemic variability relevant to EH integration in DHS.

While the initial screening identified 16 candidate models, only a subset met all requirements for detailed analysis. Drawing on the comparative reviews by Connolly et al., Groissböck et al., and Ringkjøb et al. [58], [59], [60], the selection criteria were applied to each candidate tool by assessing how well the modelling literature supported the required capabilities. A tool was included in the final set if it satisfied the core requirements and, where gaps existed, showed either (i) documented extensions in published studies or (ii) a modular structure that enables missing features to be added. This approach enabled the evaluation to account for tools that partially met specific criteria, resulting in a refined set of 7 tools suitable for EH recovery analysis in DHS contexts. These were: OSeMOSYS [121], EnergyPLAN [122], TIMES [123], EnergyPRO [124], BALMOREL [125], OEMOF [126], and Calliope [127].

The shortlist represented a mix of open-source and proprietary tools, varying widely in spatial and temporal capabilities, sectoral coverage, and user accessibility. The shortlist formed the basis for the comparative evaluation of the selected tools. Each shortlisted tool was assessed using documented functionalities and evidence from previous applications in the literature. Where possible, examples from prior studies were used to validate the functional capabilities described in the model documentation. The detailed results of this comparative evaluation are presented in the following section.

2.2 Performance of Modelling Tools Against Identified Needs

The comparison of the ESOMs presented in [P1] systematically assesses the tools' performance against stakeholder needs identified in the literature review (Section 2.1). Seven models were evaluated against the set of binary and multi-level criteria presented in Section 2.1. The scoring for each criterion reflects how the tools have been applied in real-world studies, not just their theoretical capabilities. A detailed analysis of each tool's capabilities can be found in [P1] of this thesis.

Table 5, Table 6 and Table 7 present a summary comparison of the tools based on the detailed review conducted in [P1].

Table 5: Comparison of the tools - Software, Language, and access

Tools / Criteria	Access			Modelling language
	Model	Solver	Shell	
OSeMOSYS	Open	Open	Open	Multiple languages
EnergyPlan	Open	Open	Open	Single language - Delphi Pascal
TIMES	Open	Commercial	Commercial	Single language - GAMS
EnergyPRO	Commercial	Commercial	Commercial	Source code unavailable
Balmorel	Open	Commercial	Commercial	Single language - GAMS
Oemof	Open	Open	Open	Single language - Python
Calliope	Open	Open	Open	Single language - Python

The scale used in Table 6 reflects the level of detail needed for effective EH and DHS analysis, based on the criteria interpretations in Table 4 presented in Section 2.1.

Table 6 shows that five ESOMs offered high temporal resolution, but only three of these five also included multi-sector integration, which is essential for analysing DHS operation with the electricity and cooling sectors. Spatial resolution was the weakest criterion overall, with fewer than half of the tools able to operate beyond aggregated regional nodes without significant adjustments. This is a key limitation for municipal planners and network operators, as route-specific costs, losses, and capacity constraints significantly affect project feasibility. Models with great spatial detail were often specialised network tools that lacked long-term investment-planning features, underscoring the need for better interoperability between spatial and techno-economic models. While great spatial and temporal detail improves representation, effective EH planning also depends on how easily models can be adapted and linked with other analytical tools. The spatial resolution of most tools is low, except for Calliope, which supports explicit spatial modelling. Oemof and Calliope have also been applied at high temporal resolution over extended horizons. However, both tools are more commonly used for multi-year scenario analysis, where technology choices are explored across a few selected future years, rather than for complete long-term capacity-expansion optimisation, which requires modelling continuous investment decisions over an entire 25–30-year horizon.

Table 6: Comparison of the tools – Spatial and Temporal resolution, structure and linking

Tools / Criteria	Spatial resolution	Temporal resolution	Optimisation problem	Flexibility	Interoperability
OSeMOSYS	Low	Low	MILP	High	High
EnergyPlan	Low	High – Hourly	MILP	Medium	Medium to High
TIMES	Low	Medium to high	MILP	High	High
EnergyPRO	Low	High – Hourly	MILP	Low	Low
Balmorel	Low	Medium to high	MILP	Medium	High
oemof	Low	High – Hourly	MILP	High	High
Calliope	High	High – Hourly	MILP	Medium	High

Table 5 and Table 6 summarise performance on openness and flexibility, showing that open-source models such as OSeMOSYS, oemof, and EnergyPLAN achieved the highest scores in adaptability and transparency, enabling modification of model structures and datasets to suit local contexts or sector-specific needs. These open-source tools also benefit from active user communities and support groups that offer shared resources, assistance, frequent updates, and a wider range of tested applications. Community-managed tools, such as EnergyPLAN, Calliope and Balmorel, exhibit medium flexibility. In contrast, proprietary tools, such as EnergyPRO, typically offer pre-configured datasets and robust user interfaces, reducing the learning curve for new users. However, they rank lower in flexibility and openness due to the use of closed solvers and the lack of source code availability.

While flexibility determines how readily a model can be adapted, interoperability reflects how effectively it can exchange data with other modelling tools. Interoperability remains low across proprietary models, limiting the ability to link spatial, exergy, and techno-economic analyses. Open-source tools, including OSeMOSYS, TIMES, Balmorel, oemof, and Calliope, have been linked to external tools in previous studies, thereby improving interoperability.

From a stakeholder perspective, this distinction is significant. Municipal planners, researchers, and policy analysts often prioritise transparency, replicability, and adaptability of models for novel applications. In contrast, utilities and private operators may place greater value on the stability, technical support, and streamlined workflows that proprietary tools can offer. To bridge capability and coordination gaps in EH recovery projects, transparent, replicable models are essential, as they help all stakeholders understand and validate the assumptions and system representations used in the analysis. Flexibility and interoperability, therefore, define a model’s suitability for multi-stakeholder planning by balancing transparency, ease of use, and integration capability.

Since flexibility and interoperability determine how easily a model can represent complex system interactions, they also shape how EH technologies and the related techno-economic parameters are defined in practice. All tools can represent key technical and economic parameters, including thermal storage, market interactions, policy measures, and emissions accounting (Table 7). However, they differ in how they model IEH recovery and the flexibility of their optimisation approaches. EnergyPLAN and TIMES can perform both single- and multi-objective optimisations, whereas others focus mainly on single-objective (primarily cost) minimisation. EnergyPLAN and EnergyPRO include predefined structures for EH sources, which simplifies their use but limits flexibility for more detailed or unconventional configurations. In contrast, tools such as OSeMOSYS, TIMES, and oemof require users to manually define technologies and parameters, which demands greater effort but allows full customisation. These differences influence how effectively each tool can represent EH integration under different analytical or planning needs.

Table 7: *Techno-economic parameters and objective function*

Tools / Criteria	Technical and economic parameters					Objective function
	Thermal storage	Market	Policy	Modelling EH	Emissions accounting	
OSeMOSYS	Yes	Yes	Yes	New technology and fuel addition	Yes	Single
EnergyPlan	Yes	Yes	Yes	Predefined technology structures	Yes	Single and Multi
TIMES	Yes	Yes	Yes	New technology and fuel addition	Yes	Single and Multi
EnergyPRO	Yes	Yes	Yes	Customisation using predefined technology structures	Yes	Single
Balmorel	Yes	Yes	Yes	New technology and fuel addition	Yes	Single
oemof	Yes	Yes	Yes	New technology and fuel addition	Yes	Single
Calliope	Yes	Yes	Yes	New technology and fuel addition	Yes	Single

The comparison of modelling capabilities highlights necessary trade-offs between transparency, flexibility, and detail. These variations in openness, resolution, and interoperability across tools highlight that no single ESOM can meet all stakeholder needs in isolation. The complete assessment of the tools' capabilities across the different criteria is presented in [P1] of this thesis. Based on this assessment, a dedicated Decision Support Tool (DST) was designed to choose the most suitable tool for different contexts.

2.3 Decision support tool for model selection

The assessment results informed the creation of a DST for model selection. This Excel-based framework allows users to filter available ESOMs based on project requirements and rank them according to the relative importance of the selected criteria. The DST was structured around a decision flow that first excluded models that do not meet “must-have” criteria (e.g., openness, spatial resolution requirements) and then ranked the remaining models according to their performance scores (Figure 5). Building directly on the comparative evaluation results, the DST translates these criteria into a structured decision-making framework.

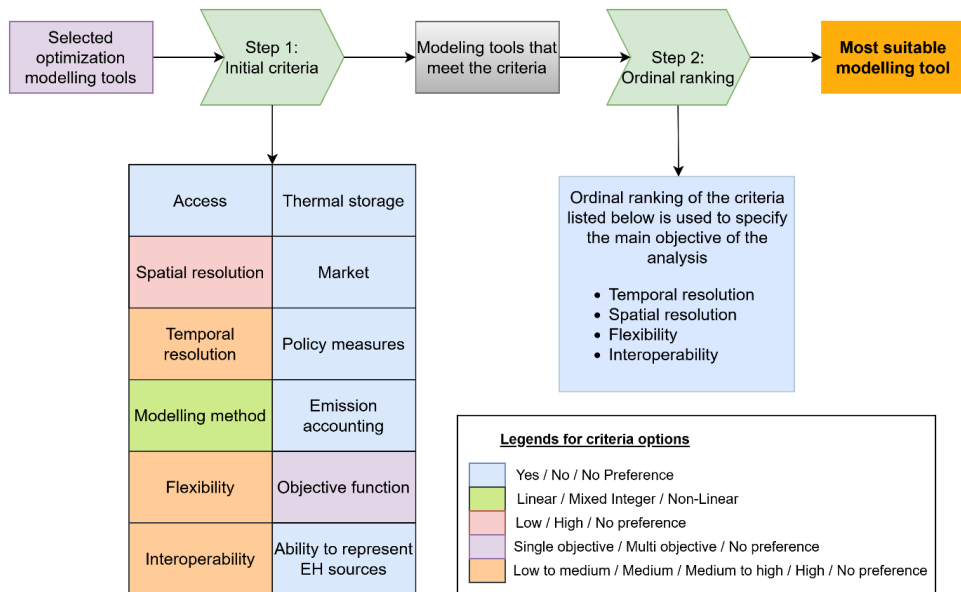


Figure 5: Structure of the decision support tool (DST) used to identify the most suitable energy system modelling tool, showing the two-step process consisting of initial screening based on key criteria and ordinal ranking of selected criteria such as temporal resolution, spatial resolution, flexibility, and interoperability.

The criteria outlined in Section 2.2 provide the basis for defining the analysis requirements the user intends to perform, and serve as the starting point for comparing the ESOMs. In the first step of the DST, each model is assessed against these criteria to evaluate the overall performance of the modelling tools. For criteria offering multiple levels, all ESOMs that meet or exceed the chosen level are retained. For instance, if the user selects “medium” temporal resolution, all tools with either medium or high-resolution capabilities will be included. Selecting “no preference” for a criterion allows all tools to remain in the list regardless of their performance in that category.

In the second step, the DST applies an ordinal ranking to identify the modelling tool most suited for the analysis. This ranking is based on four criteria: temporal resolution, spatial resolution, flexibility, and interoperability. These were selected because they offer multiple levels and

allow users to specify the most crucial objective for the analysis. Users assign a priority value from 4 to 1 to each criterion, where 4 indicates the highest priority and 1 the lowest. For example, if high temporal resolution is the most critical requirement, it would receive a score of 4. Each modelling tool has a pre-assigned score for these criteria, determined on a scale of 1 to 5, where 5 represents the strongest performance and one the weakest. These pre-scores reflect the perceived performance of each tool in the four criteria, as identified through the review, and are described in detail in [P1] of this thesis. To obtain the final ranking, each tool's score in each criterion is multiplied by the user-defined priority for that criterion, and the results are then aggregated. The tool with the highest total score is identified as the most suitable option for the intended analysis.

The DST developed in [P1] was applied to a real-world illustrative case inspired by work carried out within the Horizon 2020 REUSEHEAT project. While REUSEHEAT did not model or assess this case using the proposed DST, the project identified several potential EH recovery opportunities [28]. One of these, the Warmtelevering Leidse Regio (WLR), was selected here as a relevant and realistic example to demonstrate the application of the DST. The WLR project aims to transport IEH from the Port of Rotterdam to DHS in the greater Leiden area, supplying approximately 13,000 households and 200 companies through a 43 km pipeline [28]. The analysis considers a 10-year exploratory scenario to identify the least-cost DHS expansion and evaluate its competitiveness with decentralised heating, while accounting for regional policy and regulatory conditions. While the spatial routing had already been determined within WLR, the tool must be able to interoperate with the spatial analysis tools. Thus, the DST application focused on selecting an open-source techno-economic optimisation model with low spatial resolution and 'low to medium' temporal resolution, interoperable with spatial tools, to enable transparent and reproducible long-term investment planning. The inputs to the DST have been summarised in Table 8.

The criteria for the DST were defined based on project needs, including low-to-medium temporal resolution, low spatial resolution, high flexibility, and high interoperability. In this case, the models that meet all the criteria are OSeMOSYS and Oemof. To make the final tool selection, a ranking exercise was conducted to prioritise interoperability, flexibility, spatial resolution, and temporal resolution. Each criterion is assigned a rank from 4 to 1, where 4 denotes the highest priority and 1 the lowest. The criteria were ranked as shown in Table 9.

The final score is calculated as shown in Table 10. From the shortlisted models, OSeMOSYS and oemof met all baseline criteria. The weighted model scores showed Oemof marginally outperforming OSeMOSYS (final scores of 42 and 39, respectively), leading to its selection for this application.

Table 8: *Inputs for each criterion in the decision support tool*

Criteria	Answer
Access	Open source
Solver access	Open source
Shell	Open source
Performance with high time resolutions	Low
Language	No preference
Spatial resolution	Low
Temporal resolution	Low to medium
Modelling method	No preference
Flexibility	High
Interoperability	High
Technological richness	Yes
Thermal storage	Yes
Market	Yes
Policy measures	Yes
Emission accounting	Yes
Objective function	No preference

Table 9: *Input for the Criteria*

Criteria	Ranking
Temporal resolution	1
Spatial resolution	2
Flexibility	3
Interoperability	4

Table 10: *Calculation of the scores*

Criteria/tool	OSeMOSYS	Oemof
Temporal resolutions	2	5
Spatial resolution	2	2
Flexibility	15	15
Interoperability	20	20
Final score	39	42

While no single tool met all possible DST criteria across the broader evaluation, the test case demonstrated the DST's utility in guiding model choice for stakeholders under specific project conditions. It also showed that the DST can be adapted to identify sub-optimal but workable solutions when no model fully satisfies all requirements, by highlighting trade-offs between model capabilities and stakeholder needs. Beyond its decision-support function, the process of

entering criteria weights and visualising how tools perform against them enhances transparency, allowing users to clearly see trade-offs, strengths, and weaknesses across models. The WLR case illustrates this. Oemof was selected over OSeMOSYS because it offered higher temporal resolution, even though both met the baseline criteria. This reflects a broader pattern in the review: tools are chosen not because they satisfy every desirable feature, but because they fit the most essential project needs. Model selection is therefore a process of prioritising key functions based on context and objectives.

2.4 Implications for future model development and tool selection

The comparative evaluation in [P1] shows that no single ESOM fully meets the requirements for EH recovery analysis. While most tools can represent key techno-economic parameters and storage, they differ markedly in temporal and spatial resolution, interoperability, and flexibility of technology representation. As discussed in Section 1.2, high temporal and spatial resolution, as well as interoperability, are critical for many stakeholders. Only a few tools can capture EH integration at multiple system levels or include detailed spatial aspects of DHS. The review also identified methodological constraints that restrict how EH sources are represented. Some tools support new technology definitions or structural modifications, while others rely on rigid, predefined templates that limit modelling flexibility and diversity of scenarios. This inconsistency makes it challenging to represent EH recovery pathways accurately or to compare results across studies.

From a methodological perspective, these results highlight the need for future ESOMs to prioritise modularity, interoperability, and open-source development. The ability to exchange data with spatial-, operational-, and process-level models would enable broader assessments without embedding all functionality within a single framework. Transparent documentation, adaptable architectures, and collaboration among developers, researchers, and industry stakeholders are crucial for enhancing the suitability of models for EH recovery analysis over time.

The policy implications are equally notable. Public research and innovation programmes can support the development of open-access, interoperable tools and encourage partnerships between academia and industry to better align modelling tools with real-world decision-making needs. The experience of EU Horizon 2020 projects such as EMB3RS and REUSEHEAT demonstrates the value of such collaborations in capturing industrial requirements and translating them into practical modelling tools.

Ultimately, robust investment decisions for EH recovery should be supported by a portfolio of modelling analyses that examine different layers of the problem, allowing results to be contextualised and communicated effectively to both technical and policy audiences. This layered structure, illustrated in Figure 6, aligns with the decision-making levels discussed in Section 1.2. The top layer outlines the multi-model framework's overall purpose: to support investment decisions by considering different perspectives on the problem. The middle layer indicates that these perspectives require different types of analysis. The bottom layer shows the three modelling perspectives that correspond to these needs: component analysis to assess

technologies at the industrial site, spatial analysis to evaluate the feasibility of connecting EH sources to the DHN, and long-term energy system analysis to understand how EH fits within the broader supply system. Together, these layers illustrate how the models operate at the industrial, network, and energy system scales, and how their results can be combined and interpreted coherently for stakeholders.

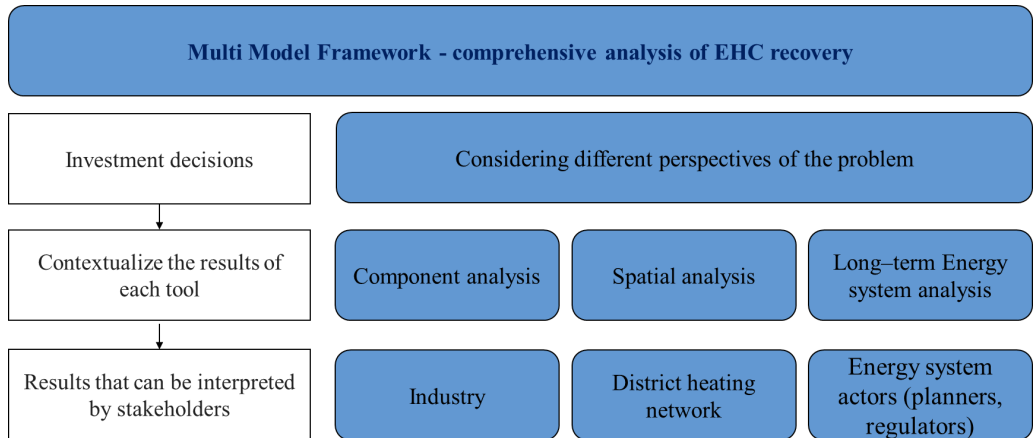


Figure 6: Conceptual representation of the multi-model framework used for the comprehensive analysis of EHC recovery, illustrating how component analysis, spatial analysis, and long-term energy system analysis are combined to support investment decisions and address the perspectives of industry, DHN, and wider energy system stakeholders.

Overall, the review reveals that existing ESOMs have significant gaps in spatial and temporal detail, interoperability, and flexibility in representing EH sources. These limitations correspond directly to barriers identified in the literature, particularly in bridging the information needs of different stakeholders, from policymakers to industrial operators. As a result, no single tool can provide the full range of technical, spatial, and operational insights needed for robust EH integration planning, underscoring the need for a multi-model approach that combines complementary tools to cover all relevant analytical dimensions. The tools selected for this thesis needed to be both technically capable and sufficiently flexible and interoperable to function within such an integrated multi-model framework. Grounding the selection in a transparent, criteria-based evaluation ensured that the modelling choices directly supported the specific challenges of analysing EH recovery in DHSs and provided a solid foundation for the quantitative analyses that follow.

The DST used in this thesis was previously demonstrated for a specific use case, where oemof ranked highest and OSeMOSYS ranked second. This exercise showed that the DST is useful for conducting a structured comparison of modelling tools based on a defined set of criteria and for identifying strong candidates. Other tools, such as PyPSA, may offer valuable functionality beyond the scope of this comparison, and different user priorities could yield different rankings. Still, the DST's balance of simplicity, flexibility, and openness aligns well with the aims of this study. However, the DST results had to be supplemented with additional criteria to fully reflect

the objectives of this thesis. In particular, the DST did not include long-term, intertemporal investment modelling, which is an essential consideration for the multi-model framework developed in this thesis. This criterion, therefore, needed to be considered alongside the DST results when selecting the ESOM.

When this additional requirement is taken into account, apparent differences among the candidate tools emerge. A central requirement was a long-term investment model capable of analysing system development over both a medium-term period of around 10 years and an extended horizon of 25-30 years. Although oemof supports investment optimisation, it is primarily designed for single-period operational and planning analysis and does not provide predefined structures for intertemporal, multi-decade capacity expansion modelling. As noted by Hilpert et al. [128] oemof represents an energy system for a one-year optimisation period, and multi-period formulations require substantial manual extensions. The oemof documentation similarly states that long-term, multi-period investment dynamics are not included by default [129]. By contrast, OSeMOSYS is explicitly developed for long-term, multi-period investment planning and system evolution, with endogenous capacity tracking and intertemporal constraints across decades. In addition, OSeMOSYS meets several of the criteria emphasised in this thesis, including openness, flexibility, and interoperability, and these align well with the DST results. OSeMOSYS provides an open, adaptable structure that meets this need and can be effectively linked to the spatial, exergy, and operational modules used in this thesis. Its relative ease of integration with other tools also makes it a practical foundation for building the multi-model framework. For these reasons, OSeMOSYS offers the most suitable balance of capabilities for this study, while recognising that oemof and other tools may be preferable under different modelling priorities. This selection forms the basis for the integrated multi-model framework developed in the next section.

3 Integrated multi-model framework for evaluating EH-DHS integration

This chapter presents the response to RQ2:

How can a multi-model framework coherently integrate spatial, techno-economic, and exergy dimensions to develop technically feasible and cost-optimal strategies for EH integration into DHS?

To address the gaps identified in Section 1.2, OSeMOSYS was complemented by a set of specialised add-on tools that extend its capabilities to capture spatial, exergy, and operational dimensions of EH recovery. The geospatial optimisation, exergy analysis, and operational optimisation tools were initially developed within previous research projects (EMB3RS, HOTMAPS). In this thesis, these modules were adopted and adapted where needed, rather than created from scratch. The author's contribution lies in designing, implementing, and testing the soft-link between these modules and OSeMOSYS; extending the modelling functionality; modifying parts of the OSeMOSYS implementation; and integrating all modules into a coherent multi-model framework tailored for EH recovery analysis. In addition, the in-depth study of model outputs at each step, as well as the overall output from the integrated framework, provides the insights necessary to inform RQ2. The following sub-sections explain each tool in detail and show how they are integrated in two steps, with each step applied to a distinct case. In addition, the resulting model output is presented and discussed to highlight the methodological insights generated by the modelling advances developed in this work and their relevance for EH integration and DHS planning.

3.1 Long-term least-cost system optimisation

OSeMOSYS is designed to support the planning of energy systems at multiple spatial scales. It is formulated as a linear optimisation problem that minimises the total discounted system cost required to meet specified energy (and non-energy) service demands over a given planning horizon [130]. In this thesis, OSeMOSYS is used to optimise investments in EH recovery technologies and their operational costs. Therefore, the main objective of the optimisation module is to minimise the total system cost as given in equation 1.

$$\begin{aligned}
Total\ cost = & \sum_{year} \left\{ \sum_{Technology} (Discounted\ technology\ investment\ costs \right. \\
& - Technology\ salvage\ value \\
& + Discounted\ technology\ operating\ costs \\
& \left. + Discounted\ technology\ emission\ penalties) \right\} \\
& + \left\{ \sum_{Storage} (Discounted\ storage\ investment\ costs \right. \\
& \left. - Storage\ salvage\ value) \right\} \tag{1}
\end{aligned}$$

The model represents the entire energy system as a network of technologies, fuels, and demands, in which each technology is characterised by techno-economic parameters such as capital cost, fixed and variable operating and maintenance costs, efficiency, lifetime, and emission factors. It can represent a broad range of heat supply technologies, including boilers, HPs, CHP units, heat exchangers, and TES, over planning horizons of several decades.

OSeMOSYS is based on energy and mass balance principles consistent with the First Law of Thermodynamics. It operates on an annual time horizon, divided into user-defined intra-annual TimeSlices, enabling the representation of annual, seasonal, or diurnal variations in demand and supply and ensuring that they are balanced at each TimeSlice. Intra-annual TimeSlices represent discrete segments of the year, such as seasons, months, or representative hours, enabling the model to approximate temporal variability without explicitly simulating every hour. Within this framework, the decision variables include capacity additions of each technology, activity levels in each time slice, and the use of storage or trade between regions. The outputs comprise optimal capacity expansion pathways, generation and use patterns, storage utilisation, and system cost breakdowns, together providing a comprehensive basis for long-term energy system planning. By default, however, OSeMOSYS does not incorporate second-law (exergy) considerations, motivating the integration of complementary tools into this framework.

For this thesis, the OSeMOSYS_PuLP Python implementation was used, enabling complete control over the code and integration with other Python-based tools [131]. In line with the open-tool practices under which OSeMOSYS has been developed and continues to be developed by multiple users, this thesis work has also introduced modifications. They were developed to improve the representation of TES by replacing the standard long-term storage formulation with a temperature-based formulation that can model tank-based TES and associated heat losses, following the approach of Niet et al. [132]. Additional changes were introduced to allow for variable operating costs at each intra-annual time step, enabling the incorporation of hourly electricity price variation, which is critical when modelling HPs as supply options. A detailed

description of these enhancements can be found in [P2] and [P4] of this thesis. These enhancements ensured that OSeMOSYS could serve as the central decision-making model in the framework, producing cost-optimal investment pathways for EH recovery and integration.

However, OSeMOSYS alone could not fully address the needs identified in RQ1, 2 and 3. While it provides robust long-term optimisation, it does not perform:

- High-resolution spatial optimisation of heating networks,
- Exergy-based technology screening for temperature compatibility, or
- Short-term operational validation at hourly resolution.

To address these limitations, three specialised open-source tools for geospatial optimisation, exergy analysis, and operational optimisation were combined with OSeMOSYS. The following section provides a detailed description of the geospatial optimisation tool.

3.2 Geospatial optimisation tool

The geospatial optimisation tool used in this study was developed in the Horizon 2020 EMB3RS project to integrate spatial considerations into EH recovery and DHS planning [133]. Formulated as a mixed-integer linear programming (MILP) model, it determines the least-cost network layout by minimising the total network length while connecting heat sources and sinks, subject to heat exchange capacity constraints. The model uses a road network graph from OpenStreetMap (OSM), where each road segment represents a potential route for pipe installation [134]. The tool is designed for water-based DHSs and requires supply and return temperatures to calculate pipe diameters and thermal losses. Network costs include both pipe and digging expenses, with the latter varying by surface type. Thermal losses are calculated based on the temperature difference between the hot water in the pipes and the surrounding ground, the thermal properties of the pipe material, and the network layout.

The optimisation is performed to maximise exchange capacities, so temporal variation is not modelled directly. To address this, the tool can be iteratively linked to an ESOM, such as OSeMOSYS, to account for the temporal resolution of heat dispatch. Outputs from the tool include pipe lengths, diameters, capacities, thermal losses, network costs, and a graphical representation of the optimal layout. These values serve as inputs to OSeMOSYS, describing how the DHN is represented in the long-term model. More details on the geospatial optimisation tool can be found in [P4] of this thesis. The standalone version of the spatial analysis tool and the corresponding documentation can be found on GitHub [133].

Together, the geospatial optimisation and energy system models define the spatial and economic boundaries of heat integration. The next step, the exergy analysis, complements this by evaluating the thermodynamic feasibility and 2nd law efficiency of each connection and identifying suitable technologies for different EH temperature levels.

3.3 Heuristic choice of technology based on Exergy Analysis

The exergy analysis model evaluates the conversion of EH into useful heat for supply through a DHN. In this study, it is used to identify temperature-feasible technology options for EH

recovery. The supply and return temperatures of the DHS are input to the tool [77]. Based on the temperature of each source, the tool selects appropriate conversion technologies and provides their techno-economic parameters to the ESOM. Sources above 120 °C are assigned a closed hydraulic circuit with thermal oil linked to a secondary water circuit supplying the DHN. In contrast, sources below the supply temperature are coupled with boosting technologies such as HPs. Source streams are characterised individually, although future extensions could optimise stream mixing.

On the demand side, the tool assigns configurations based on temperature requirements: heat exchangers for sinks below the DHN supply temperature, boosting technologies for sinks above it, and absorption chillers for process cooling. For each configuration, the model calculates the maximum deliverable capacity, conversion efficiency, capital and operating costs, and associated CO₂ emissions from auxiliary energy use, with no emissions attributed to the EH source itself. These are used as inputs in OSeMOSYS to determine the cost-optimal technology mix. Further details on the exergy analysis model can be found in [P2] of this thesis. The standalone version of the exergy analysis tool and the corresponding documentation are provided on GitHub [135] and ReadTheDocs [136], respectively.

3.4 The Multi-model framework: Version 1 - Integration of spatial, exergy and long-term capacity expansion optimisation

The modelling approach developed in this thesis integrates multiple open-source tools into a single framework that evaluates the technical, spatial, and economic feasibility of EH integration in DHSs. To achieve this, the tools were integrated through a soft-linking approach that combines OSeMOSYS with specialised models. This integration was a planned methodological choice made to meet the different needs of EH integration. By soft-linking OSeMOSYS with these specialised tools, the framework leverages the strengths of each:

- OSeMOSYS provides the strategic long-term least-cost investment plan.
- The geospatial tool captures the spatial layout and cost consideration of network extensions.
- The exergy module ensures thermodynamic feasibility.

This section details how these models are integrated into the comprehensive modelling framework, describing the data flows, iterative processes, and convergence criteria that enable spatial and exergy constraints to inform and refine long-term investment decisions.

The framework is constructed by soft linking the three components described above. The overall architecture follows an iterative process (Figure 7).

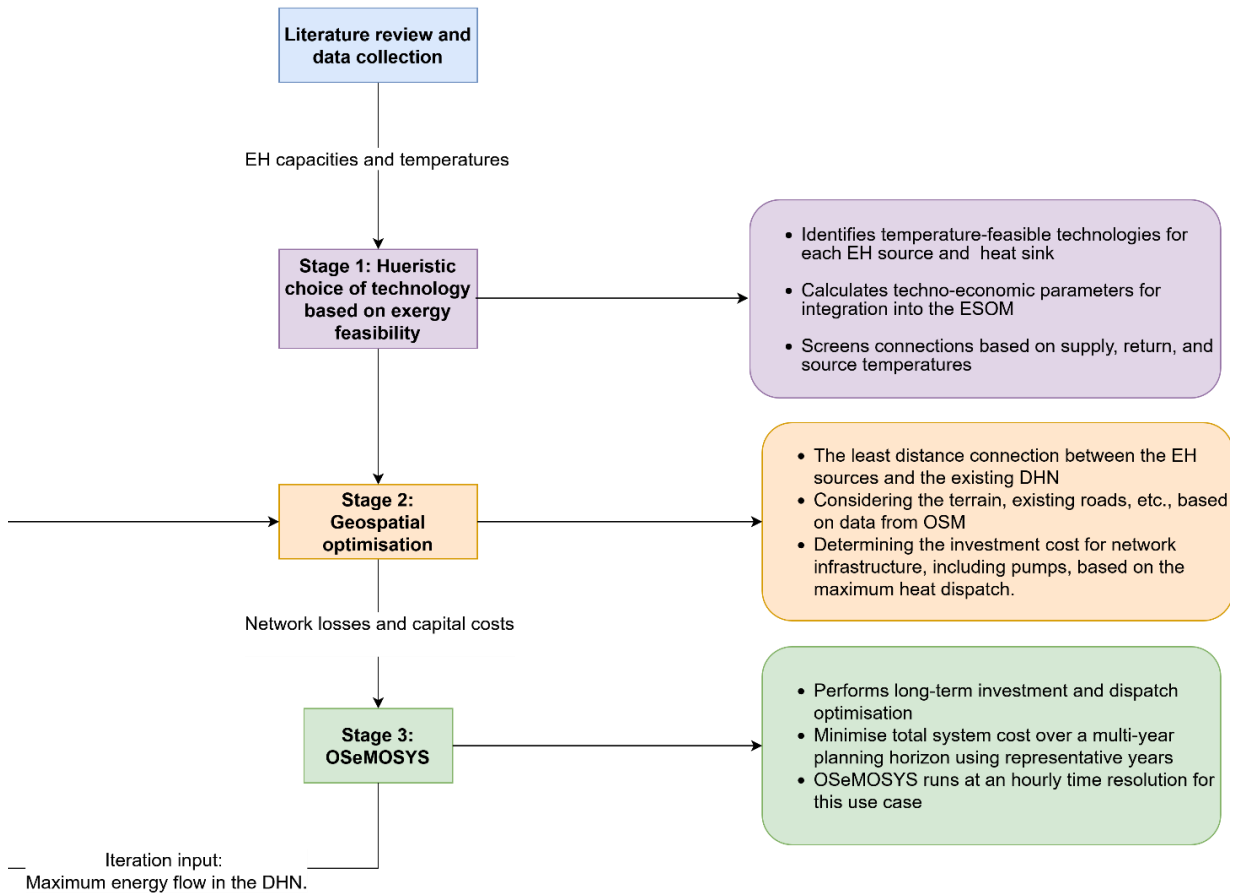


Figure 7: Overall methodology of the multi-model framework applied in [P2] and [P3], illustrating the sequential integration of exergy-based technology screening, geospatial optimisation of network connections, and long-term techno-economic optimisation using OSeMOSYS to evaluate the integration of EH into DHN.

Stage 1 involves a heuristic technology selection based on exergy analysis. The process starts with the exergy analysis tool, which selects suitable technologies by assessing temperature feasibility and estimating useful heat output based on exergy efficiency, COP, and part-load performance. The output is a source-sink technology matrix containing:

- Feasible technology options per connection temperatures.
- Maximum energy (deliverable heat) per source.
- Associated energy conversion efficiencies and costs.

Stage 2 considers geospatial optimisation. For new DHS or major expansions, the exergy model outputs (maximum capacities for each source and sink) are also fed into the geospatial optimisation. It calculates:

- Optimal network topology (branching and looping structure) with pipe diameters sized for maximum flow.
- Annual and hourly thermal losses (based on insulation, soil conductivity, and ambient temperature).
- Network investment cost (based on the least distance network and dimensioned pipe diameter)

Stage 3 involves the long-term investment and dispatch optimisation. The exergy-screened technology set, and the network's costs and losses are then provided to OSeMOSYS_PuLP, which optimises the investment and dispatch of all supply technologies over a multi-year horizon. OSeMOSYS compares the cost of network connectivity and the technologies needed for integrating the EH source with the cost of the existing technologies in the system. It then determines which sources are cost-effective to include in the heating mix and to what extent.

Based on this, it provides:

- Cost-optimal capacities of EH sources to integrate in the DHS
- Cost-optimal capacities of the different existing technologies.
- Cost-optimal intra-annual heat generation from the EH sources and the existing technologies.

Stage 4 consists of an iterative link applied to new DHS development. In [P4] of this thesis, the spatial tool is iteratively linked to OSeMOSYS for new DHS cases. In the first iteration, the spatial analysis model is run with the maximum possible heat-exchange capacities between sources and sinks, as determined by the exergy analysis tool. This results in an initial network layout that includes pipe lengths, diameters, costs, and losses. These outputs are then provided to OSeMOSYS (run at hourly resolution), which uses them to determine a cost-optimal dispatch and investment strategy. The updated hourly heat-generation values from OSeMOSYS are used to re-run the spatial model to obtain more accurate estimates of network loss and costs. This process repeats until the variation in total heat losses between iterations falls below 1%. This iterative process is visualised in Figure 8, which illustrates the data flow and feedback between the spatial model and OSeMOSYS. This iteration improves the consistency between spatial network design and long-term system optimisation, ensuring that both representations reflect realistic operating conditions.

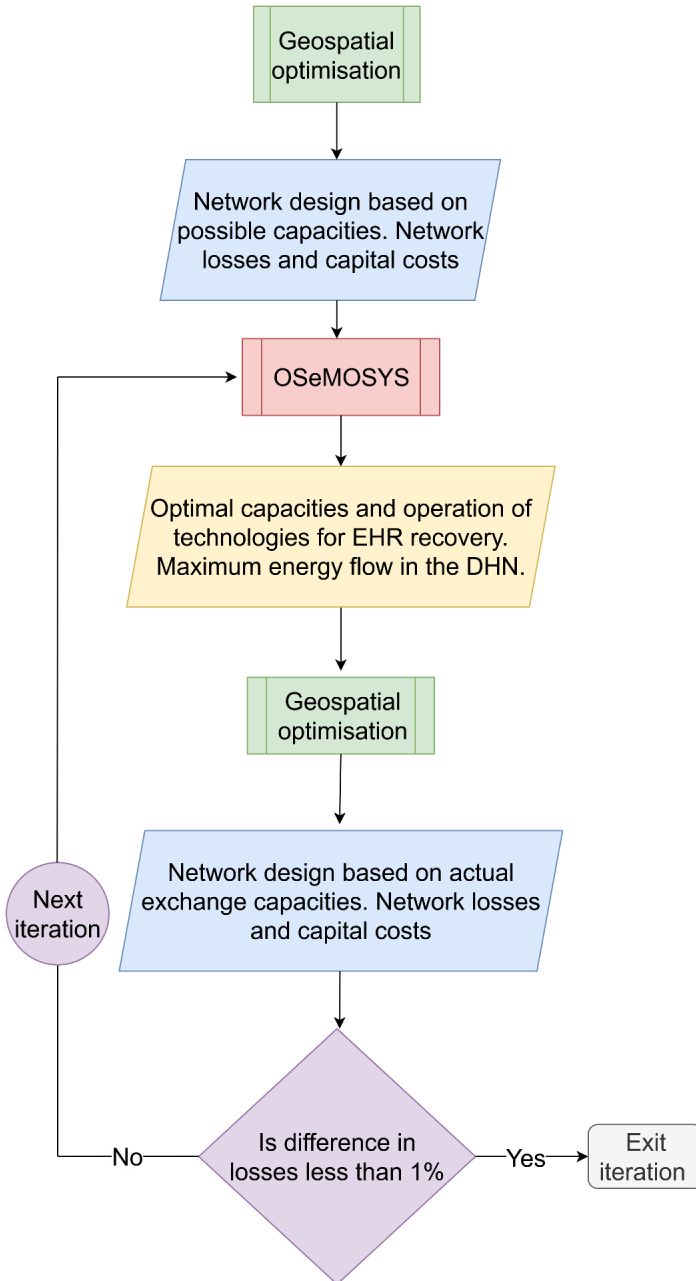


Figure 8: An iterative method is used to link OSeMOSYS with the geospatial optimisation tool, where network design and losses are estimated from spatial optimisation, inform the techno-economic optimisation in OSeMOSYS, and the resulting optimal capacities and energy flows are used to update the network design until the difference in network losses between iterations is less than 1%.

The developed multi-model framework was applied in a real-world case to test its flexibility and usefulness. The first version of the framework was applied to a new DHS in Volos, Greece, which is planned primarily around IEH sources. This version served as an initial testbed for examining the individual model components and their interaction. The subsequent framework versions, which add further functionality, are applied to a different case introduced later in this chapter.

3.4.1 Case Application: Volos Industrial Park, Greece

The Volos Industrial Park in central Greece was selected as a test case to demonstrate the application of the integrated modelling framework to a new DHS. The park hosts several industrial facilities with recoverable EH and heat demands located within feasible connection distances. Currently, these heat demands are met by natural gas boilers. Replacing natural gas with locally available IEH would reduce emissions, but doing so requires designing a new DHS and an associated distribution network. This makes the site suitable for evaluating the spatial feasibility of connecting sources and sinks, assessing temperature compatibility, and identifying cost-optimal investment pathways for an IEH-based DHS. In the case, IEH is defined as the thermal energy generated as an unavoidable by-product of industrial production processes, remaining after internal heat recovery within the facility and otherwise rejected to the environment. The case was motivated by industries within the park seeking to understand how to recover and use IEH locally. As the primary needs-owners, they were engaged throughout the modelling process and benefited from the results by gaining a clearer understanding of the potential network layout, cost-effective recovery options, and the long-term value of establishing a DHS based on IEH. The objective of the case study was to determine the cost-optimal configuration for integrating these sources into a newly built DHS, accounting for spatial routing costs, temperature compatibility, and long-term techno-economic feasibility.

Four EH sources were identified, with supply temperatures ranging from 70 °C to 900 °C and capacities ranging from 890 kW to 4.3 MW, as summarised in Table 11. These include flue gases from biomass and steel processing, as well as hot water streams. The target integration temperatures for the DHS vary by source and are determined by the selected conversion technology. On the demand side, seven sinks were identified, each with multiple temperature-dependent streams, including steam and hot water demands for industrial processes and space heating. Required sink temperatures range from 70 °C to 180 °C, with a total annual demand of approximately 40 GWh in 2022, the base year. The complete set of sink characteristics is provided in Table 12. The modelling horizon extends to 2032, with future demand projected accordingly. Although energy-efficiency measures have reduced industrial energy needs, these gains are offset by the rapid growth of industrial activity, so process heat demand is assumed to remain constant in the coming years. Space heating demand is expected to increase due to new DHS connections driven by population growth. This rise will be only partly offset by improvements in building insulation. Unlike the EU27, where Connolly et al. project a decline in heat demand, the low rate of insulation upgrades in Greece suggests an increase of about 2% between 2022 and 2032 [137]. Domestic hot water demand is expected to increase by 10% due to additional connections. Cooling demand is also assumed to increase by 10%, reflecting both higher connection rates and rising temperatures [138].

The case assumes a third-generation DHS with supply and return temperatures of 100 °C and 70 °C, respectively. The model's energy system representation includes conventional technologies such as CHP units, HPs, and the existing gas boilers. In the modelling framework, solar thermal-based heating was not included as an alternative supply option, as the analysis focuses on evaluating the substitution of natural gas through EH recovery and related technologies within the defined system boundaries. The framework (Figure 8) was applied, with an iterative soft link between the geospatial optimisation model and OSeMOSYS, to determine a cost-optimal and technically feasible network design. Further details on the system assumptions are provided in [P4] of this thesis.

Table 11: *Volos Industrial Park case study data - Sources*

Number	Supply temperature (°C)	Target temperature (°C)	Capacity (kW)	Fluid	Possible Technologies
Source 1	220	120	4340	Flue gas	Heat Exchanger, Organic Rankine Cycle
Source 2	70	30	2790	Water	Heat Pump
Source 3	180	120	890	Flue gas	Heat Exchanger
Source 4	900	500	2436	Flue gas	Heat Exchanger

Model setup and temporal resolution

The OSeMOSYS model structure and configuration were tailored to the specific needs of the case. Techno-economic optimisation was carried out at hourly resolution in OSeMOSYS, using 8,784 intra-annual timesteps (considering a leap year) to fully capture daily and seasonal variability in EH availability, electricity prices, and heating demand. To maintain computational feasibility, given the high time resolution, the model includes only two representative years, the base year 2022 and a future year 2032, across a ten-year planning horizon. These years are embedded within the same model run but are treated independently. Storage levels are set to zero at the end of each modelled year to prevent energy carryover.

Table 12: Volos Industrial Park case study data - Sinks

Number	Required temperature (°C)	Available temperature ³ (°C)	Capacity (kW)	Fluid	Annual demand (GWh)		Possible technologies
					2022	2032	
Sink 1 Stream 1	180	95	815	steam	2.99	2.99	Heat Pump
Sink 1 Stream 2	95	10	79	water	0.30	0.30	Heat exchanger
Sink 2 Stream 1	180	95	781	steam	1.28	1.28	Heat Pump
Sink 2 Stream 2	95	10	76	water	0.13	0.13	Heat exchanger
Sink 3 Stream 1	180	95	260	steam	1.51	1.51	Heat Pump
Sink 3 Stream 2	95	10	25	water	0.15	0.15	Heat exchanger
Sink 4 Stream 1	80	10	250	water	2.19	2.19	Heat exchanger
Sink 4 Stream 2	175	10	1250	steam	10.15	10.15	Heat Pump
Sink 4 Stream 3	90	10	138	water	1.21	1.21	Heat exchanger
Sink 5 Stream 1	180	64	2777	steam	4.91	4.91	Heat Pump
Sink 5 Stream 2	64	10	231	water	0.42	0.42	Heat exchanger
Sink 6 Stream 1	164	95	1539	steam	13.16	13.16	Heat Pump
Sink 6 Stream 2	95	10	153	water	1.34	1.34	Heat exchanger
Sink 7 Stream 1	60	10	596	water	1.31	1.31	Heat exchanger
Sink 7 Stream 2	7	12	497	water	0.05	0.055	Heat exchanger
Sink 7 Stream 3	80	60	480	water	0.37	0.41	Absorption Chiller

³ Here, “available temperature” corresponds to the return or inlet temperature of the sink-side heating medium, which defines the lower temperature boundary for the heat exchange or boosting process.

Data, modelling considerations, and assumptions

The input data for sources, sinks, and network characteristics were collected through site-specific mapping, industrial process characterisation, and high-resolution geospatial data from OSM. Technology-specific parameters, such as efficiencies, capital and operational costs, and emission factors, were primarily derived from the EMB3RS project technology database and complemented by literature sources and component fact-sheets [139]. Fuel prices and emission intensities were taken from national statistics and policy documents [137], [138], [140], [141], [142], [143], [144]. The electricity grid decarbonisation trajectories follow Greece's National Energy and Climate Plan [141]. Full details of the case study context and data are presented in [P2]. The focus here is on the scenario definitions, their results, and the implications for designing a new DHS based on IEH.

Scenario design

Five scenarios were developed to explore the techno-economic performance of IEH integration under different market and policy conditions of relevance to the case:

1. NG – continued use of existing natural gas-based heating technologies without DHS or IEH integration.
2. Only IEH – all heating demands met exclusively through IEH integration, replacing existing systems entirely.
3. IEH vs NG – IEH competes (based on cost optimisation) with existing technologies to meet demand.
4. Emissions Penalty – an emissions penalty applied to non-IEH technologies to reflect environmental costs.
5. Subsidy – investment subsidies applied to IEH infrastructure. A 50% capital cost reduction is assumed for EH recovery technologies, reflecting previous policy instruments and public funding schemes that have provided subsidies ranging from 12% to 90% [145].

3.4.2 Results: New District Heating System based on Excess heat from the Volos Industrial Park

This section presents the outcomes of applying the multi-model framework to the Volos DHS. It shows how the framework performs in analysing EH integration under real project conditions.

Results from the exergy analysis

The technologies chosen by the exergy analysis tool are specified in Table 11 and Table 12. The available IEH temperature and the required temperature for the heat demand primarily determine the technology choice. The exergy analysis tool also determines the maximum capacities of each technology at the source and sink, as well as its techno-economic characteristics. The detailed results of the exergy analysis tool are presented in [P2] of this thesis.

In addition to selecting suitable technologies, the exergy analysis revealed a significant temperature mismatch in the case configuration. Source temperatures range from 70 to 900 °C, sink temperatures from 64 to 180 °C, and the DHS is assumed to operate between 70 and 100

°C. Routing all heat through this grid temperature band results in substantial exergy destruction, since high-temperature sources must be cooled to the grid temperature and several sinks require reheating above 100 °C. The exergy analysis, therefore, also indicated a technically feasible alternative configuration in which high-temperature sources supply a dedicated steam network to meet sinks requiring temperatures above 100 °C. This alternative configuration is illustrated in Figure 9. However, the design and optimisation of a steam network fall outside the scope of the modelling framework developed in this thesis, which focuses on water-based DHS configurations. To isolate the effect of this temperature mismatch, a subset of the case including only hot-water sinks is analysed in parallel, allowing system performance to be assessed without the distortions introduced by high-temperature demands.

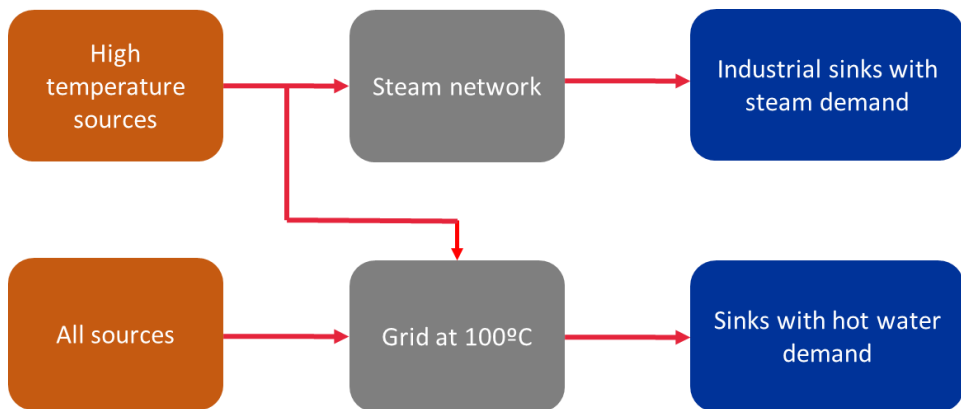


Figure 9: *Conceptual representation of an alternative configuration including a steam network, where high-temperature EH sources can supply industrial sinks with steam demand directly, while all sources can also deliver heat to a 100 °C DH grid serving sinks with hot water demand.*

Topology of the network designed by the geospatial optimisation

After the technology choice and the capacities are determined, the spatial analysis tool designs the network, and iterations are used to determine the cost-optimal system design. The initial network design in iteration 1 is based on the maximum capacities determined by the exergy analysis tool. The resulting network topology is shown in Figure 10, where red markers indicate the sources and blue markers indicate the sinks.

After the network topology is determined, iterations between OSeMOSYS and the geospatial optimisation tool are performed to determine the cost-optimal, spatially feasible investment plan and heat dispatch. The number of iterations required for convergence varied across scenarios. Some scenarios converged after two iterations, while others needed four. This is further discussed in Section 3.4.3. Once the iterations are complete, OSeMOSYS determines the cost-optimal investment plan. The following sections compare results across scenarios, focusing on the cost competitiveness of EH sources. The share of EH in final heat use is used as the indicator of competitiveness, since OSeMOSYS selects the least-cost solutions.

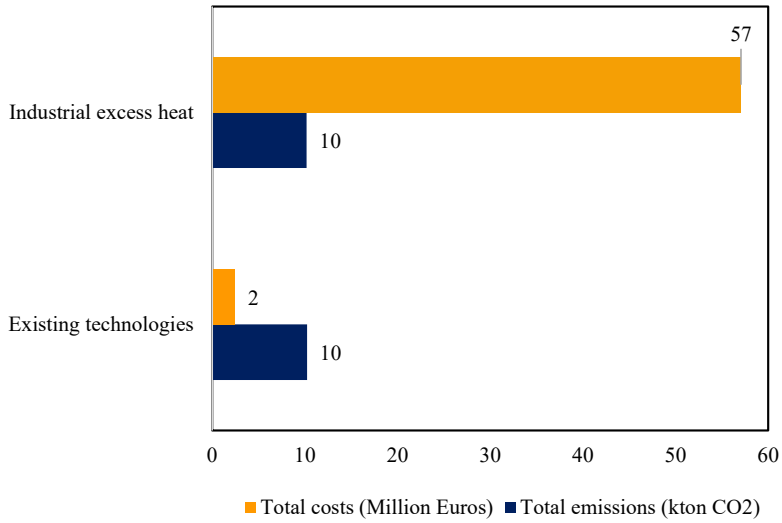


Figure 11: Comparison of total system costs and emissions in 2032 for the existing technology mix and for a system integrating industrial EH, showing total costs (million euros) and total emissions (kton CO₂).

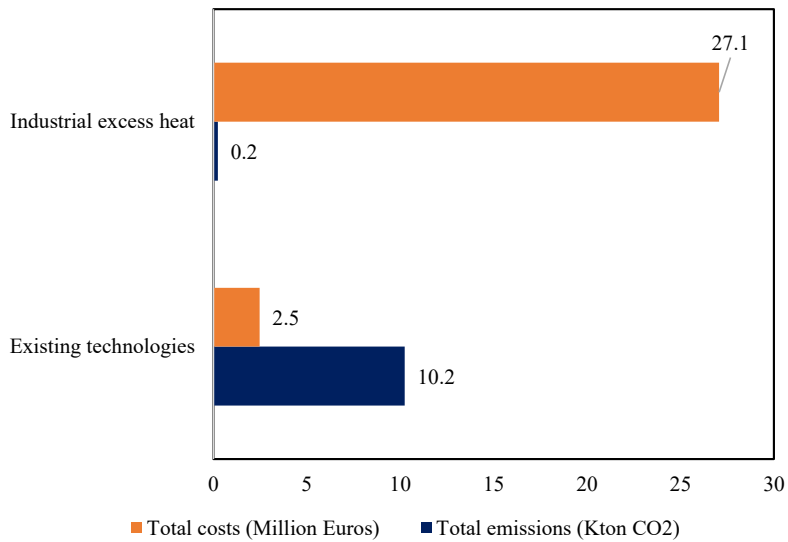
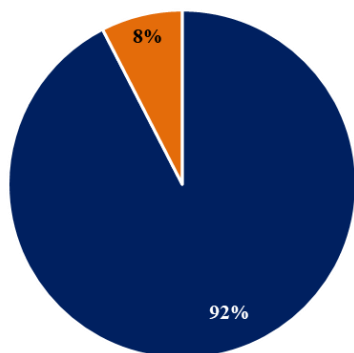


Figure 12: Comparison of total system costs and emissions in 2032 for sinks with hot water demand under the existing technology mix and under a system integrating industrial EH, showing total costs (million euros) and total emissions (kton CO₂).

Comparison of the IEH vs Reference, Emissions penalty, and Subsidy scenarios

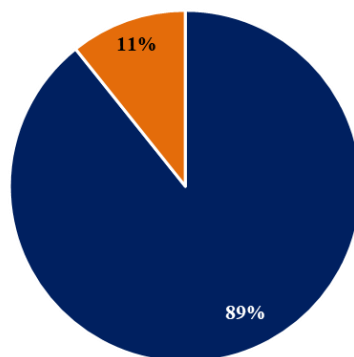
The IEH vs Reference scenario assessed EH competitiveness against existing natural gas-based systems. The Emissions Penalty scenario applied a carbon tax aligned with current Greek policy, while the Subsidy scenario assumed a 50% subsidy in EH technology investment costs. Competitiveness was evaluated using the share of EH in the heat supply mix, determined by least-cost optimisation. Figure 13 presents EH shares across scenarios.

IEH vs Reference scenario



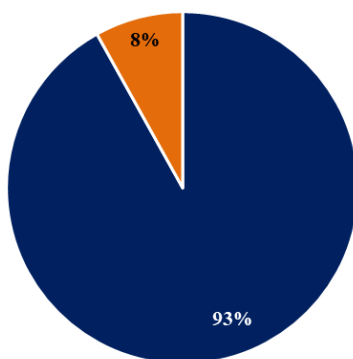
■ Natural Gas boilers ■ Excess heat

Emissions penalty scenario



■ Natural Gas boilers ■ Excess heat

Subsidy scenario



■ Natural Gas boilers ■ Excess heat

Figure 13: Share of heat supplied by EH (EH) and natural gas boilers in 2032 across different scenarios, illustrating the relative contribution of EH and gas-based heat generation in the DHS.

In the IEH vs Reference scenario, IEH accounted for 8% of total heat demand (Figure 13). The emissions penalty increased EH penetration to 11%, whereas the subsidy produced only a

marginal increase. When IEH competed with existing systems, the model initially selected high-grade sources with medium-grade sources entering the mix only after emission penalties and subsidies were introduced. This limited effect of the subsidy reflects the relatively small share of capital costs in the total lifetime costs of EH projects. In high-volume EH recovery systems, operational and variable costs, particularly electricity costs for HPs, dominate total expenditure, reducing the influence of upfront cost reductions. This suggests that investment incentives alone may have limited impact, and that operational or performance-based subsidies, such as electricity price adjustments or carbon-linked tariffs, could provide more substantial and sustained support for EH utilisation. Furthermore, in the model, EH competes against existing natural gas boilers that have no capital cost allocation, further weakening the competitiveness gain from subsidies. These findings also highlight the importance of proactive planning tools to guide investment decisions before systems become locked into fossil-based options, helping to avoid “regret” decisions and stranded assets under evolving carbon and energy price conditions.

The allocation of EH across sinks depends on temperature requirements. EH was deployed only in sinks with target supply temperatures at or below the DHS grid temperature of 100°C. High-temperature sinks require HPs, which have high operating costs due to electricity use. In the emissions penalty scenario, EH use increased in sinks with heat exchangers, since these connections have no associated direct emissions, whereas it declined in sinks requiring HPs. For the latter, the carbon tax on electricity generation (mainly coal-based in Greece) reduced the cost competitiveness of HPs.

This effect is associated with exergy destruction at the source. To isolate the impact of these losses, EH penetration was re-analysed for sinks with hot water demand only (Figure 14). In the base case, EH accounted for around 40% of the demand in these sinks, rising to 51% under emission penalties and 45% with investment subsidies. Penetration levels are therefore significantly higher in hot water sinks than in the overall system. These results also reveal a limitation of the current approach, stemming from the spatial analysis tool’s inability to model networks beyond hot water grids. An essential future enhancement would be to extend the framework to include steam network analysis.

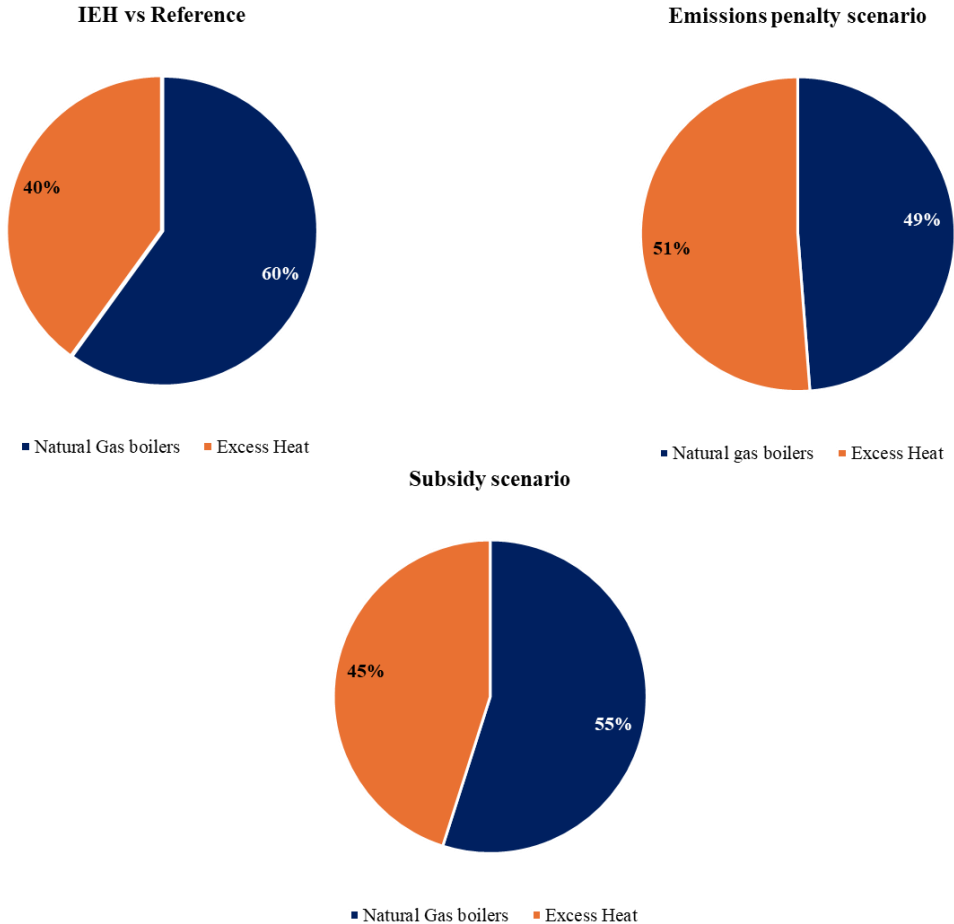


Figure 14: Comparison of three scenarios showing the penetration of EH and conventional heat supply in sinks with hot water demand, illustrating the relative contribution of EH across the analysed scenarios.

These findings underscore that in systems where electricity prices are high and HPs are essential for boosting temperature, policy measures targeting operating costs, such as reduced electricity tariffs for heat recovery or efficiency improvements, may be more effective than investment subsidies. This motivated the subsequent sensitivity analysis on operational cost parameters.

Sensitivity analysis

To build on the policy-scenario findings, a sensitivity analysis examined the effects of varying natural gas prices and carbon taxes on EH penetration. Table 13 summarises the input values. Figure 15 shows the change in EH share across the tested scenarios. The results indicate that doubling the carbon tax led to only a modest increase in EH uptake, whereas a 200% increase led to a substantial rise in the EH share. Natural gas prices had a greater influence: increasing prices from low to average led EH to meet nearly all demand (98%), whereas moving from

average to high produced a smaller gain. This indicates a threshold effect, in which EH becomes the least-cost option once the natural gas price reaches a certain level.

Table 13: *Inputs for sensitivity analysis*

Sensitivity parameter	Carbon tax (€/Ton CO ₂)		
	Emissions Penalty	100% increase	200 % increase
Natural Gas in Industry	50.1	100.2	150.4
Natural Gas in Households	115.7	231.4	347
Electricity	31.3	62.5	93.8

Sensitivity parameter	Natural Gas price(€/MWh)		
	Low	Medium	High
Natural Gas price	50	100	250

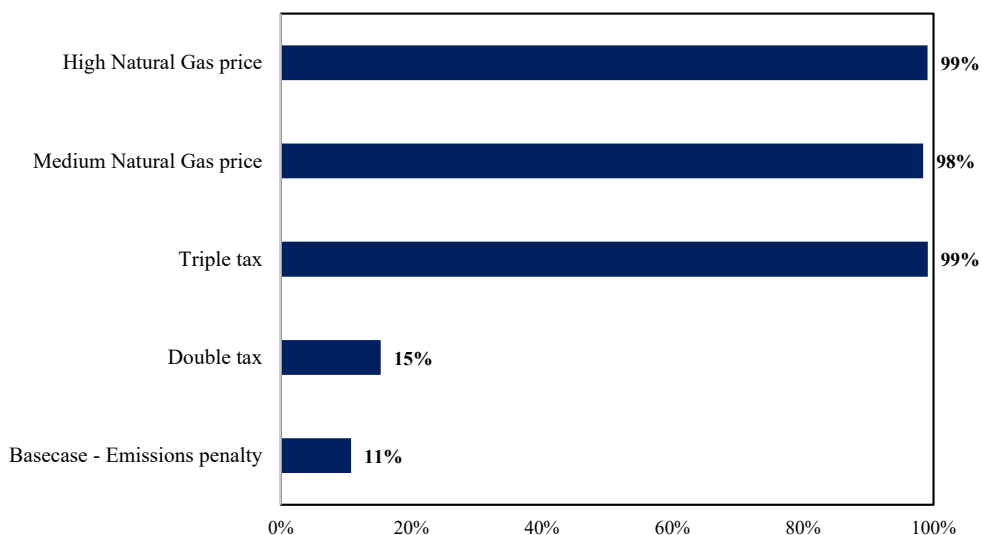


Figure 15: *Share of EH in the DH supply across different sensitivity scenarios, including variations in natural gas prices and emissions taxes.*

Given this significant sensitivity, a second analysis explored minor, incremental changes in natural gas prices to better identify the points at which the system shifts to greater EH use. Prices varied in €10/MWh increments, ranging from €50/MWh to €100/MWh. The results (Figure 16) show a 33% increase in EH share when natural gas prices rise from €50/MWh to €60/MWh, driven by greater uptake of sinks that serve hot-water demand via heat exchangers. For these sinks, EH becomes more cost-effective than natural-gas boilers at €60/MWh, owing to its lower investment and operating costs.

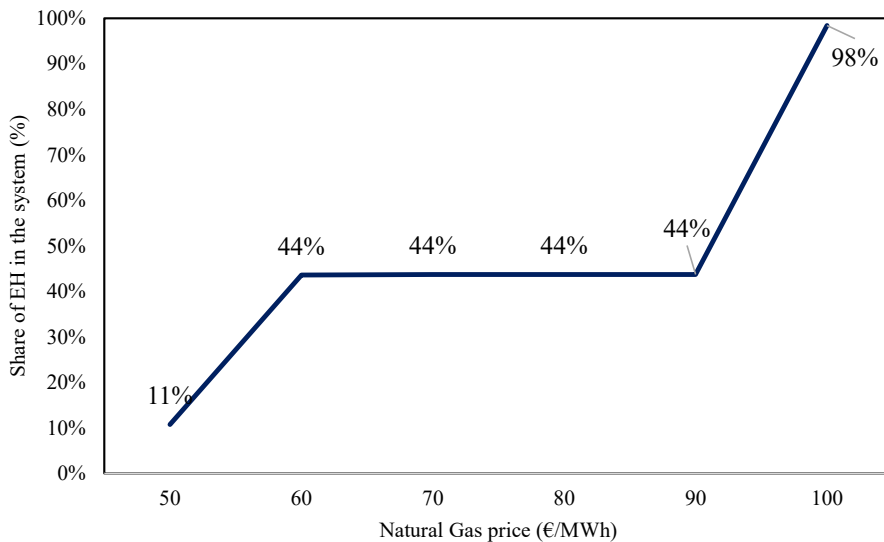


Figure 16: Sensitivity analysis showing the share of excess heat (EH) in the system for all sinks under different natural gas price levels ranging from 50 to 100 €/MWh.

However, EH did not become competitive until natural gas prices reached €100/MWh for sinks with HPs. As shown in Figure 17, the share of EH in these sinks remained constant between €60/MWh and €90/MWh, increasing only when natural-gas boilers became more expensive than HPs. The analysis, therefore, identifies two distinct price thresholds: one at which EH begins to displace natural gas in hot-water sinks, and another, higher threshold at which it becomes competitive for high-temperature demands that require HPs. The electricity price sensitivity was not tested separately, as the 10-year horizon assumes only gradual changes in the power mix based on the Greek NECP, with emission intensity declining from 400 to 250 gCO₂/kWh. Despite this reduction, electricity remained more carbon-intensive than natural gas (210 g CO₂/kWh), which would not alter the EH competitiveness.

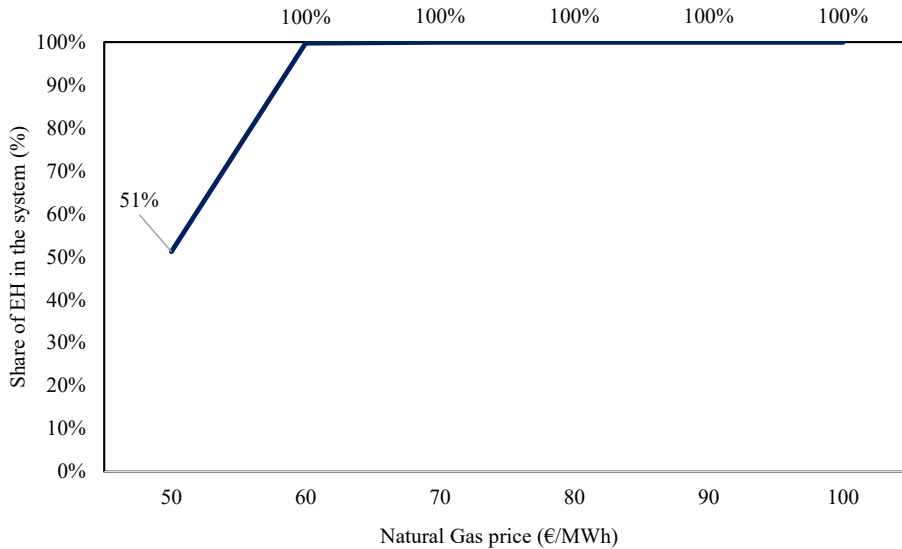


Figure 17: Sensitivity analysis showing the share of EH in the system for sinks with hot-water demand across natural-gas price levels ranging from 50 to 100 €/MWh.

The Volos case application demonstrates that the multi-model framework can identify a staged, cost-optimal investment pathway for a planned DHS based on IEH. Source temperature played a key role, with high-exergy sources dominating early system design and further expansion becoming viable only under carbon taxation or high fuel prices. At the system level, EH achieved limited emission reductions when all sinks were included because several industrial sinks required steam for process heating at 180 °C and thus needed HPs to boost temperature. The high carbon intensity of the 2022 Greek grid means that using electricity in HPs results in emissions comparable to those of natural-gas boilers. In contrast, when focusing only on hot water sinks that do not require boosting, EH emissions were about 50 times lower, underscoring the importance of matching source and sink temperatures. The cost results showed a low EH share due to high HP operating costs and competition from existing gas boilers. At the same time, carbon taxation increased EH uptake more effectively than investment subsidies. Sensitivity analysis confirmed strong fuel-price effects, with clear thresholds at €60/MWh and €100/MWh for EH competitiveness. The case also revealed a limitation of the spatial tool: it cannot optimise high-temperature steam links and requires further development for such applications. Overall, significant emission reductions are possible when high-grade sources are used nearby. Still, HP costs and network layout constrain broader EH use for replacing existing natural-gas-fired boilers. This case application [P2] addresses RQ2 by illustrating how the iterative link between long-term techno-economic optimisation and spatial routing can guide the cost-optimal design of a new DHS, ensuring that investment decisions account for realistic network costs and losses.

3.4.3 Modelling Advances and Methodological Insights - New District Heating System in Volos

In addition to the results on the DHS design for the Volos case application, the framework provided a valuable opportunity to assess its performance, adaptability, and limitations. It also provided valuable modelling insights for designing integrated workflows for EH recovery planning.

These insights concern: (i) the role of iterative linking and convergence between specialised models, (ii) computational and scalability requirements, (iii) the value of modularity and transferability, and (iv) coherence of the framework. Together, these reflections draw directly on the case study [P2] results and discussions, illustrating how the methodological choices in each context shaped the resilience and credibility of the findings.

Iterative linking and feedback loops

A key contribution of the framework was demonstrating how to iteratively link models with different scopes and resolutions. In the Volos case, the iterative soft-linking process linked spatial analysis to OSeMOSYS, using variation in network losses as the convergence criterion. Convergence was typically achieved in two iterations for low-penetration cases, and up to four iterations in high-penetration instances, as shown in Table 14.

Table 14: *Robustness of the method*

Case	Iterations needed for convergence
Only the IEH scenario	3
IEH vs Reference	2
Emissions penalty	3
Subsidy scenario	2
Sensitivity - carbon tax 100% increase	4
Sensitivity - carbon tax 200% increase	4
Sensitivity - Average gas price	3
Sensitivity - High gas price	4

This demonstrates that iterative linking is not only a technical step but also a necessary means of maintaining consistency between models operating at different levels of detail. Although it adds some complexity and computation time, it avoids the problems associated with a siloed approach and helps capture whole-system effects that a single model would miss. For example, linking the long-term optimisation with the spatial and exergy modules enabled the design of the network and the sizing of pipes based on the actual optimal dispatch. In the first iteration, the geospatial optimisation operates in a silo because it lacks information on the optimal heat flows between sources and sinks. Once the ESOM dispatch is introduced, pipe sizes change by around 25-40% across simulations, indicating that a standalone spatial analysis would

misrepresent the network design. In the opposite direction, when the geospatial optimisation updates the losses, the installed capacities of technologies in the ESOM shift by about 2-5% across iterations. Together, these effects highlight the importance of the iterative multi-model approach and the limitations of a siloed analysis. It also enhances the robustness of the solution by preventing overly optimistic source choices and unrealistic network layouts, ensuring that long-term investment plans can be implemented effectively in practice.

Computational and scalability considerations

Integrating multiple specialised models and high-resolution analyses increased the framework's computational demands. In the Volos case [P2], three to four iterations between spatial and techno-economic models were required for convergence under high EH penetration, with each OSeMOSYS run taking about three to four hours to solve using a high-performance solver. Convergence was faster in scenarios with lower EH penetration, usually within two iterations. All simulations were performed on a desktop workstation (256 GB RAM, 3.50 GHz, four cores), with total runtimes ranging from 3 to 12 hours depending on system size and scenario complexity. While this runtime adds some computational burden, feedback from industrial stakeholders in the EMB3RS project indicated that such runtimes are acceptable when the analysis provides sufficient detail to support concrete investment decisions.

These results illustrate a common challenge in energy system modelling: the trade-off between spatio-temporal detail and computational feasibility. While high temporal and spatial resolution improve realism, they also increase complexity and runtime [146], [147]. Approaches such as peak timesteps [148] or representative days [147] can capture key dynamics more efficiently, as seen in hybrid power–heat frameworks [149], [150]. These trade-offs highlight a critical methodological reflection: complex problems do not always require ever-increasing levels of detail, and the usefulness of additional granularity depends on what it contributes to the analysis. In this study, higher temporal and spatial resolution was necessary to capture interactions between dispatch, pipe sizing, losses, and technology selection that simpler models would miss. At the same time, very detailed representations can increase computational effort and reduce usability, especially in larger systems. The key insight is therefore not that detail should be avoided, but that it should be used purposefully, with modelling choices tailored to the questions being addressed and the level of insight required.

Overall, the case application demonstrates that model resolution should align with the study's purpose and available resources. A fit-for-purpose approach, detailed enough to answer the research or policy question but simple enough to remain transparent and tractable, offers the best balance between accuracy, speed, and usability. This insight is significant for the practical application of multi-model frameworks, since they will often be used in policy and planning processes where timely, transparent, and credible results are as valuable as technical precision.

Transferability beyond the case application

Beyond the Volos case, the modelling workflow developed in this thesis was applied to a broader set of real-world contexts through its use in the EU Horizon 2020 EMB3RS project [151]. The core methodological framework developed in this thesis served as the backbone of these applications. In total, the workflow was applied across seven case studies in Europe, including individual industrial sites, industrial parks, city-wide DHNs, and regional-scale assessments. The detailed description of these case studies and their problem settings is provided in [P3] of this thesis.

Across the case studies, the modelling framework was used across a wide range of conditions. These included systems with one to several EH sources, different temperature levels ranging from low-temperature EH to high-temperature industrial streams, and diverse spatial settings, from compact industrial clusters to urban DHS. The workflow was also applied to networks of varying sizes and routing complexities, and to DHS operating at various temperature levels, defined by user-specified supply and return temperatures.

The ability to apply the same analytical workflow across these varied contexts without significant structural changes demonstrates the framework's transferability. In particular, the modular structure of the workflow, with clearly separated exergy screening, network optimisation, and long-term techno-economic optimisation, allowed the framework to adapt to different problem settings while maintaining internal consistency. These applications confirm that the framework is not tailored to a single case study but can be applied more broadly to support EH integration planning across diverse geographical, technical, and infrastructural contexts.

The experience gained from these additional applications also provided practical insights into the workflow's applicability and behaviour under varying assumptions and data availability. The main validation procedures and quantitative evidence arising from these applications are synthesised and discussed in more detail in Chapter 5, where the transferability and generalisability of the framework are assessed across cases. These results also motivate extending the framework to longer time horizons, where future system evolution and changing market conditions shape EH's value.

Extending the framework to longer time horizons

The applications of the framework in the Volos case and the EMB3RS platform use an investment horizon of around ten years. This is useful for understanding short-term system development, but it also has limitations. Energy systems are transitioning quickly as countries move towards more sustainable technologies, and these wider changes will also affect the role and value of EH in the future. When designing extensive infrastructure such as a DHS, a planning horizon of only ten years may miss significant long-term shifts in fuel prices, grid mixes, technology costs, or policy conditions. A more extended analysis period of around 25 to 30 years would therefore provide a more realistic view of how the system could evolve and how EH might perform under future conditions. This longer horizon is consistent with the

typical technical lifetimes of DH infrastructure, in which network assets often operate for 30–50 years, and major generation units are depreciated over 20–30 years. Extending the ESOM to a longer horizon is possible, although it would require careful handling of time resolution and computational effort. Even so, longer-term modelling would help capture the full range of future system changes and support more robust investment planning. While OSeMOSYS was run at an hourly resolution in [P2], it does not account for operational constraints such as start-up times and costs, hourly temperature variations, and the effects on HP COPs, among others. In addition, running OSeMOSYS at hourly resolution for a longer modelling horizon of around 25–30 years is computationally expensive. Therefore, the framework is extended to include an operational optimisation model, serving as a subsequent step to validate the optimised capacities generated by OSeMOSYS. The development of the framework is explained in the next section.

3.5 Multi-Model Framework: Version 2 - Integrating operational optimisation

In response to the identified need to complement the framework with detailed operational analysis, a dispatch model was incorporated. In this study, the HotMaps Dispatch Model is used to analyse short-term DHS operations at high temporal resolution.

3.5.1 Hotmaps Dispatch Model

The long-term planning results from OSeMOSYS are complemented by a short-term operational analysis at high temporal resolution using the open-source Hotmaps Dispatch Model, developed within the Hotmaps project [152], [153]. Although the Hotmaps Dispatch Model has been applied to national-scale heating-system planning as part of the Hotmaps project, Djørup et al. have identified it. [154] as particularly relevant for regional-scale heat planning. This thesis uses it to evaluate the operational feasibility of OSeMOSYS investment strategies for integrating EH into DHS at the city level. This ensures that the long-term capacity expansion pathways are technically viable under realistic hourly demand and supply conditions.

The Hotmaps dispatch model applies a MILP approach to optimise the hourly dispatch of DHS with EH sources over a representative year. The objective function of the tool is to minimise the total system cost. This includes fuel, operation, maintenance, and emission-related costs, with the option to include investment costs if required. Although the model offers both investment-only and combined investment-and-operational optimisation modes, its investment capabilities are limited to a single target year, making OSeMOSYS more suitable for long-term capacity planning. In return, the number of inter-annual time slices in OSeMOSYS can be reduced, with Hotmaps being more computationally efficient for analysing hourly-resolution data.

3.5.2 Framework architecture

Along with the addition of the dispatch model, the framework also includes other changes to enable the analysis of an existing DHS. These adaptations are primarily driven by the transition from a new DHS design problem to an existing DHS context, and they also reflect methodological insights gained from the earlier application of the framework. The extended

multi-model framework is developed and applied in [P4] of this thesis. An overview of the workflow is shown in Figure 18.

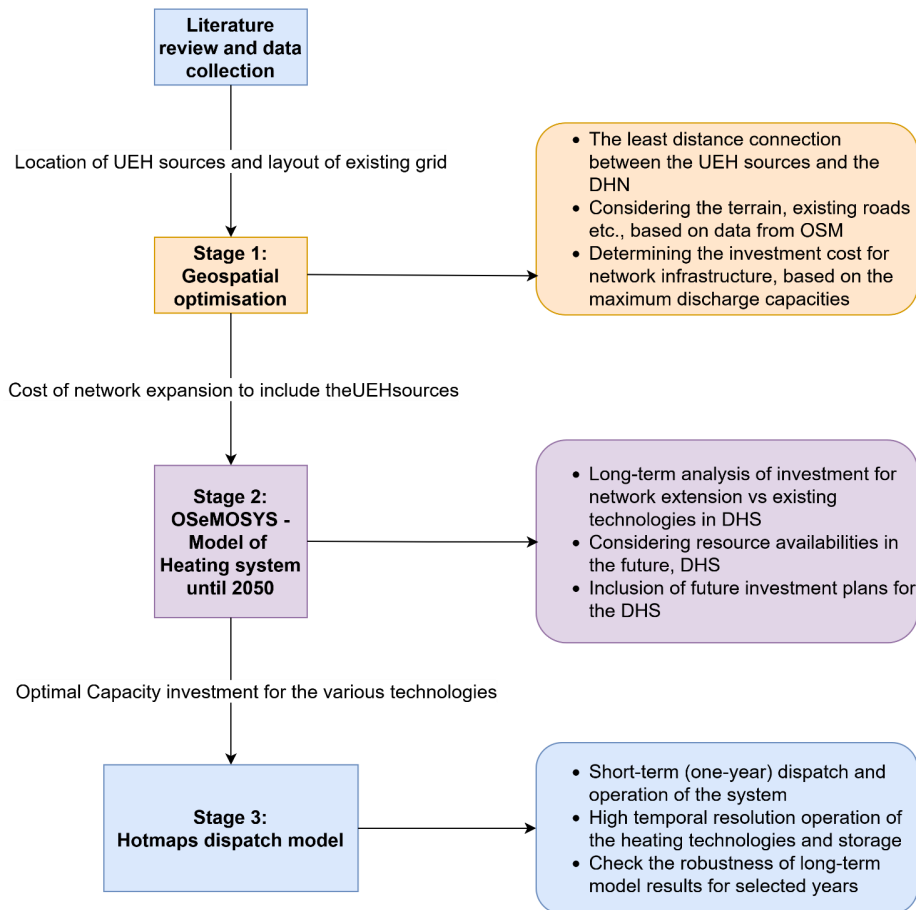


Figure 18: Methodology of the multi-model framework applied in [P4], illustrating the integration of geospatial optimisation for network expansion, long-term investment planning using OSeMOSYS, and high-temporal-resolution operational analysis using the Hotmaps dispatch model.

In the previous case, the wide range of source temperatures required a detailed exergy analysis to distinguish between sources that could be connected via heat exchangers and those that required HPs, and to assess exergy destruction in high-temperature sources. In contrast, in the present case, all UEH sources operate at temperatures below the grid-supply temperature and therefore require temperature-boosting technologies to recover heat. This condition is inherent to the case design (described in Section 3.5.3), making the choice of conversion technology unambiguous and eliminating the need for additional exergy-based screening. Consequently, the exergy analysis tool was not applied in this case, as it would not have provided further insight.

This selective use of modelling tools demonstrates the flexibility and modularity of the proposed framework, in which individual components can be added or removed based on case-specific characteristics without compromising the internal consistency of the overall analysis. The model components continue to interact coherently, ensuring that the system-level representation and optimisation logic are preserved. This modular structure allows the framework to adapt to different problem formulations while maintaining methodological rigour. The following section, therefore, presents each stage of the workflow in detail, explaining the role of each model component and how they interact.

Stage 1 – Geospatial optimisation and non-iterative link for existing DHS

Stage 1 consists of geospatial optimisation with a non-iterative link for an existing DHS. In [P4] of this thesis, the framework is adapted to an existing network context in which the main network topology and routing are fixed. In this setting, the geospatial optimisation tool is used only to optimise each potential new connection and determine its capital cost and associated heat losses, rather than to optimise network layout. These outputs are expressed as specific costs per MW of transfer capacity and specific losses per MWh and are passed directly to OSeMOSYS. Since these parameters are independent of the investment and dispatch decisions made within OSeMOSYS, an iterative feedback loop is not required to alter their values. Instead, each potential connection between an EH source and the existing network is represented in OSeMOSYS as a separate technology with fixed capital cost and efficiency parameters derived from the spatial analysis. This modelling approach, including the representation of network extensions as technologies, is described in detail in [P4] of this thesis.

Stage 2 – Long-term capacity expansion optimisation in OSeMOSYS until 2050

The calculated network costs and losses are transferred to OSeMOSYS, which evaluates the long-term viability of extending the network and integrating EH sources. OSeMOSYS optimises investments in technologies and grid extensions, as well as their operation, to find the least-cost mix for the entire DHS. This allows EH to compete with other supply options while considering detailed technology representations and dynamic investment planning. Therefore, OSeMOSYS determines which sources are cost-effective to integrate into the network. At this step, some sources are integrated into the heat-generation mix, while others are excluded based on cost-effectiveness. The main outputs include the cost-optimal capacities of EH sources, the heat they deliver each year and at each time step, and the required investments and operations for other DHS technologies.

Stage 3 – Operational validation with Hotmaps

While OSeMOSYS was run at an hourly resolution in [P2], it does not account for operational constraints such as start-up times and costs, hourly temperature variations, and the effects on HP COPs, among others. In addition, running OSeMOSYS at hourly resolution for a longer modelling horizon of around 25-30 years is computationally expensive. Therefore, an operational optimisation model that accounts for these constraints is used as a subsequent step to validate the optimised capacities generated by OSeMOSYS. The installed capacity of each OSeMOSYS technology is used as an input to the dispatch model. The model optimises the hourly dispatch of all generation and storage assets over a year, ensuring the long-term plan is

operationally feasible under realistic demand, weather, and electricity-price profiles. The Hotmaps model minimises operational costs while meeting hourly demand, capturing start-up/shut-down constraints and part-load efficiencies where applicable.

The multi-model framework, extended with operational optimisation, was also applied to a real-world case study. The case application focused on evaluating the integration of UEH sources in an existing DHS in Stockholm, Sweden.

3.5.3 Case Application 2 – An existing District Heating System in Stockholm

The Stockholm DHS serves as a case study for applying the modelling framework to an existing, large-scale network. With over 2800 km of pipelines and 80% of buildings connected, it is among the most extensive DHS networks in Europe [155]. The system is supplied by a diversified mix of heat-generation technologies, including biomass- and MSW-based CHP plants, heat-only boilers, large-scale electric HPs, and backup fossil-fuel-based boilers. The current heat generation mix is shown in Figure 19 and a schematic layout of the existing DHS infrastructure used in the model is provided in Figure 20 [156]. This layout is simplified to preserve confidentiality, but it retains the central nodes and interconnections relevant to spatial optimisation.

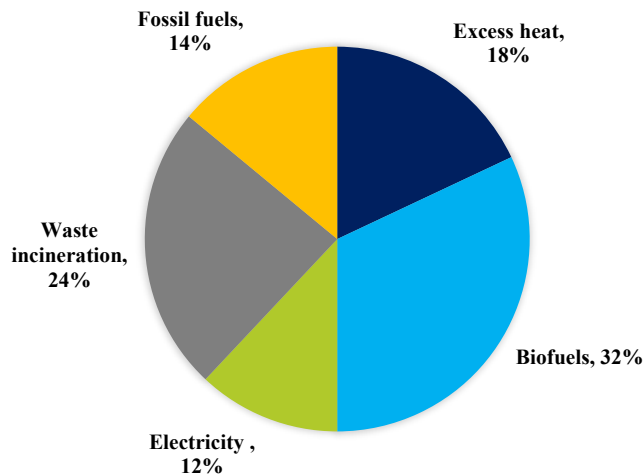


Figure 19: Heat generation mix in the Stockholm DH system in 2023, showing the shares of biofuels (32%), waste incineration (24%), excess heat (18%), fossil fuels (14%), and electricity (12%) [155].

The system operates with a maximum supply temperature of 100°C and a maximum return temperature of 56°C at the design outdoor temperature of -20°C. A reference weather-dependent supply temperature control curve from the Stockholm DHS is applied to the hourly outdoor temperature profile to generate hourly supply temperatures over the year, with a corresponding weather-dependent return temperature profile, as shown in Figure 21 [157].



Figure 20: Approximate representation of the Stockholm DH network (DHN), showing the main transmission lines and network extensions across the Stockholm region [156].

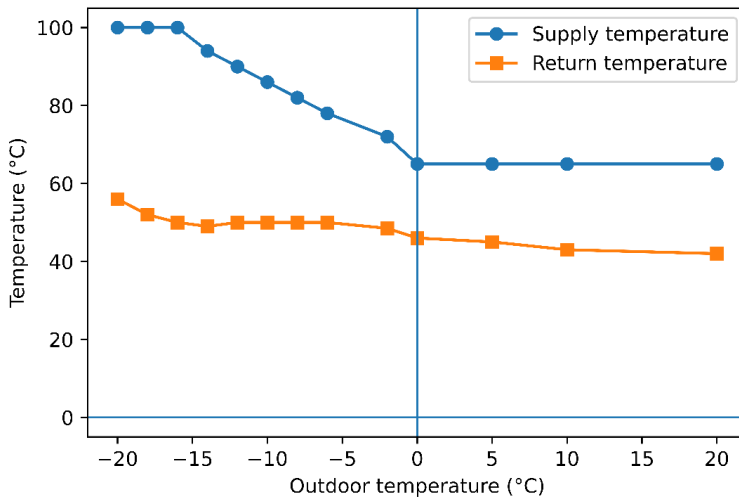


Figure 21: Reference weather-dependent supply and return temperature control curves used in the Stockholm DH case study. For each outdoor temperature, the curves specify the corresponding network supply and return temperatures applied in the model.

Since the performance of HPs depends on the temperature at which heat must be delivered to the end user, the relevant temperature level in the model is the delivery temperature at the customer side, not the plant-level supply temperature. The weather-dependent supply and return temperature profiles are therefore translated into hourly delivery and return temperatures at the customer interface. From these hourly series, demand-weighted annual averages are calculated. The demand-weighted annual average delivery temperature is 66 °C, and the corresponding average return temperature from the customer is 50 °C.

The use of an annual average temperature in OSeMOSYS is necessary because the model does not allow the COP of HPs to vary dynamically with hourly temperature changes. Instead, a representative sink temperature must be specified to determine a constant COP for each year. The demand-weighted value is used because it reflects the temperature level at which heat is effectively delivered over the year, accounting for variations in heat demand. Therefore, in OSeMOSYS, the 66 °C delivery temperature is used as the required sink temperature for calculating the COP of HPs. In contrast, the dispatch model retains the full hourly temperature series, allowing the COP and system operation to reflect exact temperature-dependent variations over time.

The city of Stockholm has significant available potential for UEH recovery [155]. In the case of Stockholm, UEH refers to thermal energy generated as an unintended by-product of commercial, service, or infrastructure activities within urban areas, remaining after internal heat recovery and otherwise discharged to the environment. UEH originates from non-industrial sources such as data centres, supermarkets, sewage treatment plants, subway stations, and ice rinks. These sources are distributed throughout the city and vary in temperature and annual heat-recovery potential. The locations and distribution of these sources are illustrated in Figure 22, while Table 15 summarises the UEH source types, temperature ranges, and estimated heat availability. In Table 15, the term ‘available excess heat’ refers to the amount of heat that can be delivered to the DHS after temperature upgrading using HPs and therefore represents the technically recoverable potential at the required supply temperature. These UEH streams were georeferenced and entered into the geospatial optimisation tool to assess the feasibility of integrating them with the existing DHS.

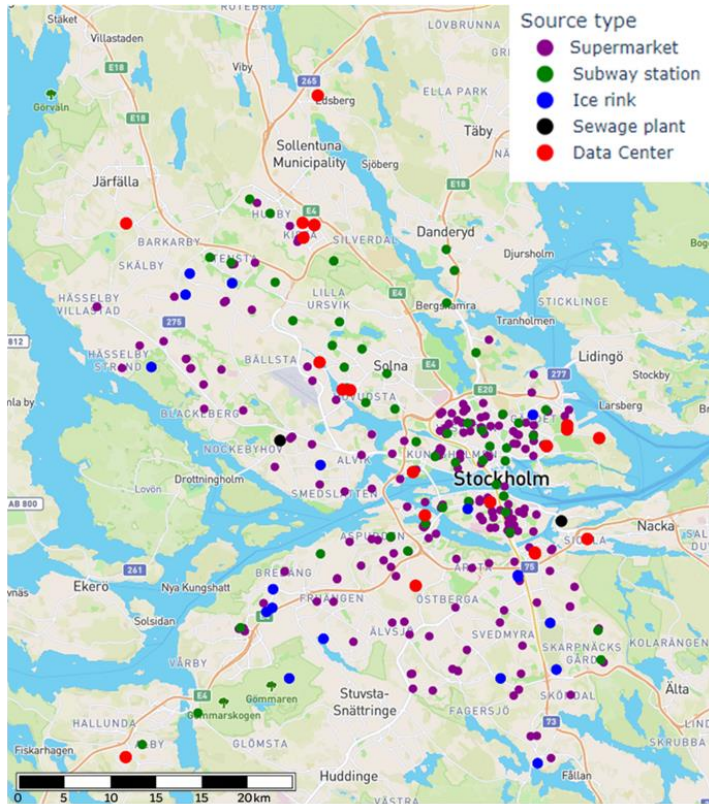


Figure 22: Spatial mapping of urban UEH sources in Stockholm, showing the locations and types of potential sources, including supermarkets, subway stations, ice rinks, sewage plants, and data centres [155].

Table 15: UEH sources in Stockholm [155].

Source Type		Available EH Per Year (GWh)	Average Source Temperature (°C)
Data centres		3200	40
Sewage Plant		36	12
Low-Temperature Sources	Subway Station	58	12
	Ice Rinks	20	7
	Supermarket	316	19
Grand Total		3630	-

The Stockholm case (further detailed in [P4] and [P5]) addresses RQ2 by demonstrating how the framework can be applied in a large, complex DHS with spatial constraints and established operational practices. The system faces several long-term challenges, including higher biomass prices, reduced MSW availability, and stricter emission targets, while a large amount of UEH remains unused. The model output focuses on feasible, cost-effective pathways for integrating

more UEH into the network under changing market and policy conditions. The results provided the utility with insights into suitable source locations, the timing of integration, and the long-term cost and risk implications of different pathways in the future DH scenarios.

Model setup and temporal resolution

The long-term optimisation considers the development of the DHS in Stockholm and the inclusion of UEH sources over a 28-year horizon from 2023 to 2050. The base year is set as 2023, aligned with available demand and supply data. To maintain computational feasibility in the large-scale system context, the intra-annual resolution is set to 288 Time Slices, constructed from 12 representative days (one per month), each with 24 hourly time steps. Each step aggregates all corresponding hours across the year, capturing seasonal and daily variations but not intra-week dynamics, such as workdays versus weekends. In addition to the regular time steps, 12 peak TimeSlices are introduced to capture the highest-demand hours in the DHS, enabling the model to reflect key baseload-peak dynamics. This adjustment enhances the accuracy of capacity expansion decisions by more closely aligning long-term investment outcomes with short-term operational requirements. Since the Hotmaps dispatch model was used to validate operational feasibility, it was not necessary to represent hourly-resolution data directly in OSeMOSYS. The choice of 288 TimeSlices is supported by earlier studies, which found minimal differences in investment decisions and system costs between 288 and 576 TimeSlices, while computation time nearly doubled [147]. This suggests that 288 intra-annual TimeSlices may represent a practical compromise between temporal accuracy and computational efficiency for long-term DHS planning using OSeMOSYS.

Data, modelling considerations, and assumptions

For the Stockholm DHS case (detailed in [P4] and [P5] of this thesis), detailed information on existing capacities, heat generation technologies, and demand profiles was obtained directly from the DH utility, Stockholm Exergi [158], [159], supported by publicly available mapping of urban EH sources [155]. Techno-economic parameters for both existing and potential new technologies were sourced from the Danish Energy Agency's technology catalogue [160]. Fuel price projections were based on 2023 market data [161], [162], [87], while electricity price trajectories and emission intensities followed national energy targets and published projections [163], [164], [165], [166]. Emission intensities are consistent with Sweden's target for fossil-free electricity by 2040 [164], [165]. In this thesis, biofuel use in DHS is assumed to be zero-emission. However, MSW use is associated with emissions (as explained in [P4]). Where primary data were unavailable, regionally appropriate values from peer-reviewed studies and international databases were applied.

Stockholm DHS - scenario design

The integration of UEH sources into the Stockholm DHS was assessed under four scenarios defined by two key parameters: electricity price level and network supply temperature. UEH sources generally require temperature boosting via HPs, with techno-economic performance determined by the temperature lift and electricity cost.

The scenarios considered are:

- High Temperature (HT) – Current supply/return temperatures at sink (66 °C/50 °C) maintained until 2050.
- Low Temperature (LT) – Progressive reduction of supply and return temperatures at sink, respectively, to 60°C/40°C by 2030, 50 °C/30 °C by 2040, and 45 °C/25 °C by 2045.
- High Electricity Price (HE) – 100% renewable-based electricity system with high price fluctuations [163].
- Low Electricity Price (LE) – Constant nuclear share at 2022 levels, leading to lower price fluctuations [163].

Therefore, in combination, there are four scenarios:

- High temperature and high electricity prices (HTHE)
- High temperature and low electricity prices (HTLE)
- Low temperature and low electricity prices (LTLE)
- Low temperature and high electricity prices (LTHE)

Since HP efficiency depends on the required temperature lift, the COP for each UEH source was calculated using a Carnot-based approach [167].

The ideal Carnot COP was first computed as:

$$COP_{carnot} = \frac{T_{sink}}{T_{sink} - T_{source}}$$

Where T_{sink} and T_{source} are sink and source temperatures expressed in Kelvin. The actual HP performance was then assumed to be 50% of the Carnot COP, representing typical commercial large-scale HP performance under real operating conditions [167]. As network temperatures decrease over time, the required temperature lift decreases, resulting in higher COP and lower electricity input per unit of delivered heat. This improves the relative performance of UEH-based HPs in LT scenarios compared to higher-temperature networks. Further details are provided in [P4] of this thesis.

3.5.4 Results: Stockholm Existing District Heating System

Three main UEH source types were identified based on the EH supply temperature: data centres, sewage treatment plants, and low-temperature sources such as ice rinks, supermarkets, and subway stations. Out of 298 candidate sources, 201 were cost-effective to integrate in the heat generation mix based on the long-term cost optimisation in OSeMOSYS (Figure 23 and Table 16).

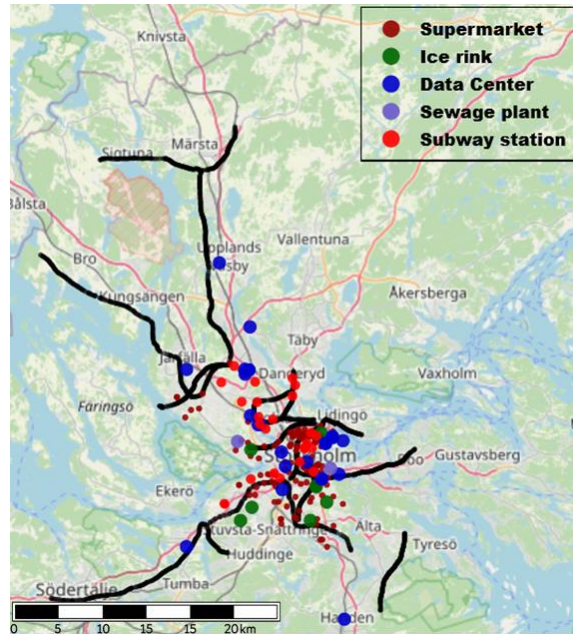


Figure 23: Selected UEH sources in Stockholm were considered in the analysis, which shows the locations of supermarkets, ice rinks, data centres, sewage plants, and subway stations relative to the existing DHN.

Table 16: Total and selected number of sources by source type

Sources		Total	Selected
Supermarket		188	136
Data centre		28	28
Low-Temperature Sources	Ice Rink	14	8
	Sewage Treatment	2	2
	Subway Station	56	27
Grand Total		288	201

In most scenarios, all data centres and sewage treatment plants were part of the cost-optimal heat-generation mix by 2035, while only a subset of smaller, low-temperature sources was integrated (Table 16). These smaller sources were generally located closer to the existing network (<4 km) due to their limited capacity, while larger sources, such as data centres, were feasible at distances exceeding 5 km (Figure 24-Figure 27). Figure 25 and Figure 26 presents the distribution of results using box plots, where the orange line indicates the median, the boxes represent the interquartile range (25th to 75th percentiles), and the whiskers show the full range of values across scenarios. The analysis indicates that connection economics are driven by both distance and capacity, with large-volume sources justifying longer network extensions. While this relationship is intuitive, the contribution here lies in the proposed framework's ability to

capture and quantify these effects simultaneously within a single, integrated modelling workflow.

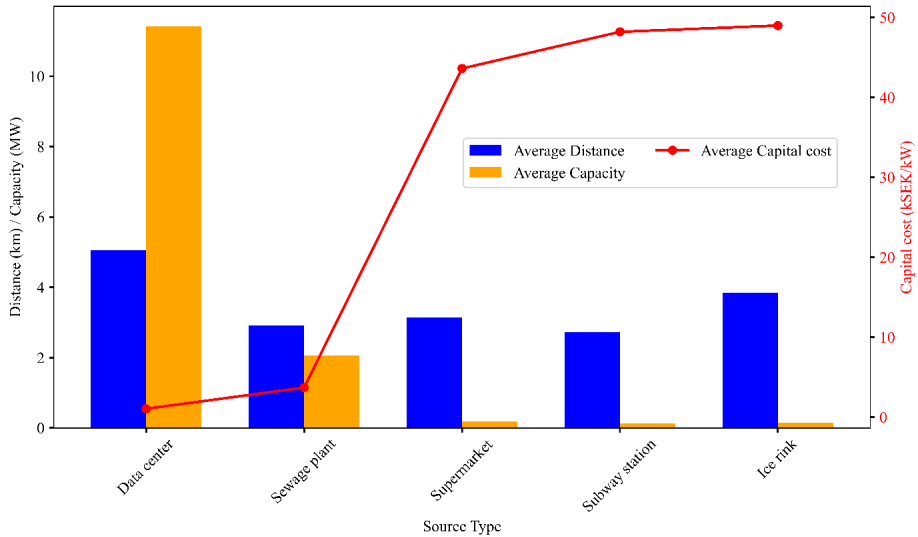


Figure 24: Comparison of geospatial optimisation results for different UEH source types, showing the average connection distance, average available capacity, and the corresponding average capital cost for network integration.

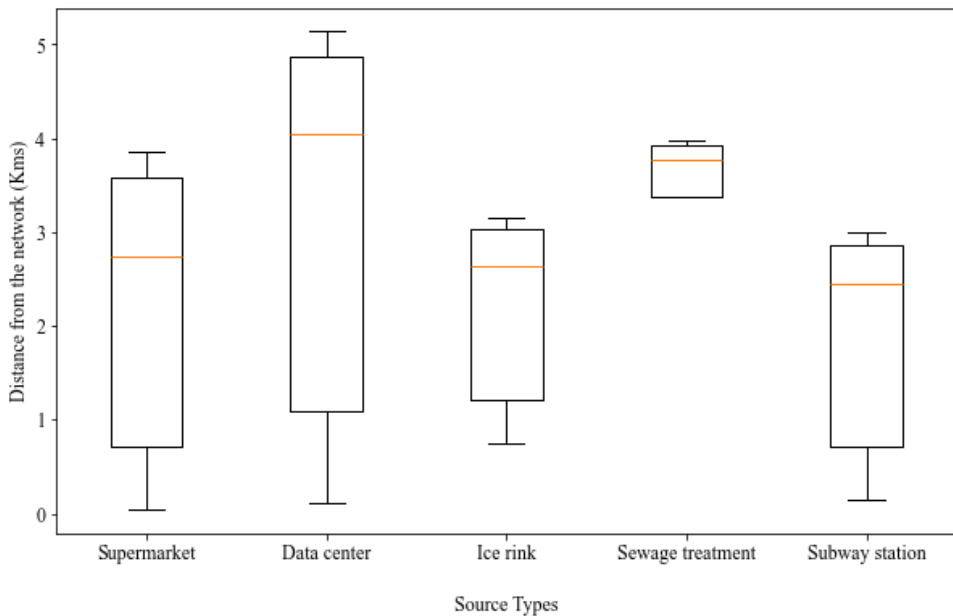


Figure 25: Distribution of connection distances for the selected UEH sources by source type, illustrated using box plots showing the range, quartiles, and median values for each category.

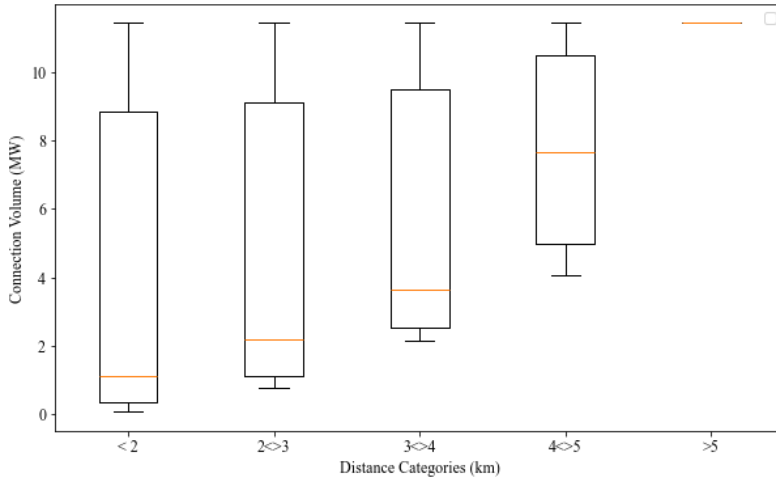


Figure 26: Distribution of connection capacities for the selected UEH sources across different distance categories, illustrated using box plots showing the range, quartiles, and median values.

The OSeMOSYS model part evaluates the role each source plays in the cost-optimal long-term (2050) investment plan for the Stockholm DH system. As shown in Figure 27 and Figure 28, data centre heat sources with HPs (DCHPs) were installed at their maximum available capacity in all scenarios, mainly because they require a relatively small temperature lift, resulting in high COPs. Also, their connection costs are low (Figure 27 - Figure 28). Sewage treatment plants as heat sources with HPs (STHPs) also made a substantial contribution, with older units replaced upon retirement and new capacity added as more facilities became available. Low-temperature sources with HPs (LTHPs), such as supermarkets, ice rinks, and subway stations, were more sensitive to electricity prices and network temperatures. These sources were rarely selected in high-price cases and performed best in low-temperature networks where COPs improved.

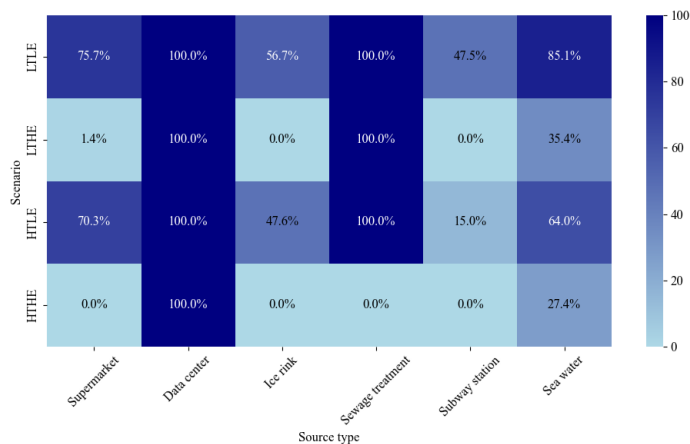


Figure 27: Share of heat recovery potential utilised in the cost-optimal solution in 2050 for each UEH source type across the analysed scenarios.

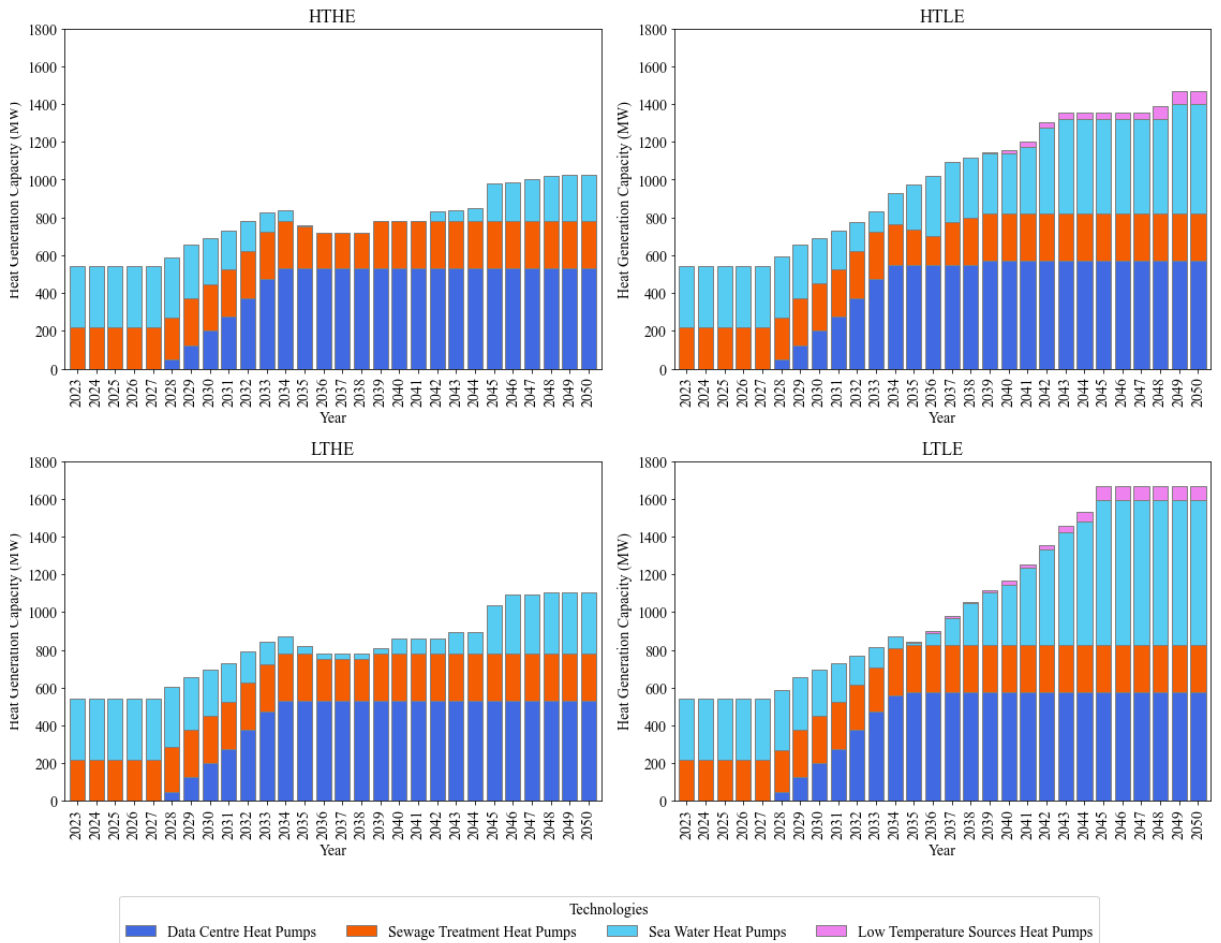


Figure 28: Cost-optimal installed capacities of UEH technologies in the Stockholm DHS across scenarios, showing the development of capacities for HPs using data centres, sewage treatment plants, seawater, and other low-temperature heat sources over time.

The share of heat provided by UEH varied over time and was affected more by electricity prices than by network temperature (Figure 29). Divergence between high- and low-price scenarios emerged after 2034, reflecting both electricity price dynamics and investment constraints (a comparison between the electricity price profiles and the EH share is provided in [P4] of this thesis). In low-price scenarios, UEH accounted for a substantial share of the supply, particularly from low-temperature sources, after 2045, when 5th-generation DH was introduced. Annual generation mixes (Figure 30) showed that, under favourable economic conditions, a large proportion of cost-effective heat supply would be sourced from UEH by 2050.

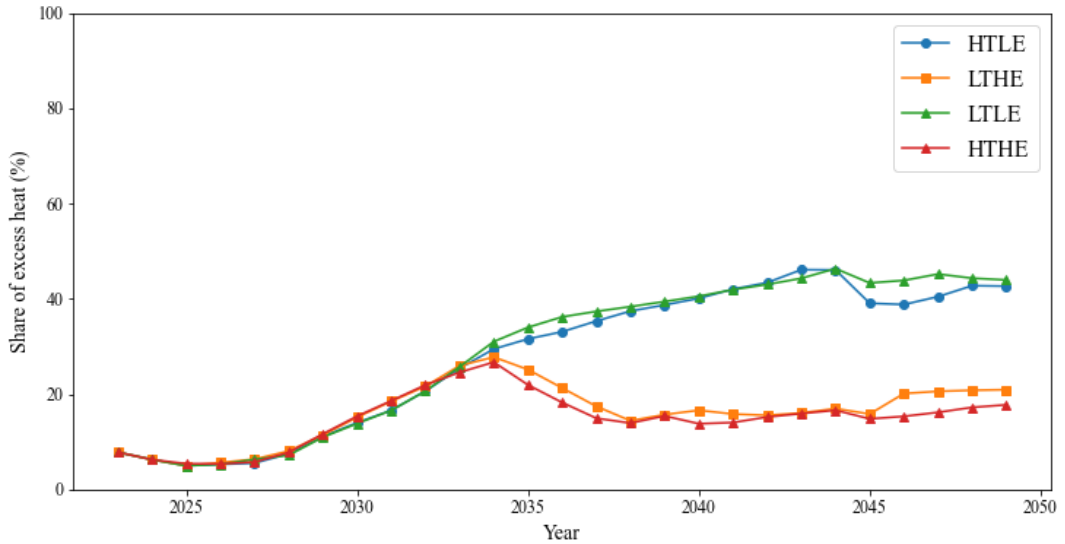


Figure 29: Share of total heat generation from UEH sources and existing sewage treatment HPs in the Stockholm DHS over time across the analysed scenarios.

The analysis by source type confirmed the cost-effectiveness of DCHP investments, with all scenarios remaining profitable. However, utilisation (MWh produced over the years) decreased in cases with high electricity prices. In low-price scenarios, DCHPs operated extensively year-round, charging storage during low-price hours. STHPs exhibited stable installed capacities but showed operational differences between scenarios, with higher full-load hours in low-price cases. Heat generation from LTHPs remained marginal, except at low temperatures and low prices.

The long-term DHS development also revealed how different technologies compete with one another. wood-chip CHP output was susceptible to electricity prices, displacing UEH in high-price scenarios. At the same time, waste-incineration CHP consistently operated at full capacity due to low marginal costs. However, heat generation from waste-incineration CHPs has decreased over the years due to constrained fuel availability. These shifts emphasised the DHS's dependence on the electricity market and MSW availability.

The operational optimisation confirmed the feasibility of all OSeMOSYS investment pathways, with the capacity invested being functional. However, notable differences in peak-hour dispatch were revealed (Figure 31). Bio-oil boilers were used more frequently in hourly optimisation than in long-term optimisation. Also, storage cycling patterns differed between high- and low-temperature scenarios. Operational modelling also indicated greater utilisation of DCHPs relative to seawater- and sewage-based HPs than OSeMOSYS, reflecting a more accurate representation of source-temperature variation.

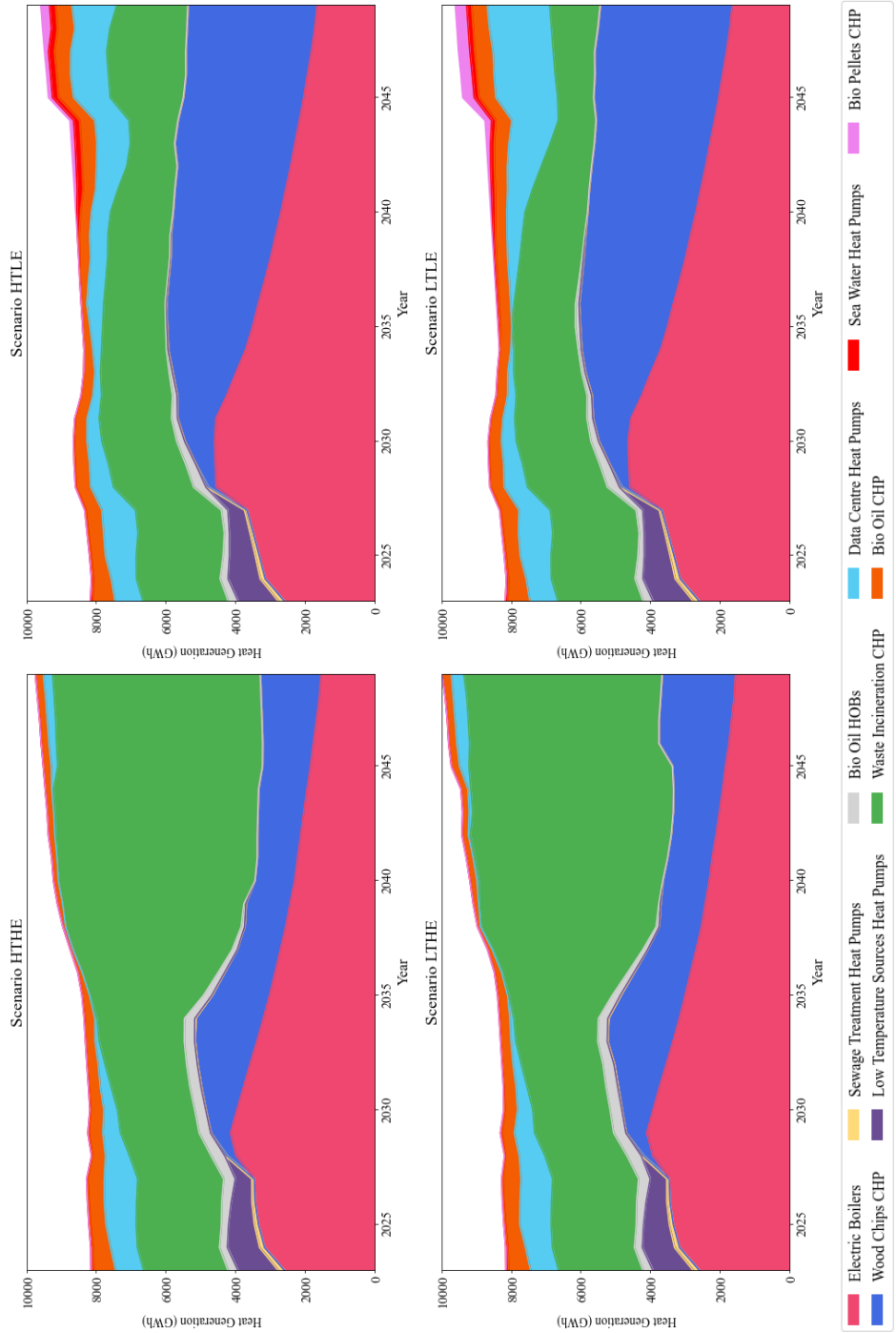


Figure 30: Annual heat generation mix in the Stockholm DHS across the analysed scenarios, showing the evolution of contributions from different heat supply technologies over time.

Overall, the results suggest that integrating UEH into an existing large-scale DHS can provide a significant and cost-effective supply under the right economic and technical conditions. The most important contributions come from high-grade, high-volume sources, such as data centres and sewage treatment plants, with low-temperature sources becoming viable when network temperatures are reduced and electricity prices are favourable.

Insights from the case for future development of EH-DHS integration

The Stockholm case shows how the multi-model framework can assess the realistic potential, limitations, and system impacts of integrating UEH into a large, mature DHS. A main result is the strong dominance of high-grade and high-volume sources, especially data centres and sewage treatment plants, which appear in all cost-optimal solutions. These sources remain profitable across all scenarios because they offer favourable COPs and lower per-MW connection costs. In contrast, low-temperature sources such as supermarkets, ice rinks, and subway stations are integrated only under favourable conditions, such as low electricity prices and reduced network supply temperatures. Their limited role highlights the importance of lowering supply temperatures, since this improves HP efficiency and increases the use of thermal storage, as shown in the operational optimisation results.

Competition from existing and planned CHP plants also shapes the integration of UEH. In scenarios with high electricity prices, wood-chip CHPs expand due to higher electricity revenues, thereby reducing the uptake of UEH. Meanwhile, waste incineration CHP continues to operate as a steady baseload unit, limited only by fuel availability. Taken together, these results underscore a broader strategic insight: in established DHSs, UEH can complement existing baseload units by improving flexibility, reducing reliance on biomass or MSW, and strengthening sector coupling. Its long-term contribution depends on market conditions, supply temperatures, and the behaviour of competing technologies, rather than solely on technical potential.

3.5.5 Modelling Advances and Methodological Insights – Existing District Heating System

Beyond the specific results for the Stockholm case application, the work also generated valuable modelling insights that helped refine and improve the integrated workflow for EH recovery planning.

Modelling advances achieved through spatial and operational integration

A key advancement of the framework is the ability to combine long-term cost optimisation with geospatial planning and high-resolution operational analysis. The integration of the spatial module provides essential benefits by identifying realistic, least-cost pipeline routes, estimating connection losses, and accounting for distance effects on the economic viability of different sources. This spatial detail enables location-specific assessments that would not be possible in a purely aggregated ESOM and helps distinguish between sources that are economically feasible to connect and those that are not. Similarly, integrating the operational dispatch model adds value by testing whether long-term investment decisions remain feasible under hourly fluctuations in heat demand, electricity prices, and HP performance. The dispatch model

enables the identification of peak-hour constraints, part-load limitations, and short-duration imbalances that the long-term model cannot capture. Together, these spatial and operational layers enhance the realism of the investment plan, ensure that key constraints are not overlooked, and show how specific sources become feasible only when both temperature compatibility and operational timing are considered.

At the same time, incorporating operational analysis raises important methodological questions about how dispatch-driven adjustments should be harmonised with long-term optimisation results. This naturally leads to the next section, which examines the interaction between local dispatch conditions and global system optima.

Integrating long-term investment and high-resolution operational dispatch

The comparison between long-term and operational optimisation models provided essential insights into system behaviour and the limits of relying on a single modelling approach. While all OSeMOSYS investment pathways were technically feasible, the hourly dispatch model indicated different priorities during peak periods and a stronger dependence on source temperature and electricity prices. These results indicate that long-term models can overestimate the use of certain UEH sources, posing a risk of stranded investments if operational conditions are not accounted for. At the same time, the operational optimisation alone cannot determine the optimal timing or scale of investments over the years in the face of changing demand, fuel prices, and policy targets. Combining the two approaches is therefore essential, as long-term optimisation identifies cost-optimal pathways, while operational modelling assesses their performance under realistic operating conditions.

Figure 31 compares the heat generation by technology between OSeMOSYS and the dispatch model in the winter month with the highest peak demand. The dispatch results show lower winter utilisation of low-temperature UEH due to high temperature lifts, offset by higher bio-oil boiler output. In contrast, UEH use increased during spring and autumn, when electricity prices were lower, and demand was moderate. OSeMOSYS smoothed seasonal variations, while the dispatch model captured sharper winter peaks and greater intra-seasonal variability. Figure 32 shows annual generation in 2050 across models and scenarios. The operational optimisation resulted in notably lower use of STHPs and SWHPs, which were replaced mainly by MSW-based CHPs and, in low-emission scenarios, by DCHPs and LTHPs. The MSW-CHP also operated slightly more often due to minimum-load constraints. These differences arise from the dispatch model's higher temporal resolution, which better captures seasonal temperature effects that limit HP operation in winter. The operational optimisation considers hourly profiles of supply and return temperatures, as well as the available temperature of the EH sources. This effect is not accurately represented in OSeMOSYS.

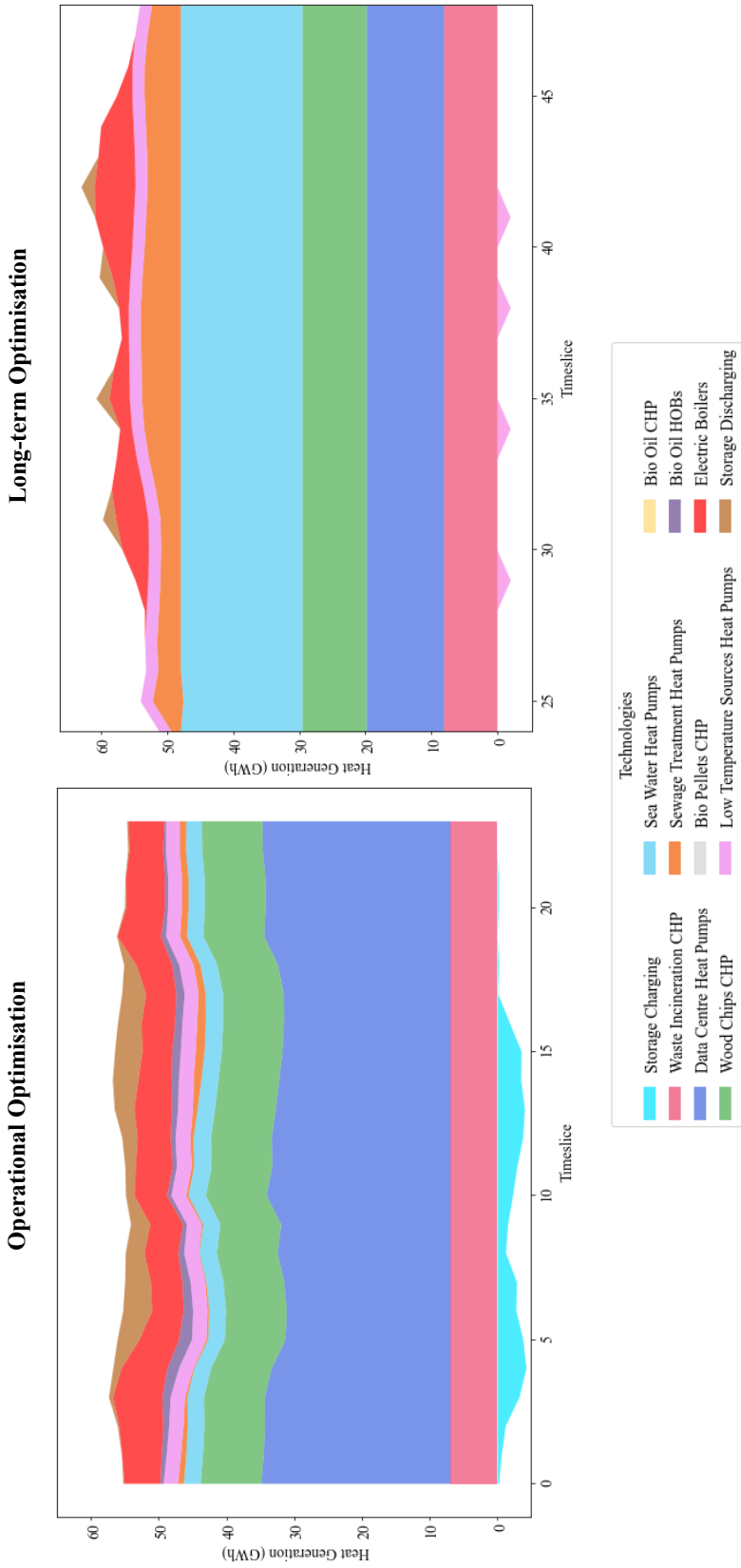


Figure 31: Comparison of intra-annual heat dispatch during the peak demand month, showing aggregated operational optimisation results (left) and the corresponding long-term OSeMOSYS dispatch representation (right)

Together, these findings show that combining long-term and operational optimisation gives a more realistic and reliable picture of UEH integration in large DHSs. Long-term modelling supports strategic investment planning, while operational optimisation ensures that these plans remain feasible under real operating conditions.

These comparisons highlight that capacity expansion models, even with relatively fine temporal granularity, cannot fully reproduce operational dynamics visible at the hourly resolution. This is consistent with earlier research showing that long-term optimisation models tend to overestimate the utilisation of intermittent or temperature-dependent resources if operational validation is not included [148], [168]. The results underscore the value of incorporating dispatch modelling into multi-model frameworks, not only to confirm feasibility but also to refine the understanding of how investment choices unfold under operational constraints.

Reconciling global and local optima

The differences between the two optimisation tools highlight a key challenge. OSeMOSYS minimises total system costs over several decades, while the dispatch model focuses on cost-optimal hourly operation within a single year. These differing objectives and time scales lead to discrepancies in the results, especially for temperature-dependent technologies such as UEH-based HPs. In high-UEH scenarios, OSeMOSYS often expands these technology capacities due to their long-term economic potential; however, the dispatch optimisation shows that their use is limited during cold winter periods when large temperature fluctuations reduce efficiency and increase electricity use. As a result, bio-oil boilers are used more often to ensure supply, as shown in Figure 31.

These findings emphasise the need for iterative or hybrid approaches that connect investment and operational models through feedback. Without this link, planners risk overestimating the value of some technologies and promoting investments that may be underused. Iterative coupling, already applied in the power sector to refine capacity dimensioning and reduce investment risk [169], [170] has not yet been widely used in DHS. Extending this to the current context would require modules that capture intra-annual variability in source temperature, outdoor conditions, and hourly demand [171]. Although computationally demanding, such a framework would align long-term cost-optimal pathways with operational feasibility, offering a stronger foundation for DHS planning. Together, the two optimisation layers provide a more complete representation of system behaviour and form a robust analytical basis for guiding long-term DHS investment planning.

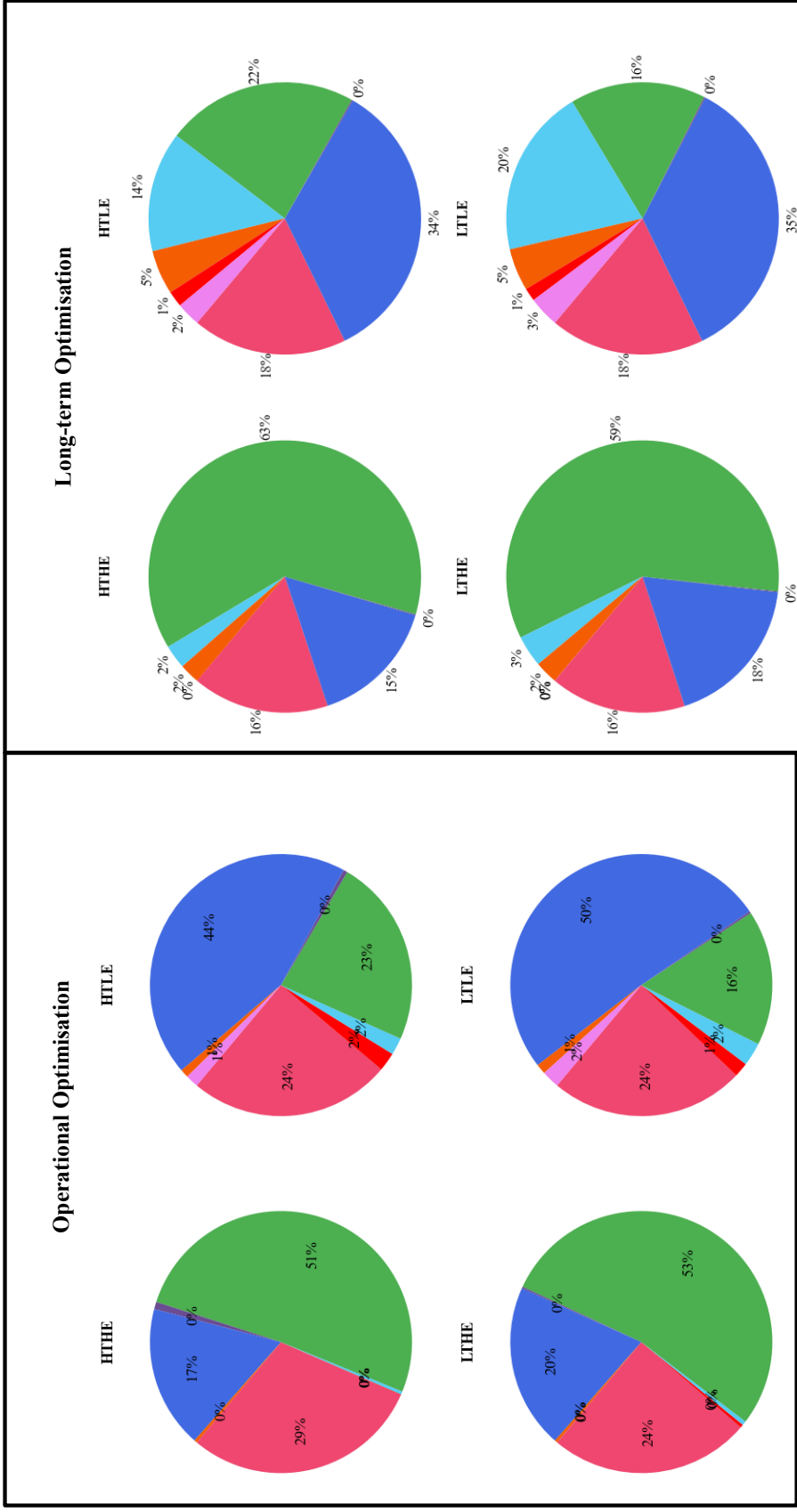


Figure 32: Share of heat generation by different technologies in 2050 across scenarios, comparing the results from the operational optimisation model (left) with those from the long-term OSeMOSYS optimisation (right).

Linking DHS modelling with power system dynamics

Another important insight from the Stockholm results is to consider the wider link between the DHS and the electricity system. In this analysis, electricity prices were treated as an input to the DHS, but in reality, the interaction goes both ways. CHP plants not only respond to electricity prices but can also influence market prices, especially in regions where CHP provides a large share of local generation. Ignoring this feedback can give an incomplete picture of CHP performance and future investment needs. A more detailed view could be achieved by linking the multi-model framework with a power system model, such as PyPSA [172]. Such a link would allow CHP output to affect electricity price formation, while also showing how higher shares of renewables, grid constraints, or changes in system adequacy influence DHS operation. This would help capture the combined effects of both systems and support more realistic planning for UEH, CHP, and DHS operations.

Need for a stochastic layer in DHS planning

During the model development stage for the Stockholm DHS case application, several rounds of discussions were held with the DH utility to validate assumptions on fuel prices, resource availability, and future system developments. These discussions showed that long-term DHS planning involves many uncertainties, which become even more critical when larger shares of UEH are included in the system. Key sources of uncertainty include changes in HP performance, variations in EH availability, future heating demand, and the cost and availability of biomass and MSW, as well as sudden events such as price spikes or unexpected source closures. To address these issues, the framework is extended with a stochastic layer that represents both continuous and discrete uncertainties. The following section presents the addition of the uncertainty analysis to the framework.

4 Multi-model Framework: Version 3 - Incorporating uncertainty and stochasticity

This Chapter presents the response to RQ3:

How can DHS be planned and adapted to integrate EH while remaining resilient to long-term uncertainties, systemic risks, and external shocks?

While the deterministic multi-model framework described in Chapter 3 can identify cost-optimal and operationally feasible EH integration strategies, it assumes no uncertainty in any of the key parameters. In practice, the decision environment is characterised by uncertainty in multiple dimensions, including technology performance, resource availability, fuel and electricity prices, and demand patterns. RQ 3 seeks to address this by introducing stochastic elements into the framework, enabling the development of investment and operational strategies that are resilient across a range of plausible futures.

Uncertainty in energy system planning can arise at multiple points in the modelling process. Following the classification by Walker et al. [173], relevant sources of uncertainty include: (i) *context uncertainty*, arising from the definition of system boundaries and the inclusion or exclusion of specific sectors; (ii) *model uncertainty*, linked to simplifications in the representation of thermodynamic or spatial processes; (iii) *input uncertainty*, due to incomplete or imperfect empirical data; (iv) *parameter uncertainty*, where fixed values such as technology lifetimes or efficiencies vary in practice; and (v) *outcome uncertainty*, reflecting the propagation of the above uncertainties through to the final results. The stochastic layer developed in this study directly addresses input and parameter uncertainties and assesses their implications for outcome uncertainty.

Stochastic optimisation offers a way to capture and quantify variability that deterministic models cannot. It uses probabilistic inputs, diverse scenarios, and robust formulations to explore alternative development pathways and to support investment strategies that remain effective under uncertainty. In energy systems research, such approaches are often used to represent variability in renewable generation, fuel prices, technology costs, and demand patterns [174], [175], [176]. Typical formulations include two-stage and multi-stage stochastic programming [89], Latin Hypercube Sampling (LHS) [177], global sensitivity analysis [178], chance-constrained optimisation [179], and Monte Carlo simulation [180], each providing structured ways to incorporate uncertainty into long-term planning. However, most existing applications to DHS remain limited to short-term operational analyses, underscoring the need for long-term, investment-oriented stochastic frameworks such as the one developed in this thesis.

4.1 Implementing Stochasticity in OSeMOSYS Inputs

To address the risks and uncertainties in long-term DH planning, this thesis extends the deterministic multi-model framework by adding a stochastic layer that captures both continuous and discrete uncertainties. The extended framework assesses the resilience of investment decisions to variations in key parameters, including HP performance, electricity prices,

biomass, MSW availability, and EH supply. OSeMOSYS remains the core model, representing investment and dispatch over a multi-decadal horizon, while the stochastic layer captures the most influential uncertainties that reflect real-world variability. The uncertainty layer is applied to the Stockholm case. As mentioned earlier, uncertainty in DHS planning was first raised during discussions with the utility while modelling the Stockholm case. While these discussions provided a starting point for identifying aspects of uncertainty, key uncertainty drivers were identified and motivated by reviewing technical, resource, and policy factors that influence the long-term viability, availability, and cost of heat sources and technologies in DHS planning (as presented in Section 1.2). These include:

- HP investment cost, influenced by refrigerant choice, ambient temperature, and regulatory shifts.
- EH availability, shaped by industrial activity levels, sectoral output, and risk of plant shutdowns.
- Heating demand, shaped by renovations of building stock, new connections, and ambient temperature
- Cost and availability of other key resources, such as biomass and MSW. In the case of MSW, the calorific value can also vary with recovery rates.
- Discrete shocks, such as electricity price spikes or abrupt EH source closures, are applied as overlays to continuous scenarios. Shock events are represented at both short and long-time scales, ranging from brief outages or price spikes to multi-year disruptions.

To represent these sources of uncertainty, the stochastic input space is created using a combination of LHS and Poisson-based shock modelling. LHS is used for continuous parameters such as HP investment costs, biomass prices, MSW availability, and calorific values. It provides a more even and representative sampling of each parameter's range compared to simple random sampling [181]. Poisson processes are used to model discrete shocks, such as electricity price spikes or unplanned EH source closures or outages, capturing their random timing over the planning horizon without needing detailed historical data [182].

Each model run represents one complete scenario. In each scenario, the model draws random samples for all continuous parameters and includes or excludes discrete shock events. This approach captures both gradual variability and sudden disruptions in the same scenario set. Each generated scenario is then run independently in OSeMOSYS, producing a complete set of investment and operational results. Table 17 lists the key parameters used in the stochastic analysis, their units, uncertainty type, and the method used to model variability.

To account for these uncertainties in OSeMOSYS, the system is disaggregated to represent each heat-generation plant and each EH source. Each year is divided into 288 intra-annual TimeSlices covering the years 2023 to 2050. Additionally, 12 peak slices capture extreme seasonal and hourly demand conditions, enabling realistic operational and investment decisions. The 12 peak slices were selected because they corresponded to the highest-demand and highest-electricity-price hours in the dataset, which were tightly clustered. Using more slices would increase computational cost, while using fewer would risk missing these critical

peak periods. These TimeSlices also provide the structure for implementing Poisson-driven shocks, such as outages or electricity price spikes, within the stochastic runs. The spatial and exergy constraints described earlier are retained to ensure that all investment strategies remain technically feasible.

Table 17: Key parameters and their uncertainty treatment in the stochastic framework

Parameter	Unit / Type	Uncertainty Type	Variation Range / Method	Distribution	Source
Biomass fuel price	SEK/MWh	Continuous (LHS)	±50% of baseline	Uniform	[160]
MSW availability	Fraction of baseline	Continuous (LHS)	50–100% of baseline	Uniform	[87]
EH availability	Fraction of baseline	Continuous (LHS)	40–100% of baseline	Uniform	[155]
HP investment cost	SEK/kW	Continuous (LHS)	Learning curve-based	Uniform	[160]
Heat demand trajectory	% annual growth/decline	Continuous (LHS)	–1% to +0.5% annually	Uniform	[183]
Industrial shutdown probability	Poisson event rate	Discrete (Poisson)	$\lambda = 0.05\text{--}0.8/\text{year}$	Uniform	Assumption.
MSW calorific value	Fraction of baseline	Continuous (LHS)	50–100% of baseline	Uniform	[87]
Electricity price spike events	Multiplier on price profile	Discrete (Shock)	1.5× to 3× price for specific TimeSlices	Uniform	Assumption.

The practical implementation of each uncertainty followed parameter-specific rules to ensure consistency and reproducibility across the scenario set. Continuous uncertainties were applied as multipliers or growth rates, replacing the annual values for 2023–2050. Discrete uncertainties were introduced via event logic that triggered parameter changes, causing shocks within the model. The sampled factors for continuous parameters and event probabilities for discrete shocks were drawn from the stochastic input space generated using LHS and Poisson-based modelling described earlier. The implementation details for each category are as follows:

- Fuel prices: Baseline cost values were multiplied by sampled factors drawn from the stochastic input space. These factors remained constant across all years, reflecting long-term price uncertainty rather than short-term fluctuations.
- Resource availability: Annual activity limits for key resources such as MSW were scaled using sampled factors to represent potential changes in supply over time. This allowed the model to test how resource constraints affect system development.

- Investment costs: Capital costs were adjusted using sampled factors that allowed both cost reductions, reflecting technological learning, and cost increases, representing risks or shifts to alternative technologies.
- Demand trajectories: Annual growth or decline rates were randomly sampled and applied to create consistent demand paths from 2023 to 2050. This approach ensured that long-term demand trends evolved smoothly over the modelling horizon.
- Fuel quality (calorific value): A three-part sampling method defined a baseline multiplier, a long-term target, and a trajectory exponent. These elements were combined to produce a monotonic change in fuel quality, reflecting gradual improvements or degradation over time.
- EH source shutdowns: Shutdowns were represented as Poisson events that determined whether and when a facility closed. Once a shutdown occurred, the affected source remained unavailable for all following years.
- EH supply outages: Outages were modelled as Poisson-driven short-term events that reduced output to zero for two consecutive TimeSlices. After the outage, supply gradually returned to normal over three to four slices.
- Electricity price spikes: Price spikes were simulated as Poisson-driven bursts lasting two to five TimeSlices. Each burst began with a sampled peak multiplier that gradually declined, and overlapping spikes combined their effects.

The implementation rules, including horizon-wide multipliers for prices and resource availability, recursive demand updates, and event-based logic used to represent outages and price spikes, are described in the supplementary information provided alongside [P5] of this thesis. After applying these uncertainty definitions, 200 stochastic scenarios were generated using the method described above. This scenario set represents a balance between the need to explore a sufficiently large uncertainty space and the computational cost of running multiple large-scale OSeMOSYS models. Test runs showed that doubling the number of scenarios increased computation time by over 90%, while yielding only minor improvements in post-processing results. In particular, the additional scenarios did not meaningfully change the formation of scenario clusters or the distribution of scenarios across clusters, confirming that the selected sample size was sufficient.

4.2 Analysis of investment Cluster and resilience in the stochastic framework

The stochastic scenario set was analysed using a structured post-processing workflow to identify representative investment archetypes, assess their resilience, and understand how key uncertainties influence system outcomes. The workflow includes steps for scenario clustering, performance evaluation, resilience assessment, and uncertainty driver analysis. Figure 33 presents an overview of this post-processing structure and its connection to the stochastic extension of the multi-model framework.

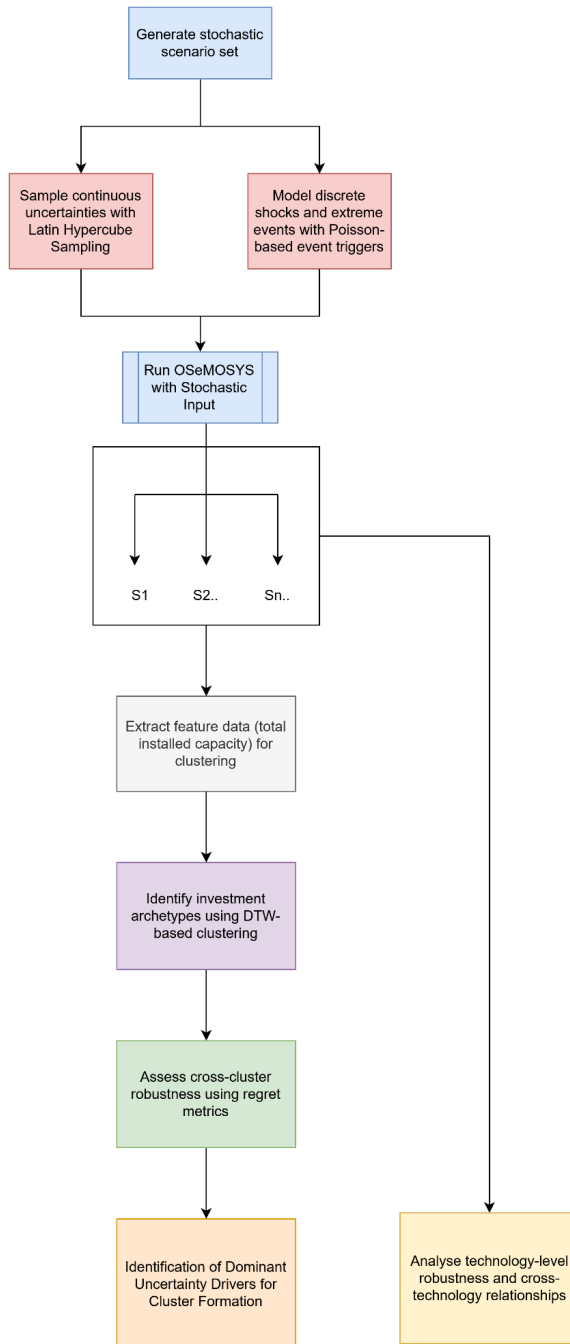


Figure 33: Workflow of the stochastic extension to the multi-model framework, showing the generation of stochastic scenarios using LHS and Poisson-based shocks, simulation with OSeMOSYS, and the identification and analysis of investment archetypes through clustering and robustness assessment.

The first stage of the post-processing identifies representative investment archetypes across the stochastic scenario set. Three feature types were tested to characterise investment behaviour: (i) annual new capacity additions, (ii) accumulated capacity, defined as the cumulative sum of yearly additions, and (iii) total installed capacity, which represents the operational capacity in each year after accounting for both new investments and existing capacity. These variables were tested in combination with K-means, K-medoids, hierarchical, and DTW (Dynamic Time Warping)-based clustering methods. Capacities were used as the clustering variable because they directly reflect long-term system structure, are comparable across scenarios, and avoid strong dependence on short-term operational conditions such as weather or hourly demand. Among the three options, total installed capacity provided the most stable and interpretable representation of system evolution. Annual additions and accumulated additions were more sensitive to short-term investment fluctuations, for example, shifts between consecutive years caused by cost shocks or temporary electricity-price changes, which introduced noise into the clustering results without altering the long-term system configuration. Total installed capacity, by contrast, captures the overarching technology mix and the system-level investment trajectory more consistently, making it the most appropriate feature for identifying robust archetypes.

Among the tested methods, DTW-based K-means was chosen for its ability to measure similarity between time-dependent capacity trajectories while allowing for differences in the timing of technology adoption. The optimal number of clusters was determined using multiple internal validation indices, including the silhouette, Davies–Bouldin, and Calinski–Harabasz scores, in combination with bootstrap resampling to verify clustering stability under stochastic variations [184], [185], [186].

After identifying the investment archetypes through clustering, Key Performance Indicators (KPIs) were calculated to compare their techno-economic and structural performance. The leading indicators include the Levelized Cost of Heat (LCOH) and emission intensity. To measure performance stability, the standard deviation of annual KPI values was used to represent variability, and the Conditional Value-at-Risk (CVaR) was used to capture downside risk [187], [188]. In this context, CVaR captures the severity of the worst-performing scenarios, reflecting the level of cost or emission risks the system would face under unfavourable future conditions. All indicators were standardised before analysis to remove scale differences and ensure comparable results across clusters. These KPIs were then used in the cross-cluster resilience assessment.

The resilience of each investment archetype was assessed using a cross-cluster regret approach based on the calculated KPIs. This method evaluates cross-scenario transferability by quantifying the penalty that occurs when a strategy optimised for one uncertainty cluster is applied under the conditions of another. For each pair of clusters (i, j) , the regret is calculated as the difference in the representative cost or emission intensity between the mean or worst-performing scenario in cluster i and the best-performing scenario in cluster j . The resulting regret, therefore, reflects how well an investment plan performs when used outside its optimal context. Clusters exhibiting low maximum and mean regrets are interpreted as robust and transferable investment strategies, showing minimal performance loss under alternative

uncertainty settings. Conversely, clusters with high regret values indicate strong dependence on specific price, policy, or technology conditions. The detailed calculation of regret is presented in [P5] of this thesis.

After evaluating the resilience of each cluster, the next step was to identify which uncertain input parameters most strongly influenced the cluster outcomes. This was done through a statistical variability analysis using the Relative Standard Deviation (RSD) method. For each uncertain parameter, the standard deviation of its cluster-wise mean values was divided by the overall standard deviation across the stochastic scenario set. This provided a relative measure of each parameter's contribution to the differences between clusters. The RSD method was compared with Analysis of Variance (ANOVA) F-tests and Mutual Information (MI) analysis, and it was selected because it offers higher numerical stability, is transparent, and can capture both linear and non-linear relationships without discretising (dividing the data into fixed groups before analysis) the data [189], [190], [191]. Variance-based global sensitivity methods, such as Sobol's or Morris screening, were not used because they require continuous output variables and far larger scenario sets, making them unsuitable for categorical outcomes, such as cluster membership, and for computationally intensive multi-model workflows.

After identifying the main uncertainty drivers at the system level, the analysis was extended to examine how individual technologies contribute to overall system stability. This step examines how technologies interact (e.g., HPs, CHPS, boilers), co-evolve, and persist under uncertainty through a set of complementary indicators that capture cross-technology and temporal dynamics. The analysis extends beyond single-technology performance to explore how investment and operational behaviours collectively shape system resilience. While the clustering analysis identified different archetypal investment pathways with distinct compositions of biomass, waste, and electrified heat sources, it did not reveal which individual technologies contribute most to these differences. Examining resilience and interaction at the technology level, therefore, provides insight into diversification effects and substitution patterns that improve system adaptability to uncertain conditions [192], [193], [194].

This step helps determine which technologies make the system more robust and which are more sensitive to uncertainty. A year-specific resilience index was calculated for each technology and year. Since the overall system configuration is built from combinations of technologies, greater stability in individual technology capacities across scenarios also contributes to a more stable and resilient system-level investment pathway. Cross-technology Pearson correlation matrices were also created to identify whether technologies act as substitutes or complements within the system. These results help explain how technology-level interactions shape the overall resilience of investment pathways. The detailed calculation of the resilience index and the Pearson correlation matrices are presented in [P5] of this thesis.

Together, these steps form an integrated framework that links stochastic input variation, clustering, resilience evaluation, and technology-level dynamics to assess the stability and adaptability of long-term DHS investment pathways. This is particularly valuable for long-term DHS planning, where investments made today will operate under future conditions that cannot

be predicted with certainty. The stochastic extension, therefore, enables a more resilient and strategic planning process, directly addressing RQ3.

4.3 Resilient District Heating Systems: Strategic Integration of Excess Heat under Uncertainty

This section presents the results of the stochastic analysis and resilience assessment of the DHS in the Stockholm case [P5]. The objective is to evaluate how uncertainties in electricity and biomass prices, EH availability, MSW characteristics, and investment costs influence long-term investment strategies and system evolution. The results highlight how investment pathways change under uncertainty, and which structural and technological factors drive their long-term stability.

4.3.1 Cluster Formation and System Archetypes

To identify structural patterns in stochastic investment trajectories, a comparative clustering analysis was conducted using K-Means, K-Medoids, Hierarchical, and DTW-based clustering. As explained in Section 4.1 these methods differ in how they group time-series data and measure similarity between trajectories. Each clustering technique was applied to three features – new capacity additions, accumulated capacity additions, and total installed capacity – to evaluate their clustering performance. Compactness and separation were assessed using silhouette scores⁴, while entropy-based metrics⁵ were used to verify the balance of scenario distribution across clusters. The results are summarised in Table 18 and show that clustering based on total installed capacity consistently achieved higher silhouette and entropy values than clustering based on other features (accumulated new capacity and new capacity). The DTW clustering technique further improved the quality of separation by capturing temporal similarity among investment trajectories, even when technology expansion phases occurred at different times. Consequently, DTW clustering of total installed capacities was selected as the most robust feature for identifying representative system archetypes under uncertainty.

Three distinct clusters emerged when DTW-based clustering was applied to the total installed capacity trajectories. As shown in Figure 34 each cluster represents a dominant long-term configuration of the DHS. Cluster 0 reflects a balanced electrification pathway, Cluster 1 is driven by biomass-based CHP, and Cluster 2 shows a hybrid mix shaped by EH variability. These clusters form the basis for the detailed analysis that follows.

These structural configurations arise from different combinations of external drivers within the stochastic framework. Variations in electricity price volatility, biomass price trajectories, HP capital costs, EH availability, and EH source shutdown frequency shape the relative attractiveness of electrified versus combustion-based technologies. The exact variations of

⁴ A metric that quantifies how well each scenario fits within its assigned cluster compared to other clusters, measuring both cohesion (similarity within a cluster) and separation (distance from other clusters). Higher values indicate clearer and more distinct clustering

⁵ An indicator of how evenly scenarios are distributed among clusters, calculated from the relative cluster sizes. Higher entropy reflects a more balanced partition, while lower values indicate dominance by a single or a few clusters.

these inputs across the identified clusters are presented in detail in [P5] of this thesis. The following paragraphs describe each cluster and interpret the capacity configurations in light of these differing input conditions. The clustering, therefore, reflects distinct system responses to quantified external drivers rather than arbitrary technology groupings.

Table 18: Comparison of clustering performance across feature representations and clustering techniques

Variable	clustering technique	Silhouette score	Size entropy	Largest cluster size %
New capacity	DTW	0.36	0.94	55.3
	Hierarchical	0.29	0.91	62.1
	KMeans	0.30	0.90	62.7
	KMedoids	0.14	0.76	64.4
Total capacity	DTW	0.48	0.99	47.3
	Hierarchical	0.33	0.97	54.2
	KMeans	0.35	0.99	46.8
	KMedoids	0.32	0.83	50.2
Accumulated capacity	DTW	0.42	0.99	45.1
	Hierarchical	0.30	0.99	50
	KMeans	0.31	0.99	47.7
	KMedoids	0.30	1.00	44.8

Cluster 0 represents a balanced and gradual electrification pathway, characterised by steady investment in EH-based HPs and SWHPs, with moderate investments in electric boilers from 2030 onwards. Biomass utilisation remains moderate, while UEH from data centres and sewage treatment sources increases progressively, with low-temperature UEH entering the system after 2040. wood-chip CHP expansion is minimal, and MSW CHP capacity declines significantly, indicating futures with low electricity prices and reduced MSW availability. A significant capacity of bio-oil boilers is installed to cover the system's peak demand.

Cluster 1 relies more on solid biofuels, particularly wood-chip CHP units, and shows limited expansion of electrified sources compared to Cluster 0. Substantial additions to CHP capacity after 2030 compensate for modest growth in data centre and seawater HPs. Bio-oil boilers are replaced mainly by CHPs and electric boilers, the latter operating at low utilisation during periods of cheap electricity. The capacity mix suggests a future of volatile, elevated electricity prices and slower escalation in biomass prices, leading to a conservative, low-risk investment strategy dominated by mature combustion technologies.

Cluster 2 presents a hybrid configuration combining features of the first two clusters. It exhibits the largest overall installed heat-generation capacity, ranging from 3.5 to 4 GW thermal, with significant investment in both data centre and seawater HPs, alongside moderate additions of bio-oil boilers and wood-chip CHPs. The simultaneous expansion of dispatchable and

electrified technologies suggests a future with moderate electricity prices but frequent EH outages and shutdowns, which necessitate greater total system capacity. Electric and bio-oil boilers, as well as CHPs, play complementary roles. While boilers compensate for temporary EH unavailability, CHPs provide backup during data centre shutdowns.

Cluster 0 shows a steady increase in EH utilisation, with DCHPs and SWHPs gradually replacing combustion-based generation. A temporary decline in EH output around 2040–2045 coincides with data centre shutdowns (Table 19), which are offset by higher wood-chip CHP generation. Cluster 1 remains biomass-dominated throughout the period, reflecting persistently high electricity prices that limit electrification, and exhibits an early reduction in MSW CHP generation, consistent with the rapid improvements in recycling. Cluster 2 achieves a balanced generation portfolio, maintaining moderate shares of biomass, electrification, and EH, but experiences reduced EH utilisation in the final decade due to recurrent outages. Increased operation of CHPs and electric boilers compensates for these losses, demonstrating operational flexibility in response to supply shocks.

The aggregate fuel mix evolution, shown in Figure 36, highlights these systemic contrasts. In Cluster 0, the share of EH increases steadily and reaches about half of total heat generation by 2050. Biomass use declines over time, and electrified sources play a supporting rather than dominant role. Cluster 1 evolves toward an increasingly biomass-centric configuration, with a biomass share exceeding 70% by 2040. Cluster 2 maintains the most balanced composition, with biomass (40–45%), EH (30–35%), and electrified sources (20–25%) contributing in relatively stable proportions. These contrasting capacity and operational profiles form the basis for the subsequent evaluation of cross-cluster regret and of the key uncertainty drivers that influence its formation.

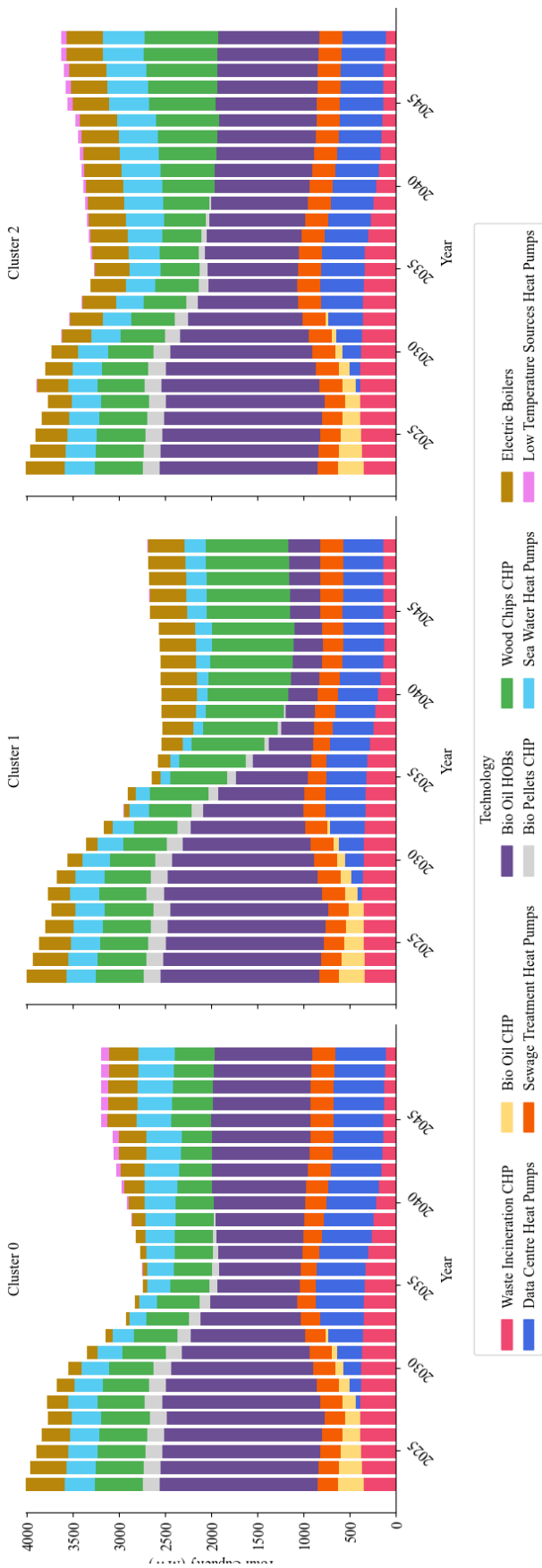


Figure 34: Mean total installed heat generation capacity by technology over time for each identified scenario cluster, illustrating the average investment trajectories across all scenarios within clusters 0, 1, and 2.

Table 19: Mean variation of inputs across clusters

Cluster	Normalised Biomass price variation	Normalised MSW recycling rate	Normalised HP capital cost	Number of data centre shutdowns	Number of EH source outages	Number of electricity price spikes
0	1.05	0.75	1.06	4	286	48
1	0.97	0.77	1.05	16	842	387
2	1.15	0.77	1.16	20	1050	94

While the preceding analysis characterises long-term investment patterns, the operational dynamics of these systems are reflected in the evolution of annual heat generation (Figure 35).

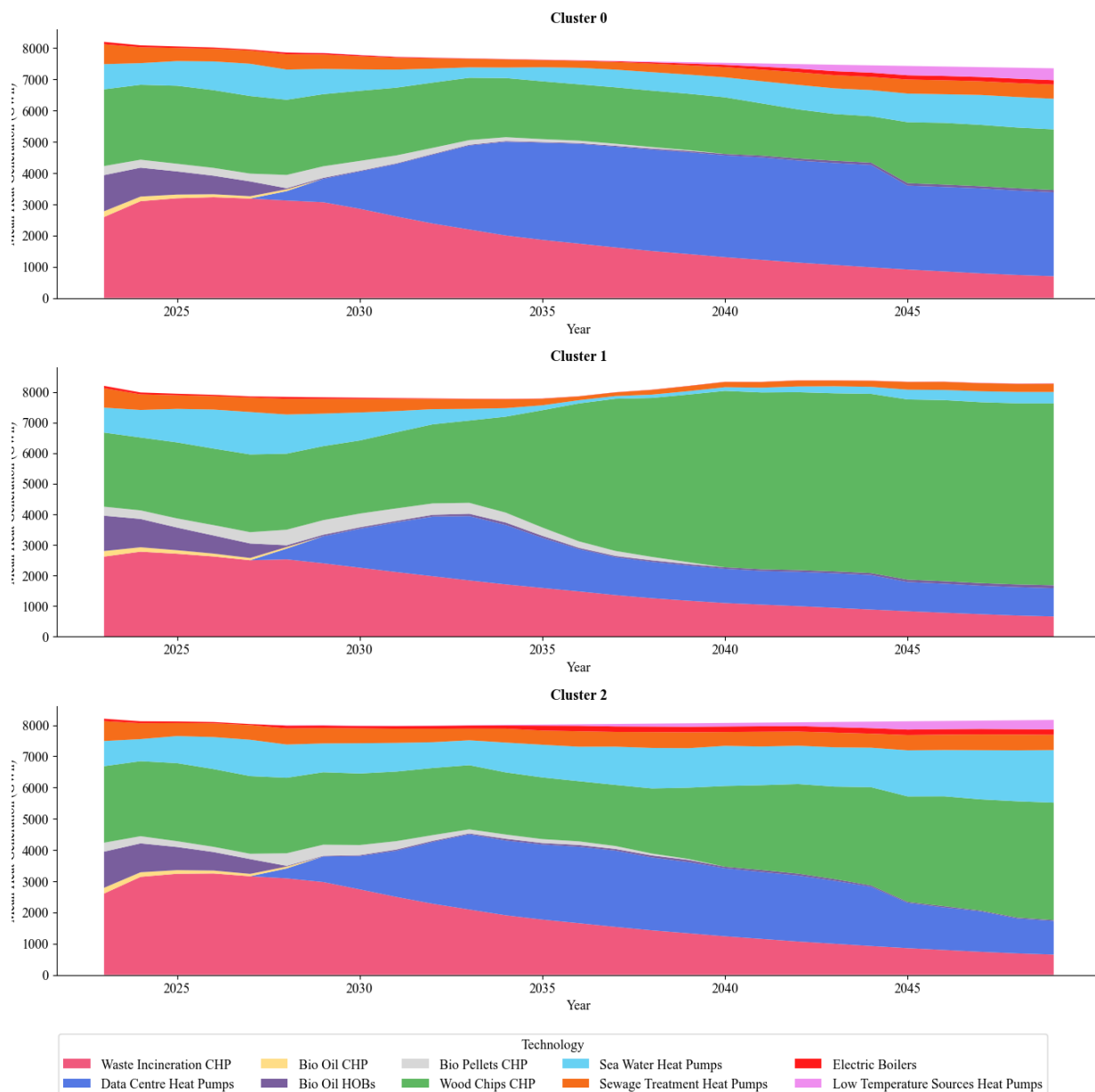


Figure 35: Mean annual heat generation by technology over time for all scenarios within each cluster, illustrating the average heat supply mix and its evolution across clusters 0, 1, and 2.

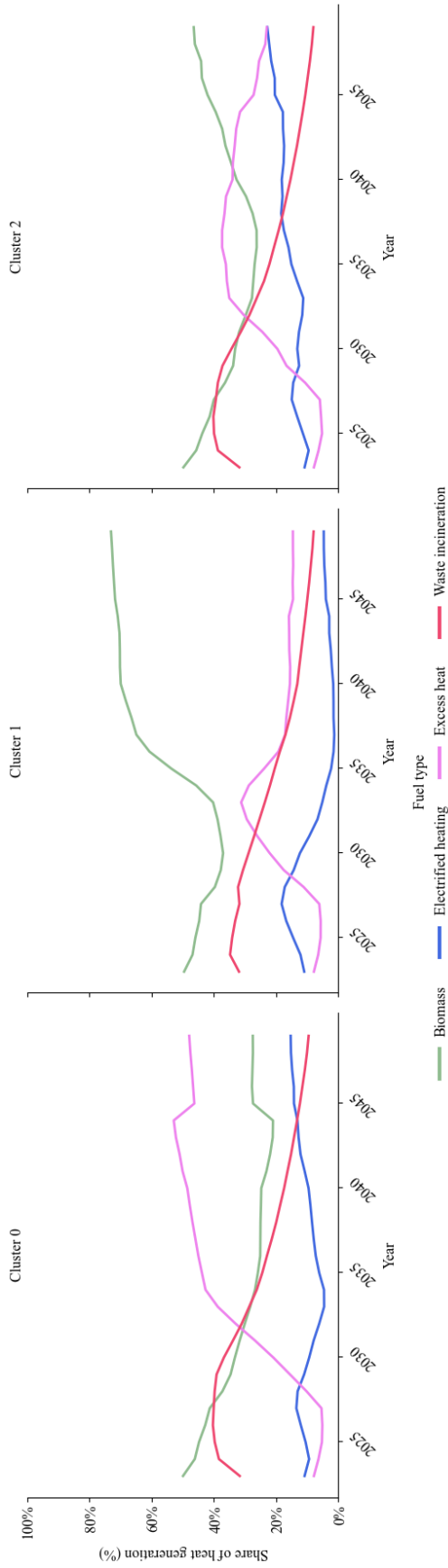


Figure 36: Evolution of fuel-type shares in total heat generation for each cluster, showing the contribution of biomass, electrified heating, EH, and waste incineration over time.

4.3.2 Key Performance Indicators (KPIs): Cost and Emission Outcomes

The techno-economic and environmental performance of the identified system clusters was evaluated using two core indicators: LCOH and heat generation emissions intensity. Figure 37 and Figure 38 illustrate the LCOH and emission intensity trends, respectively. Together, these indicators reveal how affordability and decarbonisation evolve under uncertainty and differ across system archetypes.

Across all clusters, the LCOH declines steadily throughout the modelling period. Cost reductions in emerging technologies, along with the progressive electrification of heat supply and improved access to low-cost heat sources, drive this reduction. Over time, reliance on fuel-based generation decreases, while EH recovery and HPs play a larger role in the supply mix. These technologies benefit from low operating costs and increasing performance as system conditions improve. In parallel, higher utilisation rates of installed assets help spread capital costs more effectively. Together, these developments reduce total system expenditures and contribute to more stable long-term heat supply costs.

Cluster 0 maintains the lowest median LCOH, supported by the efficient use of energy from data centres and sewage sources, as well as a progressive rollout of HPs and electric boilers after 2030. A temporary increase around 2046 coincides with data centre shutdowns, which reduce the availability of low-cost EH and trigger the use of bio-oil boilers for backup generation (appendix of [P5]). Cluster 2 achieves a similar long-term cost level, despite having a more diverse mix of technologies. Its flexible supply structure helps balance costs across different conditions. In contrast, Cluster 1, dominated by biomass CHP, exhibits the highest cost variability, with pronounced spikes around 2027 and between 2035 and 2036. These spikes align with reinvestment cycles in bio-based CHPs and increased use of bio-oil boilers as peaker units during periods of high demand or limited EH availability. Such peaker technologies, while ensuring reliability, substantially increase marginal generation costs, amplifying the observed LCOH peaks. The use of such peak load technologies has also been observed in practice. During the European energy crisis of 2022, fossil oil boilers were operated across several central European DHS to compensate for the lack of natural gas, increasing the LCOH significantly [195]. While DH utilities plan for reserve capacity equal to the largest plant's capacity, this capacity is typically provided by technologies with very high operating costs. Figure A1 in the Appendix of [P5] provides further details on the temporal deployment of bio-oil-based technologies across clusters. The narrower cost dispersion in Clusters 0 and 2 indicates greater economic resilience, while the wider spread in Cluster 1 reflects sensitivity to uncertainties in biomass prices and investment timing.

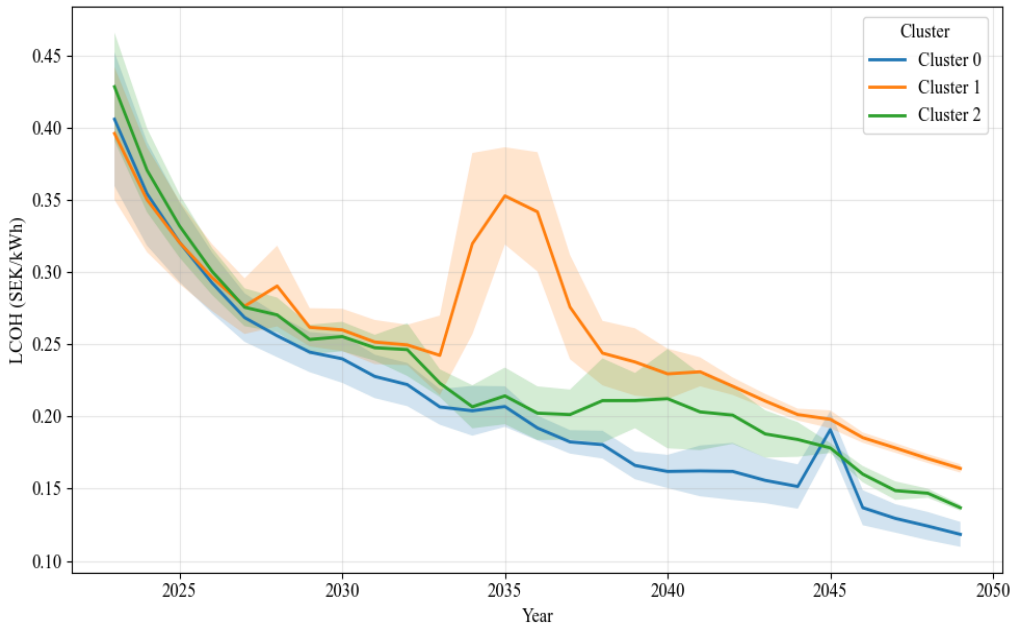


Figure 37: Evolution of the LCOH over time for each scenario cluster, showing the mean values and the associated ± 1 standard deviation uncertainty bands.

Emission intensities decline consistently across all clusters, driven by increased electrification and reduction of MSW use (Figure 38). Cluster 0 exhibits the fastest decarbonisation, falling below $0.05 \text{ kg CO}_2/\text{kWh}$ by 2050, driven by its strong EH contribution. Cluster 1 achieves moderate emission reductions by displacing MSW-based generation with bioenergy, while Cluster 2 maintains intermediate but stable emission levels, reflecting its balanced supply mix. The difference between the mean of cluster 0 and that of clusters 1 and 2 in later years arises from differences in MSW recycling rates across scenarios, which affect the residual share of heat generated from waste incineration. Overall, these trends demonstrate that diversification enhances resilience to volatility in costs and emissions, underscoring the importance of combined electrification and EH utilisation in achieving robust low-carbon heating pathways.

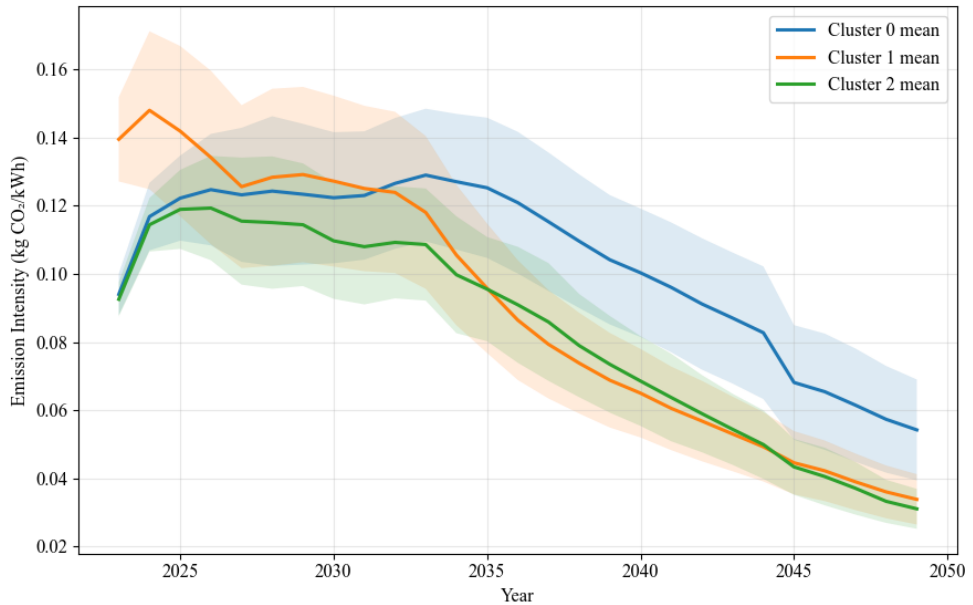


Figure 38: Cluster-wise mean emission intensity trajectories over time, showing the average emissions (kg CO₂/kWh) for each cluster with shaded envelopes indicating variability across scenarios.

Building on these emission and cost patterns, resilience at the cluster level was assessed to understand how stable or adaptable different configurations remain under varying levels of uncertainty. Cluster-level resilience indicators showed that Cluster 0 was the most coherent, whereas Cluster 2 exhibited greater internal variability, suggesting that adaptability can also represent resilience under uncertainty (supplementary information in [P5]).

4.3.3 Dominant Uncertainty Drivers for Cluster Formation

Building on the resilience assessment, this section identifies the key uncertain parameters responsible for the formation of distinct investment clusters. A statistical variability analysis based on Relative Standard Deviation (RSD) was used to measure how strongly each uncertain input separates the clusters, and this approach is well-suited for discrete outputs such as cluster membership, as described in Section 4.2.

Figure 39 presents the normalised RSD scores for all input drivers, revealing that the system’s structural differentiation is primarily driven by shocks and disruptions affecting EH and electricity availability. Electricity price spikes, EH source shutdowns, and EH source outages emerge as the dominant drivers, each with normalised importance above 0.9. These variables strongly influence whether the system evolves toward electrified, EH-integrated configurations or toward combustion-based resilience strategies. Scenarios with frequent, volatile electricity prices tend to fall into the biomass-dominated Cluster 1, while stable electricity and EH conditions favour the electrified, diversified configurations of Clusters 0 and 2. Clusters 0 and 2 are differentiated by the frequency of EH outages and EH source shutdowns. Cluster 0 has the fewest outages and shutdowns, while Cluster 2 has the most.

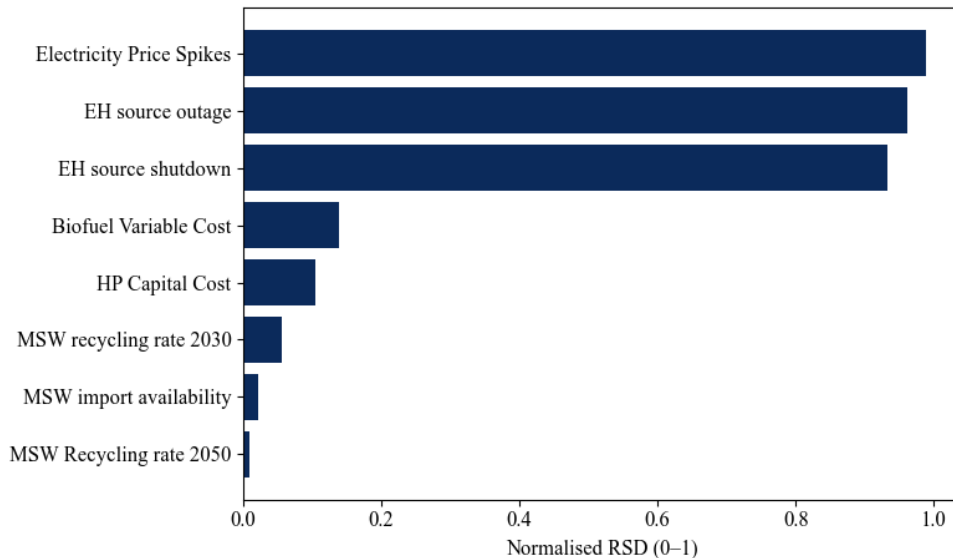


Figure 39: Key input uncertainty drivers influencing scenario cluster membership, ranked by their normalised RSD.

Investment-related uncertainties, including HP capital costs and biomass variable costs, exert a secondary influence, mainly shaping technology shares within each cluster rather than determining their overall structure. MSW-related parameters, including MSW availability and calorific value, vary little across clusters, indicating that gradual shifts in material recovery have a lesser impact on cluster formation. The supplementary information of [P5] presents the full distribution of these drivers across clusters. It confirms that the clusters accurately reflect fundamental structural differences in the uncertainty space, rather than noise or scale effects.

Overall, the statistical variability analysis aligns closely with the capacity and operational patterns observed earlier. This consistency between uncertainty drivers and system performance reinforces the validity of the clustering framework. It identifies electricity price volatility and EH reliability as the most critical uncertainties shaping resilient DH investment strategies.

4.3.4 Cross-cluster Regret Analysis

To assess resilience, a cross-cluster regret analysis was conducted to measure the performance of each pathway across various uncertainty contexts, as detailed in Section 4.2. The regret, expressed as a percentage deviation in cost or emission performance, quantifies the extent to which a pathway's effectiveness depends on its originating uncertainty assumptions. Clusters with low maximum and mean regrets are considered more robust and transferable across future contexts, while those with higher regret values indicate strong dependence on specific boundary conditions. Further methodological details are provided in [P5] of this thesis.

Table 20 summarises the mean and maximum regrets for both cost and emissions. Cluster 2 exhibits the lowest mean and maximum regret across both indicators, reflecting its diversified

and flexible configuration that maintains stable performance across a range of uncertainty settings. Cluster 0 also performs robustly on cost, benefiting from strong energy and heat integration; however, it is more emission-sensitive due to its reliance on waste incineration. Conversely, Cluster 1 achieves the lowest absolute emission intensity but shows the highest cost regret, indicating significant vulnerability to deviations from favourable biomass and electricity price conditions.

Table 20: Cross-cluster regret analysis of cost and emissions performance.

Cluster	LCOH (SEK/kWh)	Emission Intensity (kg CO ₂ /kWh)	Max Regret (Cost%)	Mean Regret (Cost %)	Max Regret (Emissions %)	Mean Regret (Emissions %)
0	0.533	0.107	2.68	-1.19	18.64	12.13
1	0.568	0.091	9.52	5.39	0.75	-4.78
2	0.519	0.090	0.00	-3.77	0.00	-5.48

These results demonstrate that diversified and EH-integrated configurations (Clusters 0 and 2) provide the best cross-scenario transferability, sustaining stable techno-economic and environmental outcomes under uncertainty. In contrast, biomass-dependent systems (Cluster 1) achieve high emissions performance under idealised assumptions but lack resilience when these conditions shift, highlighting the importance of maintaining technological diversity and operational flexibility in robust long-term investment planning.

4.3.5 Technology-Level Resilience and Correlation Analysis

Building on the cluster-level insights, this section disaggregates resilience to the level of individual heat supply technologies to examine how stability and flexibility emerge within the overall system. The analysis quantifies the time-resolved resilience index ($R_{i,t}$) for each technology. This approach captures how stable each technology remains over time and how sensitive it is to uncertainty, showing which options keep their role under different future conditions.

Figure 40 shows that DCHPs and STHPs maintain the highest resilience throughout the modelling horizon, indicating strong structural stability across diverse futures. SWHPs, electric boilers, and bio-oil boilers gain resilience over time, reflecting their role as flexible balancing options under evolving EH and electricity conditions. In contrast, biomass-based CHPs display greater variability, with resilience increasing only in the final decade in a subset of scenarios in which a higher concentration of EH outages occurred by chance. This does not reflect a time-dependent trend but the random distribution of shocks across scenarios. These results reinforce the earlier finding that the most resilient system configuration (Cluster 2) relies on a balanced mix of flexible HP technologies. In contrast, less robust pathways (Cluster 1) depend heavily on biomass.

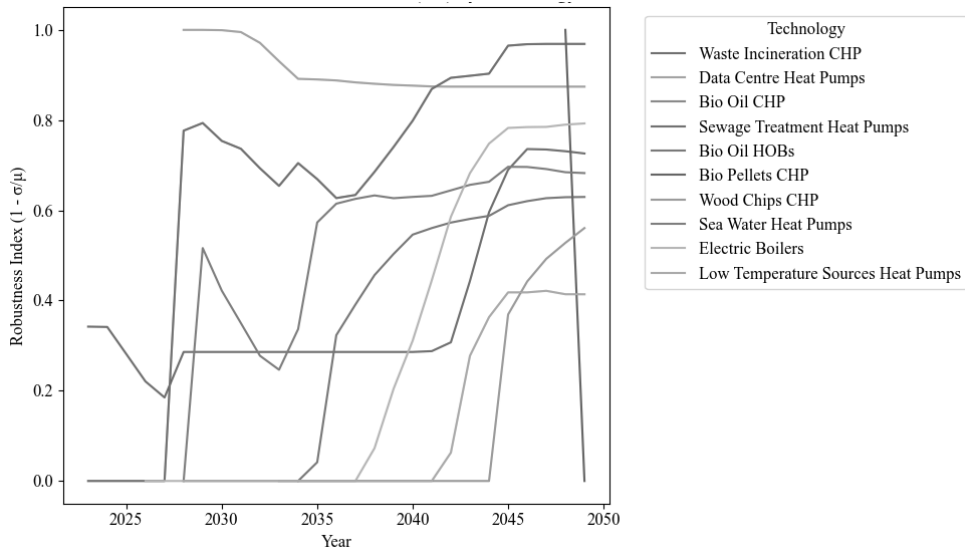


Figure 40: Time-resolved investment resilience index ($R_{i,t}$) for each heat supply technology, showing how the robustness of technology investments evolves across the analysed scenarios.

To explore how these technologies interact, pairwise correlations were computed between capacity investment trajectories across all scenarios (Figure 41). Positive correlations indicate complementary deployment, while negative correlations reveal substitution effects. Biomass CHPs are strongly negatively correlated with HPs, reflecting competition between combustion-based and electrified supply routes. Conversely, the positive correlations among EH sources, electric boilers, and bio-oil boilers indicate that these technologies work in a complementary manner, with boilers stepping in to maintain supply when EH availability changes. These patterns closely correspond to the earlier cluster typology: the diversified portfolio of Cluster 2 aligns with technologies exhibiting positive interdependence. In contrast, the biomass-dominated Cluster 1 reflects substitutive relationships and structural rigidity.

Overall, resilient system trajectories emerge from portfolios that combine persistent, low-inertia technologies with flexible adaptation to uncertainty. Data centre, sewage, and seawater HPs, together with electric boilers, demonstrate sustained flexibility that stabilises both cost and emissions performance. In contrast, a firm reliance on biomass and waste incineration creates path dependence, exposing it to price and policy risks. Supporting analyses of cost–risk trade-offs and Pareto frontiers in the Appendix of [P5] confirm that technological resilience is achieved through balanced portfolios integrating EH utilisation, electrified heating, and dispatchable backup capacity (boilers).

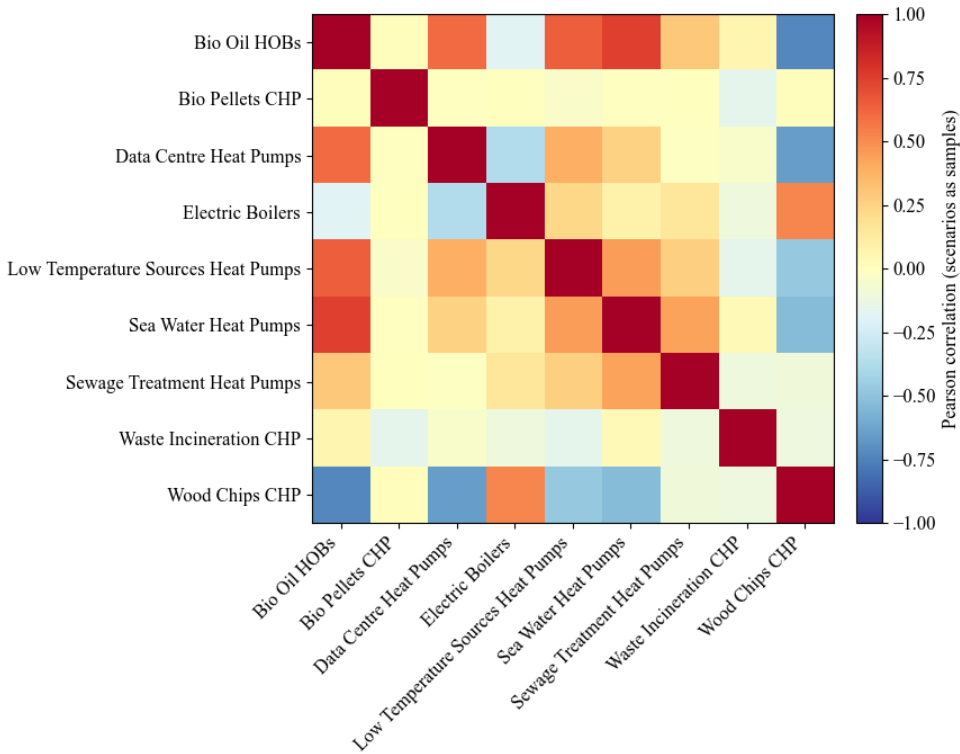


Figure 41: Cross-technology correlation matrix showing pairwise Pearson correlation coefficients between technology capacity trajectories across scenarios.

4.3.6 Policy Implications for Resilient District Heating Pathways

The results of the clustering and resilience analyses provide valuable insights for building a resilient DHS under uncertain conditions. Systems that combine EH recovery, large-scale HPs, and flexible electric boilers perform best over the long term. These mixed systems keep costs stable and reduce emissions by linking EH, electrification, and thermal storage. The findings show that having a diverse mix of technologies is more critical for resilience than relying on a single option. Flexible, low-temperature DHNs that work closely with the electricity system improve both adaptability and decarbonisation, as also shown in recent studies on integrated energy systems [196], [197]. Resilience is not fixed; it develops over time as flexible technologies adapt to changing conditions. These technical insights also have clear policy and planning implications, underscoring how governance and incentives can support the design of resilient, flexible systems.

From a policy perspective, the results suggest that long-term DH planning should shift from fixed technology-specific targets to policies that reward flexibility. Resilience stems from having technologies with varying levels of flexibility, rather than adding spare capacity. Policies such as dynamic tariffs, support for thermal storage, and frameworks for third-party

EH integration can strengthen system adaptability and long-term stability [67], [83]. By focusing on flexibility rather than single-technology incentives, decision-makers can make DHS more responsive to changing market and environmental conditions. These policy insights can be turned into action using the framework developed in this study, which links long-term planning with data-driven monitoring.

The framework offers a practical approach to integrating investment planning with real-world developments. By linking measurable indicators, such as EH use and HP shares, to each cluster's resilience results, policymakers can set clear checkpoints to review and adjust strategies. The stochastic results also help define early warning signals: changes in heat supply, source reliability, or electricity prices signal weakening system resilience. This allows planners to take corrective actions before long-term lock-ins occur. The approach supports a gradual move from fixed master plans to flexible, adaptive DH strategies, aligned with the EU Fit for 55 package and national carbon neutrality targets for 2045 [199]. These practical insights are enabled by the framework's methodological advances, which combine stochastic analysis, clustering, and resilience assessment into a single workflow.

This framework integrates stochastic scenario analysis, DTW clustering, and ex-post resilience evaluation into a unified analytical process. The DTW method helps group investment pathways that change over time yet share similar structures, providing a clearer picture of how transitions unfold. It performs better than static clustering methods like K-Means or Hierarchical clustering for analysing time-dependent energy system changes [200], [201]. The use of RSD-based driver attribution also helps identify key uncertainties transparently and efficiently, working as a simpler alternative to complex global sensitivity methods such as Sobol or Morris screening [202], [203], which quantify the contribution of input uncertainties to output variance through repeated model evaluations. Together, these elements bridge the gap between deterministic optimisation and exploratory modelling, making it easier to understand how DHS behave under uncertainty. By linking system structure and performance, the framework shows how stable and flexible configurations can keep costs and emissions low even as conditions change.

4.3.7 Modelling Advances and Methodological Insights

This study demonstrates the value of combining stochastic scenario modelling, dynamic clustering, and ex-post robustness assessment into a unified analytical workflow. The framework moves beyond single-scenario deterministic analysis by generating a vast ensemble of futures LHS and Poisson-based shocks. This allows the optimisation model to be tested under many combinations of electricity prices, EH availability, fuel costs, and policy parameters. The addition of stochasticity provides a richer understanding of how system transitions unfold over time and enables the identification of broad patterns that remain stable across many plausible futures. This approach offers essential benefits for long-term planning, including capturing path dependency, revealing lock-in risks, and enabling more straightforward interpretation of transition dynamics.

DTW clustering is another key methodological advance. Unlike static clustering methods such as K-Means or Hierarchical clustering, DTW can group investment pathways that share similar structural patterns even when their transitions occur at different times. This is particularly relevant for energy system planning, where investment timing can vary due to input uncertainties. DTW provides a more meaningful characterisation of long-term strategies, but it comes with higher computational requirements and relies on careful feature scaling. Despite these limitations, the DTW-based clustering produced interpretable pathway families that helped reveal how different combinations of EH, HPs, and electric boilers form coherent transition strategies.

The ex-post robustness assessment adds another layer of methodological value. Using RSD for driver attribution offers transparency and interpretability, allowing the key uncertainties influencing pathway performance to be identified without the complexity of global sensitivity analyses such as Sobol or Morris screening. The regret-based comparison across clusters provides a practical way to see which configurations perform well in varied conditions. This does not constitute a full minimal-regret or Robust Decision Making (RDM) framework, since adaptive decision-making and vulnerability mapping are not integrated into the optimisation itself. However, the workflow lays a clear foundation for such approaches, showing how regret metrics and performance distributions can complement deterministic planning tools.

However, these analytical gains come at a nontrivial computational cost, which is essential to acknowledge when considering the framework's practical applicability. Each stochastic optimisation run required approximately 2 to 12 hours to complete, with over-constrained runs arising from certain combinations of stochastic inputs typically taking longer to converge and completing the whole set of scenarios required close to four weeks of continuous computation, executed in batches across three desktop computers equipped with high-speed processors and 256 GB of RAM each. While this computational effort was necessary to enable a rich exploration of uncertainty and pathway diversity, it also poses a practical limitation, as the associated time and hardware requirements may constrain its applicability in more resource-constrained settings.

At the same time, several methodological limitations point to avenues for improvement. The stochastic sampling covers a meaningful but incomplete set of uncertainties; broader uncertainty spaces, including technology learning rates, policy shifts, and spatial constraints, could be explored in future research. The robustness evaluation remains ex post, meaning resilience is assessed after optimisation rather than embedded in the optimisation process. Integrating minimal-regret principles directly into the optimisation, while maintaining computational feasibility, would represent an essential next step. Likewise, while the framework captures temporal patterns well, it could be strengthened by incorporating adaptive decision rules or multi-level governance interactions. Despite these limitations, the study shows that combining stochastic sampling, temporal clustering, and robustness evaluation provides a practical and interpretable approach to exploring uncertainty, bridging deterministic optimisation and exploratory modelling traditions in a way that is both rigorous and accessible for energy system planners.

5 Synthesis of Modelling Advances and Methodological Insights from the Multi-Model Framework

The previous chapters applied the multi-model framework to different DH contexts and presented detailed case-specific results. This section brings those experiences together and reflects on the framework itself as a methodological contribution. The focus is on how the framework is structured, how the individual models interact in it, and what types of planning questions it can support. Rather than revisiting the case study outcomes, this discussion groups the insights into a set of methodological themes, including flexibility and adaptability, modularity and interoperability, integration of spatial, exergy, economic, and operational aspects, the design of soft-linked data flows, coherence across timescales, scenario diversity, stakeholder-oriented design, and transferability and reproducibility. Together, these themes summarise the framework's added value and practical limitations as a decision-support approach for EH integration in DHS.

5.1 Flexibility and Adaptability Across System Contexts

The two case applications demonstrate the flexibility of the multi-model framework across contrasting DH contexts. In Volos, the framework was applied to a new DHS based on the IEH recovery approach. In Stockholm, the application targeted an existing DHS with diverse existing supply assets, integrating UEH from multiple small and large sources into an established network. Taken together, these examples illustrate that the framework is not tied to a specific DHS type but can adapt to the structural conditions of different planning contexts, making it a flexible decision-support tool for EH integration in DHS. However, the influence of factors such as fuel prices, electricity markets, competing technologies, and operational constraints varies across systems. This highlights the need to adapt scenarios and model linkages to the structural and market conditions of each case.

This adaptability is rooted in the framework's modular structure, which allows individual components to function independently while seamlessly exchanging data. A key strength of the framework developed in this thesis is its modular and interoperable design. This allowed the components to function independently while exchanging data seamlessly. The modular structure provided clear advantages: it supported case-specific tailoring, avoided lock-in to a single modelling platform, and improved transparency by allowing assumptions and outputs to be traced and refined in each module. Because modules can be adapted or replaced, the framework can accommodate differences in spatial scale, system maturity, and data resolution.

This flexibility also makes the framework easy to adapt to different contexts and system scales with minimal changes, and it was further strengthened by direct feedback from industrial stakeholders and DH operators. Their input highlighted the need for adjustable settings and the ability to model varying system conditions, leading to new functions that better represent techno-economic dynamics and enhance usability. The components can also be replaced or expanded depending on data availability and the research focus. For example, future work could extend the spatial module to include steam or thermal oil networks or improve the capacity expansion component to account for the power market in sector-coupled analysis.

Throughout this work, the framework's flexibility became clear in its adaptation to different analytical needs with only limited adjustments. By enabling both iterative (new DHS) and non-iterative (existing DHS) linkages, the framework is flexible enough to be applied to new projects, system expansions, or retrofits. The spatial detail could be scaled, from complete topology optimisation and loss estimation to assessing the shortest connections for a particular source. High-resolution operational modelling could be added where dispatch feasibility required it, while in other cases, the intra-annual time slices in the techno-economic model were enough. New technology options could be introduced into the techno-economic modules without altering the workflow structure. The framework also accommodated varying levels of data detail, from unit-level information to aggregated technology groups, as needed. The temporal resolution could be adjusted to balance accuracy and computational effort, and additional analytical components could be integrated at any point due to the modular design. Several changes could be made to the capacity investment optimisation to better represent specific EH technologies or the electricity system without hindering the other components. Together, these experiences showed that the framework could be reused, reconfigured, and extended with relatively minor changes to support different planning questions.

The use of open-source tools further enhances the framework's adaptability. All tools used in the modelling framework are both freely available and have been widely applied across various country contexts and energy sectors. Groissböck et al. find that while open-source energy system optimisation tools may initially require more technical familiarity, they are increasingly mature and capable of supporting serious analytical use [204]. Gardumi et al. [205] and Niet et al. [206] demonstrate how open frameworks, such as OSeMOSYS, evolve into platforms for co-development and community building, where shared modelling practices enhance trust and long-term capacity development. Limpens et al. further highlight that regional open-source models, such as EnergyScopeTD, promote replicability and adaptability by incorporating user interaction and spatial flexibility [207]. The Open Energy Modelling Initiative also documents how open platforms encourage broader stakeholder participation in energy planning by removing licensing barriers and enabling collaborative model enhancement [208]. Together, these studies demonstrate that open-source design not only enhances transparency but also fosters knowledge exchange and inclusiveness in energy system modelling.

These experiences demonstrate that modularity and open-source design are not only technical features but also methodological enablers. It enables the framework to be adapted across various geographical scales and system maturity levels and supports easy integration with emerging sectoral models. It also increases inclusivity by allowing a variety of users and developers to contribute to, modify, and extend the tools. Adaptability, therefore, extends beyond simply repeating the same workflow and opens the door to broader applications in integrated energy systems analysis.

5.2 Coherence of the Multi-Model Framework

Coherence in the multi-model framework arises from the complementarity of its tools rather than their integration into a single platform. Each module serves a distinct role: the exergy

model identifies technically feasible sources; the spatial module quantifies distance-related costs and losses; OSeMOSYS determines least-cost investment pathways; and the dispatch model tests operational feasibility. Together, they ensure that thermal, spatial, economic, and operational aspects are consistently represented within a single methodological framework.

Structured data flows and iterative linking strengthen this coherence. Outputs from one model serve as inputs to the next, with repeated runs until convergence. This ensures consistency between long-term planning and short-term operations, even though operational feedback was applied only as ex post validation in this study. Establishing a complete feedback loop in future work would further align strategic investment decisions with operational feasibility.

Soft linking maintains independent modules while enabling iterative data exchange. This approach preserves transparency, flexibility, and computational efficiency, thereby avoiding the rigidity and heavy data dependencies associated with fully integrated systems. Previous studies confirm that soft-linked frameworks are particularly effective for complex, multi-layered systems such as DHS, as they combine analytical depth with adaptability [73], [74], [211]. Iterative soft-linking establishes a transparent, reproducible workflow in which complementary models collectively generate investment strategies that are both cost-optimal and operationally feasible.

5.2.1 Evidence of coherence from broader application

In addition to the case studies presented in this thesis, the coherence of the multi-model framework can also be assessed through its broader application in the EU Horizon 2020 project EMB3RS. As part of this project, a decision-support platform was developed to apply advanced modelling workflows to real-world EH recovery cases. The multi-model framework developed in this thesis serves as the core analytical backbone of the modelling workflow implemented in this platform, structuring the sequence and interactions among exergy-based screening, spatial analysis, and techno-economic optimisation. The platform applied this workflow across seven real-world case studies in Europe, including individual industrial sites, industrial parks, city-wide DHNs, and regional-scale assessments [P3].

Across the EMB3RS platform case studies, the framework handled a wide range of technical and spatial conditions. These included systems with 1 to 7 EH sources, cases with multiple parallel heat streams, and different temperature levels, ranging from low-temperature EH to high-temperature industrial streams. The workflow was applied across various spatial scales, from compact industrial clusters to large urban DHS, and to networks of varying sizes and routing complexities. It was also used for DHSs operating at different supply and return temperature levels defined by the user. The ability to apply the same framework-based analytical sequence across these varied contexts without significant structural changes provides strong evidence of the framework's internal coherence.

The validation activities carried out within the EMB3RS platform further support this assessment. The workflow, built based on the framework developed in this thesis, was tested using structured test cases and by comparing integrated simulation results with offline

calculations and standalone analyses. In most cases, deviations between framework outputs and reference values were limited and attributable to differences in underlying assumptions rather than to inconsistencies in the workflow structure. Feedback sessions with industrial stakeholders involved in the EMB3RS project further confirmed that the results were plausible and interpretable from an operational and investment perspective.

Beyond demonstrating coherence, the broader uptake of the framework within the EMB3RS platform also illustrates its suitability for repeated application across cases and users. Because the framework defines a clear, modular structure and transparent data flows, the same workflow could be applied systematically across multiple studies without extensive case-specific restructuring. This repeated, consistent use of the framework within a shared platform environment provides an essential link to the question of reproducibility, which is addressed in the following section.

5.3 Reproducibility

Detailed input datasets, parameter tables, and scenario-specific adjustments are provided in the appended papers and, where applicable, made openly available via Zenodo [212], [213]. The code for each development step of the multi-model framework is available on GitHub [214], [215]. This ensures that the models can be readily updated as improved datasets become available. In cases where confidential or proprietary data were used, for example, the unit-level capacities of different heat generation plants in the Stockholm DHS, the information has been anonymised and aggregated into technology groups so that no sensitive data are disclosed. By providing all other input data and maintaining consistency in the aggregated datasets, the studies remain fully reproducible, despite using partially confidential sources. Additional details on the input data and sources are provided in the appended papers.

6 Conclusions

This section concludes the thesis. First, a short general conclusion is presented, after which each research question is addressed in more depth. Following this, the most critical limitations of the work are discussed, and a final section presents the thesis's impact.

The overall aim of the thesis was to advance modelling approaches for integrating EH into DHS, with a particular focus on capturing long-term capacity investment planning, spatial, exergy (for cases with high-temperature IEH), and operational dimensions, and on addressing the uncertainty associated with long-term system development.

6.1 Summary of response to the research questions

The thesis has explored the role of EH recovery in future DHS through a combination of methodological development and case-study analysis, structured into five research papers. Each paper contributed to a different aspect of the overall aim, together forming a coherent framework for evaluating EH integration under uncertainty.

Paper 1 reviewed the integration of EH in DHS, covering technical, economic, and institutional aspects. It examined known barriers and enablers for IEH recovery, including distance to the network, temperature mismatches, variability in heat availability, and gaps in data and stakeholder coordination. It also provided an assessment of existing modelling tools for EH recovery, evaluating their capabilities against the needs of planners and industrial actors. Through this analysis, Paper 1 identified the main strengths of current techno-economic models and highlighted significant limitations in spatial representation, source quality assessment, operational feasibility, and institutional conditions.

Paper 2 developed and applied a multi-model framework to a new DHS in Volos, Greece. By combining exergy analysis, spatial optimisation, and techno-economic modelling, it developed cost-optimal investment pathways for the integration of IEH. It examined the effects of policy incentives and fuel price changes on system competitiveness.

Paper 3 demonstrates how the multi-model framework developed in the thesis was implemented in the EMB3Rs platform, which builds on key methodological elements introduced in [P1] and [P2]. Its application across multiple case studies demonstrated how the framework can support early-stage planning and screening for EH integration. The practical insights gained from these applications informed subsequent methodological refinements developed in [P4] and [P5].

Paper 4 extended the framework to an existing DHS in Stockholm, Sweden, focusing on UEH sources, including data centres, metro stations, ice rinks, supermarkets, and sewage treatment plants. This case demonstrated how electricity market conditions and competition with CHPs shape the feasibility of EH integration, and how operational optimisation can reveal constraints and utilisation patterns not visible in long-term planning models.

Paper 5 examined how uncertainty and risk can be addressed in long-term DH planning using a stochastic optimisation framework. The study evaluated EH integration under both continuous and discrete uncertainties and identified three distinct system clusters with different mixes of biomass, EH, and electrification. Electricity price spikes, EH shutdowns, and EH outages were the most influential drivers. The most resilient systems combined diverse technologies, especially large-scale HPs, and flexible backup units.

Together, these studies advance both the methodological tools available for analysing EH integration and the understanding of its role in future DHS. They demonstrate that EH can make a significant contribution to decarbonisation and system flexibility. However, its value depends on spatial context, electricity market dynamics, and supporting policies.

6.1.1 Conclusions for RQ1

The first research question examined how well existing ESOMs meet the analytical needs of decision-makers in EH recovery planning. The review of ESOMs, along with the assessment of stakeholder needs, revealed that although current models encompass many core features of energy system analysis, they fail to capture the comprehensive effects of strategic energy system integration.

Current ESOMs provide robust representations of technology costs, energy balances, and policy instruments, and they can capture long-term investment dynamics at a system level. However, they are limited in representing spatial variation, heat quality, and operational constraints. These aspects are essential for EH recovery, where the value of a source depends on its temperature, its distance from demand, and the stability of its output over time. The review also revealed that many models are not sufficiently flexible to handle multi-vector systems, in which heat, power, and other energy carriers interact, limiting their applicability for sector coupling and electrification.

From a stakeholder perspective, transparency and usability emerged as major requirements. Industrial actors, municipalities, and utilities emphasised the need for tools that are both technically credible and interpretable, enabling them to evaluate trade-offs between costs, emissions, and risks. Proprietary or overly complex models were seen as barriers to engagement, whereas open-source platforms with modular structures, such as OSeMOSYS, were identified as promising foundations for further development. The conclusion for RQ1 is therefore that while existing models provide a basis for analysing EH recovery, they require significant extensions to capture spatial, exergy, and operational dimensions, and to align with stakeholder needs for transparency, flexibility, and interpretability.

6.1.2 Conclusions for RQ2

The second research question explored how a multi-model framework could improve the analysis of EH integration into DHS. The framework developed in this thesis combined exergy analysis, spatial network optimisation, techno-economic optimisation, and operational validation. Its application to both a new and an existing system demonstrated the added value of integrating these perspectives and highlighted the methodological trade-offs involved.

In the Volos case, the framework identified cost-optimal investment pathways for IEH. It demonstrated that spatial proximity and source temperature significantly influence early system development, with medium-grade sources becoming viable only under favourable policies. The iterative link between the spatial model and OSeMOSYS was essential for producing realistic network layouts. In the Stockholm case, the framework was extended to a large existing DHS, where electricity prices and competition from CHP units significantly influenced the uptake of UEH sources, such as data centres and sewage treatment plants. Operational optimisation confirmed the feasibility of OSeMOSYS investment pathways. Still, it revealed distinct utilisation patterns at hourly resolution, especially for temperature-dependent HPs, highlighting the need to align long-term investment decisions with short-term operational behaviour and to recognise the role of storage in supporting system resilience.

The main conclusion for RQ2 is that the multi-model framework provides a more comprehensive and reliable picture of EH recovery than any single model. It links exergy, spatial, techno-economic, and operational analyses, helping connect long-term investment planning with real operational needs. Although the approach is more complex and requires careful handling of model links, it shows that multi-model methods are essential for robust EH integration studies. Its modular design also makes it suitable for both new and existing DHSs.

6.1.3 Conclusions for RQ3

The third research question examined how DHS can be planned and adapted to integrate EH while remaining resilient to long-term uncertainties, systemic risks, and external shocks. To address this, a stochastic–clustering–resilience framework was developed, linking uncertainty sampling through LHS with OSeMOSYS-based optimisation and post-processing analyses using DTW clustering and regret evaluation. This approach enabled the identification of representative investment pathways and the measurement of their resilience across various uncertain future conditions. By capturing both continuous variability and discrete shocks, the framework provided a comprehensive basis for exploring how uncertainty shapes the composition of technology, investment timing, and system adaptability in future DHS transitions.

The results show three main investment pathways that reflect how a DHS may evolve under uncertainty. One pathway is balanced and increasingly electrified, with a strong role for EH. A second pathway is more conservative and depends mainly on biomass. The third is a flexible and diversified pathway that combines EH, HPs, and electric boilers. The analysis also reveals that electricity price spikes, EH source shutdowns, and short-term outages are the most significant factors influencing these long-term transitions.

When comparing costs, emissions, and regret, the diversified systems performed best. They had the lowest long-term costs and emissions and remained stable under various future conditions. Systems that relied too heavily on biomass were initially cheaper but became more sensitive to price changes and policy shifts.

At the technological level, the results showed that flexible, low-inertia technologies, such as HPs, EH recovery, and electric boilers, made systems more robust. In contrast, heavy use of

combustion-based technologies reduced flexibility. Overall, the study found that resilient DHS depend on diversity and adaptability. Combining electrification, EH use, and flexible operation creates systems that can remain efficient, low-cost, and low-carbon even as future conditions change.

6.2 Limitations and future work

This thesis is subject to several limitations that should be recognised when interpreting the results. These limitations arise from both the modelling framework itself and the empirical scope of the case studies. At the same time, they point towards essential directions for future work that can build on and extend the contributions of this thesis.

A first limitation concerns data availability and resolution. While the case studies included detailed information on EH sources, gaps remained in the temporal variability, operational constraints, and the long-term evolution of industrial activity. For example, several assumptions were made about the shutdowns of EH sources or technological changes that may affect the long-term availability of EH. Future research should therefore seek to improve empirical data on source temperatures, seasonal availability, and demand profiles, ideally through closer collaboration with industry and utilities.

A second limitation lies in the scope of the spatial analysis. The routing tool used in this thesis was limited to water-based networks, so high-temperature steam networks could not be explicitly represented. While this limitation is less critical from a district energy perspective, where there is a clear transition towards lower-temperature (4th- and 5th-generation) systems, it remains relevant in industrial contexts, where steam is still widely used for process heating. As a result, specific industrial sinks with steam demand could not be analysed in detail within the current framework. Although the modular structure of the framework would, in principle, allow the inclusion of steam or thermal oil networks, extending the spatial module to support high-temperature fluids was beyond the scope of this work. Future development in this direction would enhance the framework's applicability to a broader range of industrial symbiosis configurations. In addition, the exact network layout of existing DHSs is typically confidential and not publicly accessible, leading to approximate representations and associated inaccuracies in geospatial optimisation. Nevertheless, the approximate layouts were validated through interactions with network owners and found to be reasonable for this analysis.

A third limitation relates to computational complexity and methodological tractability. The integration of stochastic sampling, iterative soft-linking, and hourly operational optimisation substantially increased the framework's computational burden. Although convergence was achieved and feasibility validated, the need to evaluate large sets of scenarios and perform DTW clustering further compounded the computational demands. The sensitivity of DTW results to data scaling and clustering technique settings introduces an additional layer of uncertainty, as different preprocessing or parameter choices can yield slightly different cluster outcomes. For this reason, complete stochastic optimisation could not be implemented, and scenario set analysis was adopted as a practical alternative for representing uncertainty. Moreover, variance-based global sensitivity methods, such as Sobol's or Morris screening, were not applied because

the clustering outputs are categorical rather than continuous. Instead, a statistical variability analysis was employed, providing transparent, interpretable attribution of uncertainty drivers while maintaining low computational cost. Future work could explore decomposition techniques, dimensionality reduction, or high-performance computing to improve scalability and support more integrated stochastic optimisation within a multi-model workflow

A fourth limitation is that the framework adopts a partial-equilibrium techno-economic optimisation approach and therefore does not include market-wide feedback effects. Electricity prices were treated as an exogenous input, even though large-scale deployment of HPs or CHP may influence market outcomes. Similarly, heat and electricity demand were assumed to be exogenous and price-inelastic, so potential reductions in consumption in response to higher energy prices were not endogenously modelled. In reality, higher prices may induce efficiency improvements, fuel switching, or behavioural adjustments, which could affect both energy demand levels and technology competitiveness. Neglecting these feedback and price-elasticity effects may overstate or understate EH competitiveness in certain scenarios and may overestimate pathway stability. Future research could address these limitations by linking DH models to power system tools such as PyPSA or by incorporating demand elasticity to capture market equilibrium dynamics more accurately.

Finally, the analysis of policy and institutional dimensions was limited. While policy instruments such as carbon taxation and subsidies were included in scenarios, the modelling framework did not account for institutional barriers, ownership structures, or transaction costs that may affect the realisation of EH recovery projects. [P3] of this thesis addressed these issues qualitatively, but future research should aim to integrate policy analysis more systematically with techno-economic modelling. This could include modelling of market rules, incentive schemes, or governance structures that condition the uptake of new technologies. Furthermore, the framework captures only direct operational emissions and electricity-related emissions using exogenous emission factors. However, indirect emissions such as upstream fuel extraction, infrastructure embodied emissions, and broader life-cycle effects were not explicitly represented. In addition, electricity emission factors were treated as given and did not account for potential changes in the marginal generation mix resulting from large-scale electrification. As a result, the emissions results should be interpreted as operational rather than as full life-cycle or economy-wide impacts. Future research could integrate life-cycle assessment methods or dynamic marginal emission factors to enhance the robustness of emissions accounting.

In summary, while the thesis establishes a new and integrated multi-model framework for EH recovery in DHS, its application to a selected national context limits the broader generalisation of the model's specific insights. Extending the framework to other geographical and institutional settings would help test its transferability and strengthen its policy relevance. Taken together with the limitations discussed above, these points indicate clear directions for future work and further refinement.

6.3 Scientific Contributions and Impact of the Thesis

In addition to the seven publications appended to this thesis, this work has yielded several further contributions. These contributions are grouped into methodological advancements, applications, outreach, and impact.

Methodological additions

- Developed a multi-model framework linking exergy analysis, spatial least-cost routing, techno-economic optimisation (OSeMOSYS), and operational validation.
- Developed models and soft-linked workflows for integrating exergy, spatial, and techno-economic tools, which formed the core analytical backbone of the modelling workflow implemented within the EMB3RS platform, as discussed in Chapter 5.
- Contributed to platform-oriented model integration methodologies and their application across multiple real-world case studies, based on stakeholder requirements.
- Extended the OSeMOSYS framework with iterative soft-linking capabilities, enabling convergence across spatial and techno-economic layers. Applied OSeMOSYS for the first time to a full-fledged DHS analysis.
- Modified the Python version of OSeMOSYS to make it more modular, high-performance, and quicker with post-processing functions, and adapted equations to model thermal energy storage, time-specific variable costs, and efficiencies.
- Advanced the methodological treatment of uncertainty in long-term DH planning by integrating stochastic optimisation with clustering-based post-processing.
- Demonstrated the feasibility of capturing both continuous uncertainties (e.g., fuel and electricity prices) and discrete shocks (e.g., industrial shutdowns, extreme events) in a unified modelling framework.

Applications

- Applied the multi-model framework to a new DHS in Volos, Greece, identifying phased investment pathways for IEH integration and testing sensitivity to policy instruments and fuel prices.
- Extended the framework to an existing DHS in Stockholm, Sweden, analysing the role of UEH sources such as data centres and sewage treatment plants under diverse electricity price scenarios.
- Evaluated the resilience of Swedish DH investment pathways under conditions of electrification and constrained resources, highlighting the role of thermal storage and diversified portfolios in ensuring resilience.
- Conducted comparative analysis across new and existing DHS to draw cross-case insights on spatial proximity, source quality, and operational considerations.
- Contributed to broader sector coupling research by analysing the interactions between EH, HPs, CHP, biomass, and electricity price dynamics based on the case study of the DHS in Oskarshamn, Sweden.

Outreach, capacity building, and impact

- Co-authored four peer-reviewed publications, first authored two peer-reviewed articles.
- Contributed two book chapters that synthesise the technical and institutional knowledge developed in this thesis, summarising key insights on excess heat recovery and its role in district heating and industrial energy systems.
- Presented research findings at international conferences and workshops on energy system modelling and DH, contributing to policy dialogues on the role of EH in low-carbon transitions.
- Contributed to the development of open source modelling workflows, building on OSeMOSYS and related tools, enabling greater transparency and replicability of results.
- Supported the development and dissemination of the open-access EMB3RS platform, demonstrating the practical uptake of the framework beyond the thesis case studies.
- Developed training material and led two stakeholder workshops to support capacity building and knowledge transfer related to excess heat recovery modelling.
- Supported training and capacity-building activities on energy system modelling and CLEWs modelling using OSeMOSYS, contributing to the dissemination of open-source modelling approaches in academic and practitioner communities.
- CLEWs (using OSeMOSYS) trainer at Energy Modelling Platform for Africa 2022, ICTP Summer school on Modelling tools, 2024 and EPIC Africa CLEWs Summer

school, 2024, contributing to further uptake of open-source tools and methodologies.

- Provided empirical and methodological evidence of direct relevance to Swedish DH stakeholders, including utilities and policymakers, supporting ongoing debates on electrification, flexibility, and resource diversification in heat supply.
- The developed modelling tool, together with the results and insights from the supported work that contributed to the Clean Energy Roadmap for the State of Goa, published by GIZ [216]
- Supported the modelling effort for developing a national-level CLEWs model for Ghana and Lao PDR.

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