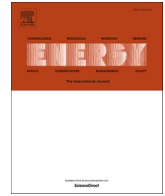


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City-scale exergy-aware district heating interconnection: A GIS–graph–MCDM–MILP framework with multi-source waste heat integration

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ABSTRACT

The transition to sustainable urban heating systems is a key priority in achieving decarbonization targets, particularly in densely populated cities. This study proposes a five-phase framework methodology based on the hybrid GIS, graph theory, MCDM, and optimization to integrate existing and future district heating into one large-scale district heating network through available underground corridors and by leveraging locally available renewable energy and waste heat sources specifically shallow geothermal, data centers, industrial waste heat, waste water treatment, combined heat and power, and powerplants. It will also enable an inter-system heat exchange and coalition-based operation among district heating networks. Moreover, GIS-based spatial analysis is used to identify high heat demand zones across the city and assess their proximity to heat sources and underground corridors to expand the large-scale thermal distribution along its route. The methodology evaluates candidate routing corridors and source–demand pairings based on multiple criteria, including annualized system cost, carbon emissions, exergy utilization, temperature compatibility, and spatial impedance through underground infrastructure. A TOPSIS-based ranking filters strategic corridors prior to mixed-integer linear optimization, which minimizes total annualized cost, CO₂ penalties, and exergy destruction while respecting fourth-generation DH temperature constraints. The findings for the case study in Dublin reveal that the innovative use of its existing underground infrastructure, combined with GIS-driven spatial planning, presents a transformative opportunity for scaling renewable-based district heating systems. Techno-economic and exergy optimization shows exergy efficiency rising from 28% to more than 52% for an optimized low-temperature network with heat-pump boosting, with central scenarios reducing annual operational CO₂ to 32% of the current system and optimistic designs approaching 89–94% reductions. Typical simple payback estimates fall in the range of 18 to 24 years under tunnel-reuse and heat-pump-assisted scenarios.

Nomenclature

English notations	Subscripts and superscripts
$\dot{E}$ Thermal exergy flow (kW)	<i>air</i> Corridor air
$\dot{Q}$ Heat flow (kW)	<i>max</i> Maximum
$\dot{W}$ Electricity consumption (kW)	<i>min</i> Minimum
$\dot{m}$ Mass flow rate (kg/s)	<i>n</i> Graph vertex
q_{pc} Wastewater per capita (m ³ /person/day)	<i>pp</i> Powerplant
$\mathcal{C}$ Criteria set	– Negative ideal
$\mathcal{B}$ Ideal solutions (–)	<i>em</i> Emission
$\mathcal{E}$ Specific heat (kJ/kgK)	<i>exist</i> Existing DH
ℓ Pipe perimeter (m)	<i>a, b</i> Tunnel name

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P_o Population (person)	<i>rec</i> Recovery
$\mathcal{R}$ Interest rate (–)	<i>elec</i> Electricity cost
$\Re$ Recover factor (–)	<i>in</i> Input
SCR System Cost Ratio (–)	<i>raw</i> Raw output
A Area (m ²)	<i>c</i> Cluster
C Cost (€, €/m)	<i>e</i> Edge
CO ₂ Emission objective function (kg)	<i>baseline</i> Existing DHs
COP Coefficient of performance (–)	<i>ww</i> Waste water
Cap DH capacity (kW, kJ)	<i>HP</i> Heat pump
D Pipe diameter (m)	<i>eff</i> Effective distance
G Spatial interaction score (–)	<i>carbon</i> Carbon
H Operating time (h)	<i>pipe</i> Piping cost
L Length (m)	<i>total</i> Total

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<i>LCOC</i>	Cost criteria (–)	+	Ideal
<i>LCOE</i>	Levelized cost per energy (kW/€)	ex	Exergy criteria
<i>M</i>	Exponent (1/ <i>m</i>)	plan	Planned DH
<i>N</i>	Evaluation horizon (years)	ideal	Theoretical generation
<i>OI</i>	Overlap index	pert	Perturbed solution
<i>P</i>	Pressure (Pa)	pump	Circulating pump
<i>Peak</i>	DH peak load (kW, kJ)	soil	Soil
<i>Q</i>	Heat demand (kJ)	ann	Annual
<i>RM</i>	Reserve margin (kW, kJ)	source	Heat source
<i>T</i>	Temperature (°C, K)	env	Environment (soil, air)
<i>U</i>	Overall loss coefficient (kW/m ² ·°C)	dem	Demand
<i>Z</i>	Objective function (€)	opt	Optimized
<i>d</i>	Distance (m)	sup	Supply temperature
<i>f</i>	Friction factor (–)	peak	Peak load
<i>r</i>	Route (–)	base	Base
<i>w</i>	Time weighting factor	use	Useful exergy
<i>W</i>	Criteria weighting factor	sub	Substation
<i>x</i>	Route direction (m)	⊥	Perpendicular
<i>y</i>	Route binary variable	input	Input
<i>years</i>	Life time (years)	k	Criteria number
<i>ℳ</i>	Demand strength (kW, kJ)	policy	Policy
<i>ℳ</i>	Weighted graph (–)	i,j,k	Node
<i>ℳ</i>	DH coalition set (–0)	heat	Thermal cost
<i>ℳ</i>	Source strength (kW, kJ)	u,v	Nodes
<i>ℳ</i>	Tunnel set (–)	cor	Corridor
<i>ℳ</i>	Set of nodes (–)	path	Path
<i>a</i>	Availability factor (–)	real	Realistic generation
<i>d</i>	Euclidean distance (–)	fuel	Fuel
<i>f</i>	Recovery factor (–)	out	Output
<i>h</i>	COP correction factor (–)	sw	Surface water
<i>r</i>	Discount rate (–)	conv	Conversion factor
<i>y</i>	Specific time (year)	dc	Data center
		rej	Rejected heat
		temp	Temperature
		t	Time
		loss	Heat loss
Greek notations			
<i>ω</i>	Route preference factor (–)	gen	Heat generation
<i>λ</i>	Thermal dissipation penalty (€/m ² ·°C)	tun	Tunnel
<i>θ</i>	Relaxation threshold (–)	water	Water
<i>ℰ</i>	Set of edges (–)	p	Specific heat
<i>ρ</i>	Density (kg/m ³)	ret	Return temperature
<i>σ</i>	Heat demand density (kJ/m ²)	req	Required temperature
<i>δ</i>	Demand temporal profile (–)	cap	Capital
<i>η</i>	Efficiency (–)	ind	Industrial
<i>α, β, γ</i>	Calibration exponents (–)	flue	Flue gas
<i>ν</i>	Planning discount parameter (–)	del	Delivered heat
<i>κ</i>	Sensitivity parameter (–)		
<i>Θ</i>	Temperature compatibility factor (–)	boiler	Industrial boiler
<i>Φ</i>	Strategic interaction score (–)	usable	Useable heat
<i>Ψ</i>	Regulatory multiplier (–)		
<i>Π</i>	DH coalition interconnection score (–)		
<i>ε</i>	Specific thermal exergy factor (–)	LCOE	Levelized cost of energy
<i>ψ</i>	Exergy heat flow (kW, kJ)	DHC	District heating and cooling
<i>τ</i>	Objective function weight (–)	DH	District heating
		GIS	Geographical Information System
Abbreviations		O&M	Operating and maintenance
LOO	Leave-one-out	MCDM	Multi-criteria decision making
LHS	Latin hypercubesSampling	MILP	Mixed-integer linear programming
NDCF	Normalized discounted cash flow	WWT	Wastewater treatment

1. Introduction

Attaining the European Union's 2050 objective of near-full decarbonization requires a fundamental restructuring of high-emission sectors [1] [2]. The building sector represents the most significant energy sink [3] in the Europe, responsible for 40% of final energy consumption and 36% of associated emissions [4] [5]. On the other hand, as shown in

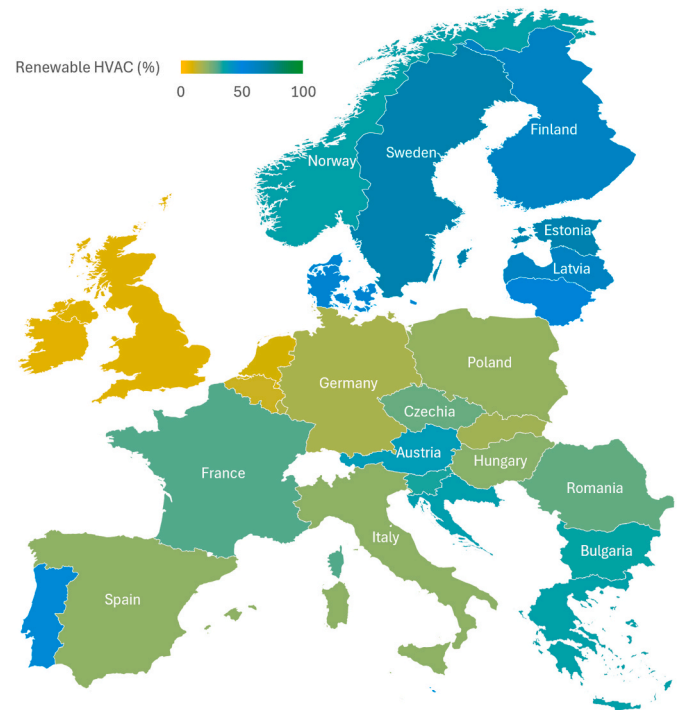


Fig. 1. Recent share (%) of renewable energies for heating, cooling, and ventilation in EU (data from Ref. [6]).

Fig. 1, approximately 26% of the energy consumed for heating, cooling, and ventilation in 2023 comes from renewable sources [6]. Given that urban populations are expected to comprise 68% of the global total by 2050, the challenge of delivering carbon-neutral thermal services—heating, cooling, and hot water—becomes increasingly acute [7]. Current demand is characterized by the dominance of heating loads in 25 of the 28 EU countries, though this hierarchy is subject to potential disruption from ongoing electrification trends [8]. From a techno-economic perspective, the efficacy of demand-side efficiency measures is constrained by a saturation point; beyond this threshold, the deployment of local renewable energy technologies and relevant city infrastructures [9] [10] for spatial source-demand matching offers a superior cost-benefit ratio compared to incremental efficiency gains [11]. As a thermal distribution-centric technology, district heating (DH) offers a robust framework for enhancing resource efficiency through the integration of diversified energy streams. The utilization of waste heat [12]—recognized for its abundance and favorable environmental profile—remains a cornerstone of this approach [13]. Beyond waste heat recovery, DH infrastructures enable the deployment of site-specific renewables, including solar [14] and geothermal energy [15], alongside high-efficiency heat pump technologies [16], contingent upon regional technical feasibility. The inherent flexibility of DH systems allows for the spatial transfer of energy within a city from optimal production sites to high-density demand centers, thereby optimizing the transition toward a diversified and resilient thermal energy mix. District heating remains economically viable when the combined costs of heat generation and distribution are lower than those associated with decentralized, individual heating systems [17]. However, within DH systems, a supply-demand discrepancy occurs when the empirical thermal output diverges from the prescribed theoretical baseline beyond a critical tolerance threshold. Consequently, the robust characterization of this matching state necessitates an accurate derivation of the theoretical heat requirement [18]. This discrepancy between supply and demand for DH is more pronounced in high-density urban areas [19]. As a result, as investigated in the current research, it is beneficial to interconnect existing DH networks through available underground routes and

integrate nearby renewable and waste heat sources to increase the efficiency and load coverage. This approach enhances the climate-neutral potential of the system, reduces reliance on fossil-based DH, increases network resilience, and expands the number of customers served at the city scale. On the other hand, the design of a DHC systems is influenced by multiple factors, including the characteristics of heat and electricity sources, the demands of connected loads, the choice between centralized or distributed plant configurations, and the requirements for system redundancy and resilience [20]. For instance, the selection of heat sources plays a critical role in the design of DH systems: Malcher et al. concluded that the composition of the energy mixes in both power and district heating supply and the presence of combined heat and power (CHP) plants emerges as the most effective approach for reducing emissions across the EU countries they analyzed. Specifically, a 1% increase in the share of low-carbon heat sources has the potential to reduce emissions by 0.8–1.3 kg CO₂e per GJ of heat produced [21]. The following paragraphs summarizes recent publications based on Geographic Information System (GIS) and multicriteria decision analysis (MCDA) as well as importance of transporting/exporting extra or waste heat as a prosumer.

1.1. Literature review

Recent research has increasingly leveraged GIS-based methodologies to evaluate distribution network optimization in DH systems. Chicherin evaluated railway and highway tunnels as waste heat sources for 5th generation of district heating and cooling (5GDHC) systems using GIS-based analysis. A case study in Belgium showed significant heat recovery potential, with estimated heat transfer rates of 5 to 74 W/m² and annual recovery potentials ranging from 2 to 2858 MWh/year [22]. Buonomano developed a GIS-based framework for designing urban renewable energy communities by combining geospatial data with detailed building energy simulations. In a case study of Naples, the results show that planning and aggregation strategies are crucial, enabling self-consumption levels of up to 100%, renewable coverage of demand up to 80%, and life-cycle cost savings reaching €80 million. Conversely, poorly structured or random community formation results in wide performance disparities, with self-consumption varying between roughly 30% and 90%. However, this research was not applied to a DH or city-scale application [23]. Jebamalai introduced an automated GIS tool for the optimal design of DH networks under predefined constraints with a case study of over 2300 buildings to assess the impact of network pressure levels, substation sizes, and demand reduction scenarios on network performance and costs. A 50% reduction in space heating demand results in only a 9–16% reduction in network deployment costs indicating limited cost sensitivity to demand reduction [24]. Guo et al. proposed a methodology to assess the techno-economic feasibility of integrating industrial waste heat into low-temperature DH networks in existing urban areas. The approach combines GIS-based georeferenced data on buildings, industries, and road networks to derive DH pipeline routing under predefined assumptions. Most configurations achieve payback periods of approximately 6 years, with a maximum of 8.5 years [25].

To support informed decision-making in the design of DHC systems, several studies have applied MCDA methods to account for trade-offs. Daugavietis et al. evaluated five MCDA methods for sustainability assessment of district heating and cooling (DHC) systems and finds that TOPSIS is the most sensitive to changes in criteria weights. Sensitivity analysis using three approaches indicates that higher-weighted criteria in TOPSIS cause greater ranking variation [26]. To address the complexities of selecting sustainable DH systems, Wang et al. proposed a comprehensive framework based on Stochastic Multicriteria Acceptability Analysis (SMAA). Unlike deterministic approaches, this method

explicitly quantifies uncertainties associated with both criteria values and decision-maker weights and validated through the assessment of seven DH alternatives within a Chinese context, revealing that the internalization of uncertainty significantly improves decision robustness [27]. Eslami et al. classified regions based on their potential for integrated renewable DH systems using ArcGIS and the AHP method, considering economic, technical, and environmental criteria. System design and sizing were optimized with the lowest cost achieved by a hybrid PV–wind–grid configuration, however, a fully renewable configuration resulted in a significantly higher value due to battery costs, high capital investment, and reduced equipment lifetime [28]. Arsalan et al. presented an exergo-economic and exergo-environmental optimization of a geothermal DH system incorporating a heat pump coupled with a thermal energy storage unit, satisfying a MCDM framework. The results demonstrated the proposed system's enhanced thermodynamic, economic, and environmental performance [29].

While previous research has primarily focused on DH planning or design, the scale of implementation is critical for achieving significant energy and climate impacts. City-scale DH systems, as a high-impact solution, stand out particularly relevant for meeting the Paris Agreement targets which require aggressive urban decarbonization [30]. Rämä et al. introduced dynamically distributed DH at the city scale and presents a preliminary techno-economic assessment of its application in Helsinki. Their findings indicate marginal viability under contemporary cost structures, with projected payback periods surpassing 20 years. Lower storage costs or larger seasonal cost differences would significantly improve profitability. However, the evaluation focused specifically on the storage investment and its direct economic impact, excluding the broader investment in heat pump capacity [31]. Ziemele et al. proposed a framework to assess waste heat integration into district heating systems, using Riga as a case study. System dynamics modelling shows that integrating waste heat significantly reduces primary energy use and CO₂ emissions, bringing the system closer to carbon neutrality, though not fully achieving it. The findings indicate that integrating waste heat reduces the primary energy factor by 2.6 times and avoids 86% of CO₂ emissions [32].

Recent literature has introduced several GIS-enabled optimization frameworks for district heating that integrate multiple waste-heat sources and other renewables. Using GIS and heat-transfer modeling on railway and highway tunnels, Chicherin found substantial but spatially scattered heat recovery (on the order of 0.8–2.9 GWh/year) from tunnels at 20–40°C [33]. A later study develops a top-down GIS-driven design for a 5th-generation DH network: it uses building and weather data with a minimum-spanning-tree algorithm to connect all producers and consumers. This approach optimizes costs, CO₂, and renewable integration, yielding a fully meshed network and significant CO₂ savings compared to a conventional layout [34]. Similarly, Wang and Zhou designed a multi-source waste-heat DH system for northern China that integrates a biomass CHP, coal boilers, and cascaded absorption heat pumps to recover flue-gas and cooling-water heat. Their model coordinates these sources (plus peak boilers) and shows 3235 MWh/yr additional power output and 1821 tCO₂/year emissions avoided by upgrading low-grade waste heat via serial Analytic Hierarchy Process (AHP). This two-stage heat recovery strategy exploits multiple waste streams and highlights the synergistic efficiency gains from coordinated source operation [35]. Eslami et al. presented a GIS-based site-selection and MILP model for district heating in Gaziantep, Turkey. They overlay spatial layers (population, heat density, renewables) using Boolean/fuzzy GIS toolboxes, then apply AHP and MILP to design optimal hybrid DH systems with solar thermal, PV, wind, and heat pumps. Their MILP minimizes levelized cost of energy (LCOE), yielding an optimal system with 78% renewable penetration and LCOE €0.044/kWh [28]. Salenbien et al. integrated GIS into a non-linear

topology optimization (not MILP) for DH networks. Using building GIS data and an optimization algorithm, they derive cost-minimizing network layouts that satisfy diverse heat demands and temperature levels. Their case study shows that including geographic constraints and building characteristics leads to more accurate, efficient designs [36]. Nie et al. proposed a novel graph-based optimization (Steiner-tree plus heuristics) to speed up DH network design with GIS data. Benchmarking against MILP, they achieve near-optimal solutions (5–19% cost gap) in a fraction of the time by iteratively selecting buildings to connect. Both studies confirm the value of GIS for realistic topology planning, though they do not explicitly model waste-heat sources or exergy [37]. A multi-period optimization approach by Wack et al. illustrates the integration of multiple low-grade sources. Their MILP-based topology design evolves from separate branched networks to a single meshed network that connects many producers. The optimized network is rich in low-temperature waste heat sources: waste-heat share increases to 42.8% and project cost drops 17.9% compared to simpler designs. This shows that allowing sources to cooperate (by connecting them in one network) dramatically boosts waste-heat utilization [38]. Verzano et al. developed a model for a city-scale DH network in Bulgaria that recovers server-cooling waste heat from data centers. Under optimal operation with heat pumps and thermal storage, exergy efficiency jumps from 28% to 52%, and annual CO₂ falls to 32% of today's levels. In particular, integrating heat pumps allows low-temperature waste heat (data-center exhaust at 60–75°C) to be upgraded, making the network both thermodynamically efficient and low-carbon. This work explicitly shows how combining multi-source heat (data centers, DHC returns, etc.) with storage yields substantial benefits [39]. Tervo et al. modeled a 21 MW data-center supplying waste heat to a Finnish DH grid. Using EnergyPRO simulations under five future-price scenarios, they find that substituting this waste heat for high-carbon fuels (peat) reduces CO₂ emissions and system costs substantially [40]. While Ravi et al. use MILP for optimal dispatch with an explicit exergy objective, Tervo et al. use scenario-driven cost–emission analysis; both highlight data-center waste heat integration but do not employ GIS or underground routing [41].

Analyzing the comparative landscape reveals that while the individual aspects of the proposed framework in previous studies are partially addressed in isolation, no single study comprehensively unifies these domains. For instance, studies such as Yang et al. [42] and Jodeiri et al. [43] provide high-resolution physical models for geothermal and waste heat integration, but lack the spatial GIS-based routing algorithms necessary to evaluate street-level pipeline layouts.

The transition toward 4th or 5th generation DH and the development of smart energy systems create favorable conditions for the effective integration of prosumers. Consumers increasingly participate in on-site heat and power generation, thereby transitioning from passive users to active prosumers [44]. Sdringola et al. investigated a bidirectional district heating substation designed to enable users to function as prosumers by exporting surplus solar energy or waste heat to the network. Results projected that self-sufficiency rose from 8% in the baseline case to 20% and then 27%. Solar energy production increased due to reduced storage operating temperatures, which lowered the average temperature of the solar collectors and improved their performance [45]. Gianaroli proposed a non-invasive retrofit of an existing DH network substation in Turin, allowing bidirectional heat exchange and the injection of surplus solar thermal energy into the network as the prosumer. The original infrastructure is preserved, with only limited additional components and a dedicated control strategy. On an annual basis, direct self-consumption reaches 14.9%, while overall solar energy utilization increases to 78.4% when including energy fed into the network [46]. It is also shown that thermal prosumers significantly influence network thermo-hydraulic behavior, reducing heat and mass flow from the transport system and increasing user energy autonomy. The findings confirm the feasibility of

integrating heat pump-based prosumers into existing high-temperature DH networks and highlight their potential to enhance flexibility and support decarbonization [47]. A case study in Germany demonstrates that integrating prosumers into flexible district heating networks can lower overall heating costs; however, it also highlights the need for advanced and intelligent control strategies for both substations and heat generation units. The experimental results underline the importance of testing and validating these control approaches in laboratory settings before real-world implementation [48].

1.2. Novelty of the current research

Despite extensive research on GIS-assisted DH planning, network optimization, and renewable heat integration, most existing studies focus on individual DH systems, predefined service areas, or fixed source–sink configurations. Limited attention has been given to the development of a city-scale thermal backbone capable of simultaneously interconnecting multiple existing DH systems, integrating distributed renewable and waste heat resources, and supporting future DH expansion within a unified planning framework. The novelty of the present work lies in four main contributions.

- (1) **Five-phase hierarchical funnel framework for large-scale DH planning:** The proposed methodology introduces a structured five-phase GIS–graph theory–gravity model–MCDM–MILP framework that progressively reduces the search space from thousands of potential spatial connections to a manageable set of technically and economically viable network configurations. Unlike conventional approaches that perform optimization directly on large candidate sets, the funnel architecture distributes decision-making across multiple stages, increasing computational robustness while reducing sensitivity to individual assumptions or parameters. Each phase performs a dedicated screening function while partially validating the outcomes of preceding phases, thereby improving the reliability of final network selection.
- (2) **Explicit incorporation of underground utility corridors as strategic thermal transmission infrastructure:** A central contribution of this work is the integration of existing underground utility tunnels and corridors into the district heating planning process. Rather than treating underground infrastructure merely as a GIS layer, the framework introduces a dedicated corridor preprocessing stage that identifies, filters, and evaluates tunnel assets as potential long-distance thermal transmission pathways. This enables the exploitation of existing urban infrastructure to reduce excavation requirements, construction costs, traffic disruption, and implementation barriers associated with large-scale district heating deployment.
- (3) **City-scale integration of existing district-heating systems, future district-heating development zones, and distributed thermal prosumers:** Most previous studies focus on optimizing individual district heating networks independently. In contrast, the proposed framework evaluates the interconnection of multiple existing district heating systems, allowing networks to operate as coordinated thermal resources capable of sharing surplus capacity and improving system resilience. Simultaneously, future district heating development zones are incorporated into the planning process through spatial demand clustering and gravity-based source–demand matching. This creates a unified city-scale planning methodology that considers both current infrastructure and long-term expansion opportunities within the same optimization framework.

(4) **Integrated spatial-economic-environmental-exergy decision framework:** The proposed methodology combines GIS-derived spatial analysis, gravity-based interaction modelling, thermodynamic exergy assessment, environmental performance evaluation, techno-economic analysis, and multi-criteria decision-making within a unified planning workflow. Unlike conventional district heating planning approaches that primarily focus on economic cost minimization, the proposed framework simultaneously considers spatial accessibility, network interconnectivity, carbon-emission reduction potential, thermodynamic performance, and economic feasibility. Exergy-based indicators are introduced alongside environmental and economic criteria prior to the final optimization stage, while the MILP formulation explicitly incorporates annualized cost, CO₂ emissions, and exergy destruction as competing objectives. This enables candidate interconnection routes and expansion strategies to be evaluated from multiple complementary perspectives, supporting the development of climate-neutral district heating systems.

2. Methodology: framework

The methodology follows a hierarchical funnel approach as shown in Fig. 2: beginning with high-level spatial data integration, progressing through strategic selection of waste/renewable heat sources, and culminating in a rigorous mathematical optimization of the network's topology. By leveraging existing underground utility tunnels as cost-reducer pathways, the model minimizes urban piping/excavation distribution costs and structural disruption, prioritizing high-efficiency routing through complex urban environments. The technical core of the study integrates Geographic Information Systems (GIS) with Graph Theory to establish a computational “search space” of potential thermal corridors. This is followed by a MCDM analysis and the Gravity Method to filter candidate supply-demand connections. In particular, TOPSIS as the MCDM analysis is used that ranks district heating planning

alternatives by measuring their relative closeness to an ideal solution that maximizes performance (e.g., efficiency, emissions reduction) and minimizes costs. Finally, a Mixed-Integer Linear Programming (MILP) model is deployed to identify the global optimum for source dispatch, and routing. The objective is to maximize the utilization of diverse available heat sources while minimizing total annualized costs and carbon intensity when existing districts are inter-connected.

The proposed methodology follows a hierarchical five-phase funnel architecture in which the solution space is progressively reduced from broad spatial and technical inputs to a final optimized district heating configuration. As illustrated in Fig. 3, the workflow is organized into three linked blocks: data inputs, methodological phases, and data outputs/hand-offs. The framework is intentionally sequential, but it is not strictly one-way; instead, it includes feedback and sensitivity loops that allow earlier assumptions to be revisited when the optimization results indicate infeasibility, weak convergence, or insufficient robustness. The workflow begins with raw geospatial datasets, including urban topology, underground corridors, existing district heating networks, heat-source locations, and heat-demand layers. These spatial inputs, together with the technical, economic, environmental, and operational parameters summarized in Table 1 (appears at the end of methodology section), are used to build the model inputs for Phases I–IV. Baseline decentralized configurations are reserved for Phase V, where they are used as the reference case for impact assessment.

Phase I: It performs spatial integration and graph pre-processing. Its role is to transform the urban GIS layers into a cost-weighted graph representation of the city and to identify feasible routing corridors. The main outputs of this phase are the cost-weighted graph $G(V, E)$, candidate shortest paths, corridor distances, and the feasible tunnel set. These outputs define the spatial search space used in the subsequent phases.

Phase II: It quantifies thermal supply and demand. Waste heat potentials, useable source capacities, existing district heating demand, and future expansion clusters are identified from the spatial datasets. The outputs of this phase are candidate source clusters, candidate demand clusters, and thermal/hydraulic loss estimates, which are passed to the

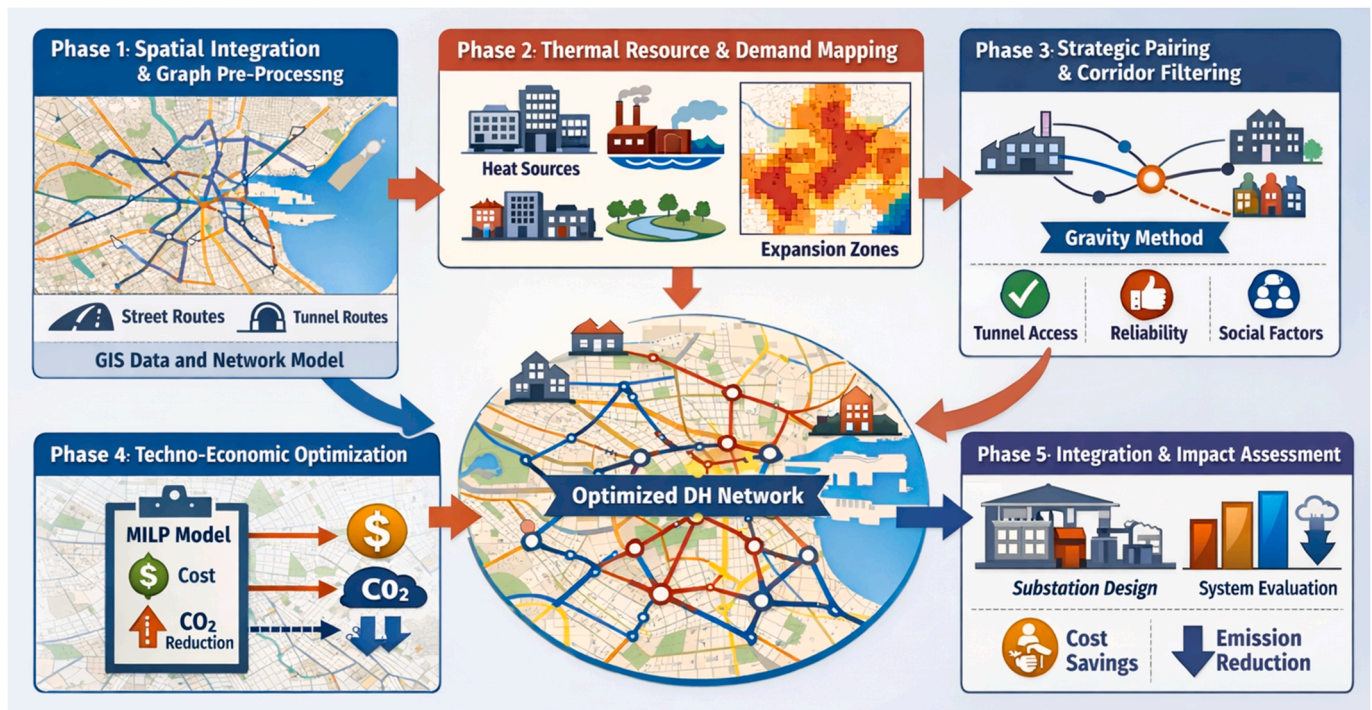


Fig. 2. Overview of the proposed 5-phase framework for large-scale climate-neutral district heating design.

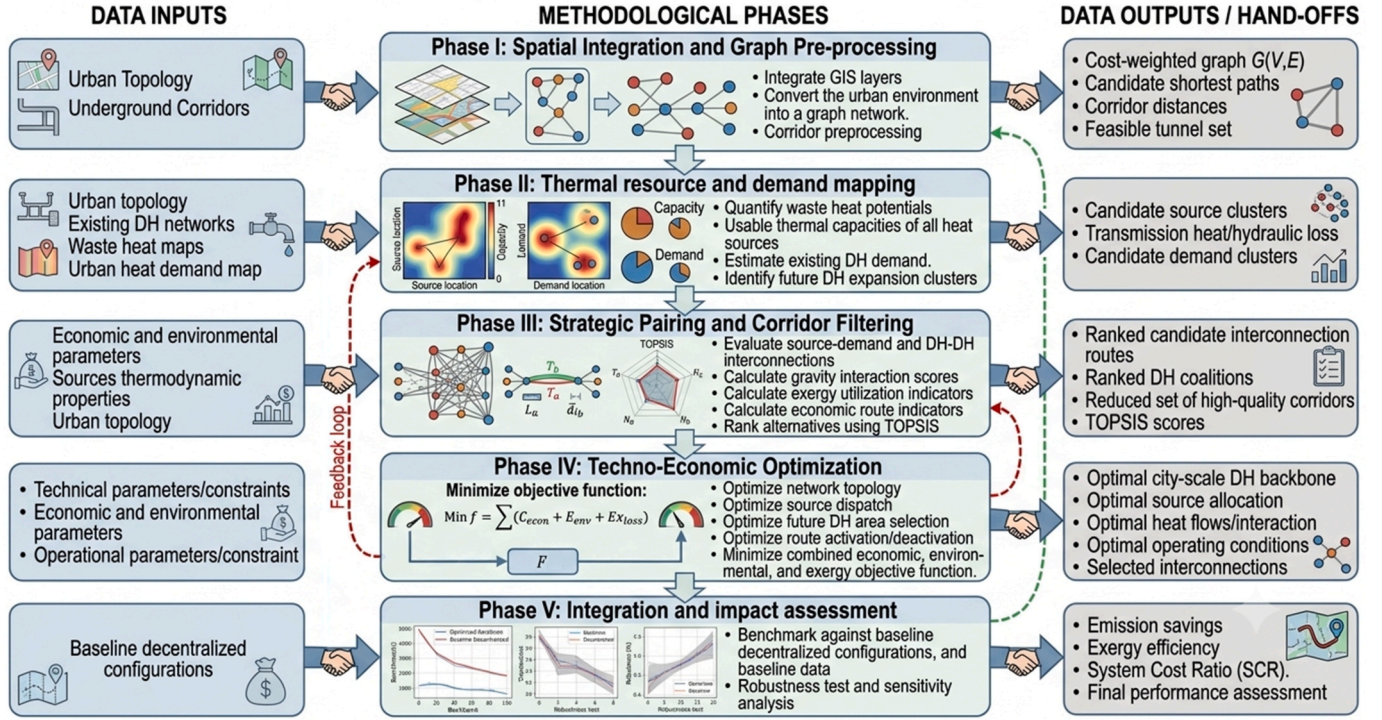


Fig. 3. Methodological workflow illustrating the sequence, interactions, and feedback Relationships within the integrated five-phase GIS-MCDA-optimization framework.

pairing and ranking stage.

Phase III: It carries out strategic pairing and corridor filtering. Here, source-demand and district-heating-district-heating interconnections are evaluated using gravity interaction scores, exergy utilization indicators, and economic route indicators, and the alternatives are ranked using TOPSIS. The outputs of this phase are ranked candidate interconnection routes, ranked DH coalitions, reduced sets of high-quality corridors, and TOPSIS scores. These ranked alternatives form the candidate pool for the optimization stage.

Phase IV: It performs techno-economic optimization. The MILP model selects the final network topology, source allocation, route activation, future DH area selection, and operating conditions while minimizing the combined economic, environmental, and exergy objective function. The outputs are the optimal city-scale DH backbone, optimal source allocation, optimal heat flows, optimal operating conditions, and the selected interconnections.

Phase V: It integrates and assesses the results. The optimized system is benchmarked against baseline decentralized configurations and baseline data. This phase provides final performance indicators, including emission savings, exergy efficiency, the System Cost Ratio (SCR), and the overall robustness and sensitivity assessment.

The interaction between phases is therefore as follows: **Phase I** → **Phase III** supplies feasible spatial corridors and effective route distances; **Phase II** → **Phase III** supplies source capacities, demand clusters, and thermal properties; **Phase III** → **Phase IV** provides the reduced and ranked candidate corridor set; and **Phase IV** → **Phase V** provides the final optimized configuration for impact assessment. In addition, two feedback mechanisms are used. First, if Phase IV produces an infeasible or weakly converged MILP solution, the model returns to earlier screening stages to relax the corridor selections and expand the TOPSIS inclusion boundaries. Second, the green dashed sensitivity loop from Phase V to Phase II is used to revisit demand-cluster assumptions and other planning sensitivities when robustness testing indicates that further recalibration is needed.

To ensure the model is grounded in realistic urban conditions,

multiple geospatial datasets for the case study are integrated within a unified Geographic Information System (GIS) framework.

- Urban street and road networks;
- Existing underground utility corridors, ducts, and tunnels;
- Locations of incumbent DH infrastructure and waste/renewable heat sources;
- Heat demand aggregation points.

All spatial layers are harmonized into a common coordinate reference system with enforced topological consistency. Linear features are segmented at intersections to facilitate the construction of a node-based graph structure suitable for path analysis as explained in the following sections.

2.1. Phase I: Spatial integration and graph pre-processing

The urban domain is represented as a weighted graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ denotes the set of nodes and $\mathcal{E}$ represents the set of edges:

Nodes: Four categories of nodes are considered within the framework: (i) existing district-heating systems, (ii) future district-heating development zones identified through spatial clustering, (iii) renewable and waste-heat sources, and (iv) corridor junction points extracted from the GIS database. Existing and future district-heating nodes are associated (weighted) with their corresponding thermal demand, while renewable and waste-heat source nodes are characterized (weighted) by source-specific attributes including available thermal capacity, source temperature, and recovery potential (See Phase II and III). Corridor junction nodes serve primarily as transition points between underground corridors and surface routes and therefore do not possess thermal weighting attributes. However, selected junctions may subsequently function as hydraulic substations depending on pressure-drop requirements and network configuration.

Edges: Edges represent physically accessible thermal transmission pathways identified during the GIS preprocessing stage. These include

Table 1

Model input parameters used in the four-phase framework for DH integration.

Parameter	Baseline value	Plausible range	Notes and reference
Pipe install cost	€800/m	€600-€1200/m (depending on pipe DN and trenching/tunnel works)	SEAI used inner-city example pipe costs €782-€869/m – an empirical baseline for Dublin inner-city [49].
Route preference multiplier	tunnel = 0.6 existing duct = 0.75 Street trench = 1.0 greenfield = 1.2	0.5-1.5	Practical modelling choice: reflect lower civil/traffic disturbance cost when routing in tunnels/ducts vs open-street trenching. Calibrated with local pipe €/m (SEAI) [49].
Relaxation threshold	0.20	0.10-0.30	Common in routing relaxations to keep near-optimal alternatives [50].
Pipe loss coefficient	0.11 W/mK	0.11-0.21 W/mK typical DN40 to DN50 twin pre-insulated corresponds to $\Delta T = 35-50$ K	Manufacturer data and EN-253 based calculations give heat loss per m in this band [51].
Insulation thermal conductivity	0.025 W/mK	0.021-0.029 W/mK	EN-253 give conductivity for foam used in pre-insulated DH pipes [52].
Supply and return temperature constraint	To be optimized	Supply: 45-65°C Return: 17-35°C	These are the standard ranges used for 4th-gen/low-temperature district heating [53].
Heat pump COP	Function of lift and source	3.0 – 6.5 (varies strongly with source temp and lift)	COP depends on source/target temps; practical COPs for water-to-water/brine-to-water commonly to 4-5 [54].
Data center electricity-to-heat conversion efficiency	0.98	0.95-0.99	Almost all electricity becomes heat [55].
Data center outlet temperature	Air-cooled: 35 °C Liquid-cooled: 50 °C	Air: 25-45 °C Liquid: 40-65 °C	Case studies show typical ranges 25–40°C for air-cooled, higher for liquid cooled [56].
Data center availability factor	0.98	0.95-0.99	Data centers are high-availability assets in year-round supply modeling [57].
Wastewater per capita	0.13 m ³ /p/day	0.12-0.20 m ³ /p/day	Irish EPA/water department data [58]
Wastewater heat recovery	0.55	0.4-0.60	Literature reviews and field tests report/recoverable fraction with drain/greywater exchangers often 40–60% [59].
Powerplant recovery	once-through: 0.75 cooling-tower: 0.5 air-cooled: 0.3	once-through: 0.7-0.8 cooling-tower: 0.4-0.6 air-cooled: 0.2-0.4	These ranges match techno-economic assessments for power plant waste-heat capture [60].
Industrial flue-gas loss fraction	0.80	0.65-0.90	Many industrial boilers lose a large

Table 1 (continued)

Parameter	Baseline value	Plausible range	Notes and reference
Recoverable flue-gas fraction	0.60	0.40-0.80	share of fuel input to flue gases; economizers can recover some part [60] [61].
Pump efficiency	0.8	0.70 -0.90	Practical recoverability limited by acid-dew point and integration constraints [62].
Heat exchanger effectiveness	0.5	0.45-0.65	Planning manuals and DH modeling tools commonly recommend combined pump and motor hydraulic/electrical efficiencies [63].
Pipe	Primary: DN 700 Secondary: DN 300 Local: DN 100 Building: DN 45	Primary mains: DN 400-1000 Secondary mains: DN 150-400 Local branch lines: DN 50-150 Building connections: DN 25-65	Experimental studies report effectiveness for common tube-in-tube/plate drain heat exchangers [64].
Powerplant cycle efficiency	55%	55%-65%	largest diameters near heat sources and progressively smaller diameters closer to the customers [65].
Soil temperature	10.9 °C	5.2-16.6 °C	For combined-cycle gas turbine in Ireland [66]. Baseline for Poolbeg Thermal Station in Dublin. Average 10-cm soil temp for Dublin; varies by location/season [67].
Environmental reference temperature	5.3-5.5-6.8-8.8-1.4-14.2-16.1-15.9-3.9-11.0-7.8-6.0 °C	5.3-16.1 °C	Used for exergy calculations based on Dublin long-term monthly averages (12 values for 12 months listed).
Planning discount parameter	0	0-5	Existing and planned (future) DHs have the same priority.
Expected realization year	1 year	1-25 years	Strategic planning parameter used to represent the availability of future DH systems in the fully realized network configuration; not intended to model phased construction scheduling.
Sensitivity parameter.	0.05	0.02-0.08	Exponent controlling how strongly supply/demand temperature mismatch penalizes the score.
Criteria weighting factor	0.25 (baseline for all criteria)	0.212-0.288	Range for sensitivity analysis ($\pm 15\%$).
Source temperatures	Source-type location-based specific temperatures	CHP: 70-120 °C IND: 70-130 °C PP: 90-130 °C SW: 10-25 °C WWT: 15-25 °C DC: 25-40 °C	Based on reported energy sources in Ireland [68].

(continued on next page)

Table 1 (continued)

Parameter	Baseline value	Plausible range	Notes and reference
Regulatory priority	Both 1	(air), 50-65 °C (liquid) 0.5-2.0	Neutral, no additional weighting [69].
Emissions reduction potential			
Cost (heat)	house: 0.125 €/kWh Ind: 0.065 €/kWh	Residential: 0.12 – 0.13 €/kWh Industrial/business: 0.06 – 0.07 €/kWh	SEAI nationally reported averages [70].
Cost (electricity)	€0.12/kWh (120 €/MWh)	0.06 – 0.25 €/kWh	SEAI/Eurostat business/large-user banding for Ireland as a baseline; large consumers pay noticeably less than households [70].
Cost (pump)	Med: 500 €/kWh Large: 800 €/kWh	Medium DH pumping stations (50-500 kW _e): 300-700 €/kWh Large DH pumping stations (>500 kW _e): 600-1000 €/kWh	Installed pump cost including motor/control/instrumentation [71].
Cost (heat pump)	850 €/kWh	700-1000 €/kWh	Large heat pump capital cost strongly depends on technology and scale. DH heat pumps report typical project costs in the given band [72].
Discount rate	4%	3-7%	Irish reported public sector standard test discount rate on Dec 2025 is 4% [73].
Project lifetime	25 years	20-30 years	Typical planning horizons for infrastructure and DH investments [74].
Recovery temperature fraction	0.65	0.5-0.75	Varies with acid-dew constraints [75] [76].
Flue-gas loss fraction	0.8	0.75-0.90	Majority of waste heat to flue gases unless economized [75] [76].
Exergy multiplier	Residential: 0.125 €/kWh Ind: 0.065 €/kWh	Residential: 0.12 – 0.13 €/kWh Industrial/business: 0.06 – 0.07 €/kWh	Defined based on cost of heating.
CO ₂ penalty	80 €/ton	50-120 €/ton	Used a mid-range EU shadow price. Market EU recent values [77].
CO ₂ multiplier	80 €/ton	50-120 €/ton	Defined based on CO ₂ penalty. 1 full year.
Representative periods	8760 h	0-8760	
Heat pump capacity	To be optimized	5-20 MW thermal	Single large source integration [78] [79].
Interest rate	4%	3-7%	Used same baseline as discount rate for consistency; adjust in private financing scenarios [73].
Density (wastewater)	1015 kg/m ³	1000-1030 kg/m ³	Small variation due to solids/temperature [80].
Boiler efficiency	85%	70%-90%	Common in manufacturing, food

Table 1 (continued)

Parameter	Baseline value	Plausible range	Notes and reference
System efficiency factor	Variable (See Fig. 10)	0.3-0.6	processing, chemicals [81].
Heat-to-power ratio	1.8	0.5-3.0	Range for modern heat pumps [82]. Typical CHP units differ by technology; gas engines often have heat-to-power ratios in the 1.0–2.5 range [83] [84].

underground utility corridors, existing ducts, and road-adjacent routes that remain feasible after the corridor filtering procedures described in the current Phase (Phase I). Each edge is assigned a routing weight that reflects the relative cost and complexity of utilizing that pathway as represented by Equation (1) and Equation (2) below. The weighting formulation incorporates transmission distance, corridor type, and installation difficulty. Existing utility tunnels and dedicated underground corridors receive lower routing weights than conventional street-trenching alternatives due to their lower construction costs, reduced excavation requirements, and diminished disruption to urban infrastructure.

It should be noted that the graph-theory stage is concerned exclusively with the spatial feasibility and routing characteristics of the network. Although source nodes and demand nodes contain technical attributes such as thermal capacity, temperature, and heat demand, these parameters are not used for weighting or ranking during Phase I. Their role at this stage is limited to identifying the physical locations of potential sources and sinks within the graph structure. The evaluation of source quality, demand attractiveness, thermal compatibility, exergy performance, environmental benefits, and techno-economic suitability is performed subsequently during the gravity-model and MCDA stages (Phase II and Phase III). Consequently, Phase I focuses solely on generating technically feasible corridor alternatives, while the relative desirability of individual source-demand combinations is assessed in the later decision-making stages.

Each edge $e \in \mathcal{E}$ is characterized by its physical length L_e and its route type r_e . To reflect the technical and economic advantages of utilizing existing underground infrastructure, a route-dependent cost formulation is applied. The generalized installation cost C_e for edge e is defined as:

$$C_e = L_e C_{base} \omega(r_e) \quad (1)$$

Where C_{base} is the baseline unit cost of DH pipe installation (€/m) and $\omega(r_e)$ is a route preference factor defined as:

$$\omega(r_e) = \begin{cases} 1 & \text{if } r_e \in \text{existing tunnels} \\ > 1 & \text{if } r_e \in \text{greenfield/street} \end{cases} \quad (2)$$

It should be noted that the route preference factor $\omega(r_e)$ in Equations (1) and (2) does not represent a subjective preference for particular corridors, nor is it used as a decision criterion in the upcoming MCDM analysis. Rather, it is a dimensionless cost-normalization factor introduced solely in Phase I to convert route-specific construction costs into a unified cost-weighted graph representation. The values reported in Table 1 at the end of the methodology section were derived from Dublin-specific installation cost estimates reported by SEAI [49] as the case study and expressed relative to conventional street trenching. For example, if street installation costs €1000/m and tunnel installation costs €600/m, the corresponding multiplier becomes $\omega = 0.6$. Similarly, a greenfield installation cost of €1200/m would correspond to $\omega = 1.2$. Therefore, $\omega(r_e)$ simply condenses route-dependent construction costs into a single normalized parameter for preliminary corridor screening. The factor is only applied within Equation (1) during the Phase I graph construction and route pre-screening process. In subsequent phases,

candidate routes are evaluated using their actual GIS-derived corridor lengths, thermal characteristics, hydraulic performance, exergy metrics, gravity-model interaction scores, and economic indicators. Consequently, the final route selection is not determined by the route preference factor itself but by the multi-criteria and optimization procedures applied in Phases III and IV. This weighting mechanism reflects the lower relative installation costs associated with existing corridors while still allowing alternative routes to remain feasible within the search space. Furthermore, to maintain thermodynamic consistency, the model adopts a 4th or 5th generations (4GDH) temperature regime (T_{sup}, T_{ret}). Heat losses are integrated via a linear proxy embedded in the edge cost:

$$C_{total,e} = C_e + \lambda(T_{sup} - T_{env})L_e \quad (3)$$

Where λ represents the economic penalty associated with thermal dissipation. This approach penalizes excessively long routes during the initial routing phase without requiring non-linear thermal hydraulic simulations. Utilizing the cost-weighted graph, shortest-path algorithms are employed to identify the optimal routing corridors between node pairs (i, j). The minimum-cost path is determined by:

$$C_{ij}^{path} = \min_{(i,j)} \sum_{e \in (i,j)} C_{total,e} \quad (4)$$

A relaxation threshold θ (e.g., 20% or 0.2) is applied to discard any path that is excessively more expensive than the optimal path:

$$C_{ij}^{path} \leq (1 + \theta) \min_{(i,j)} \sum_{e \in (i,j)} C_{total,e} \quad (5)$$

Further to equations (4) and (5) above (for initial cost filtering), to ensure that only technically feasible routes are retained, graph preprocessing applies the accessibility, connectivity, and routing constraints described by Equations (6)–(15). These constraints eliminate isolated segments, disconnected subgraphs, duplicate pathways, and infeasible routing alternatives. In addition, the route-relaxation procedure illustrated in Fig. 4 retains only near-optimal alternatives within the prescribed relaxation threshold, thereby reducing computational complexity while preserving routing diversity. Any corridor satisfying the imposed constraints and relaxation criteria is retained as a candidate transmission pathway for subsequent evaluation. In particular, in phase I, each tunnel corridor is treated as a super-edge enabling long-distance heat transmission between all access points connected to it. For each tunnel corridor $\mathcal{T}_{cor}$, $d_{\perp}(n, \mathcal{T}_{cor})$ represents perpendicular pipe

connections between node $n \in \mathcal{V}$ and tunnel $\mathcal{T}_{cor}$ weighted by perpendicular distance. Then, the set of accessible nodes is defined as:

$$\mathcal{N}_{cor} = \{ n \in \mathcal{V} \mid d_{\perp}(n, \mathcal{T}_{cor}) \leq d_{max} \} \quad (6)$$

Where d_{max} denotes the maximum allowable perpendicular pipe length for economic constructability. The access degree of tunnel $\mathcal{T}_{cor}$ is then defined as:

$$\deg(\mathcal{T}_{cor}) = |\mathcal{N}_{cor}| \quad (7)$$

The quantity in equation (7) reflects the potential interconnection capacity of the corridor. Tunnels that serve fewer than two system nodes cannot facilitate heat exchange between network elements and therefore provide no structural benefit to the DH backbone. These tunnels are removed according to:

$$\deg(\mathcal{T}_{cor}) < 2 \Rightarrow \mathcal{T}_{cor} \text{ eliminated} \quad (8)$$

This operation corresponds to pruning degree-one structures in graph theory and prevents dead-end corridors from entering subsequent optimization. Parallel or spatially overlapping tunnels frequently arise in urban subsurface planning. A tunnel $\mathcal{T}_{cor,a}$ is considered dominated by tunnel $\mathcal{T}_{cor,b}$ if:

$$L_a > L_b \quad (9)$$

$$\bar{d}_{cor,a} \geq \bar{d}_{cor,b} \text{ for all } n \in \mathcal{N}_{cor,a} \cap \mathcal{N}_{cor,b} \quad (10)$$

$$\mathcal{N}_{cor,a} \subseteq \mathcal{N}_{cor,b} \quad (11)$$

where:

$$\bar{d}_{cor} = \frac{1}{|\mathcal{N}_{cor}|} \sum_{n \in \mathcal{N}_{cor}} d_{\perp}(n, \mathcal{T}_{cor}) \quad (12)$$

Equation (12) defines the average perpendicular access distance for a corridor. If all three conditions hold, tunnel $\mathcal{T}_{cor,a}$ is removed since it is longer, less accessible, and provides no unique connectivity. In graph-theoretic terms, the dominated tunnel never lies on any shortest path between node pairs. To ensure the DH network remains fully interconnected, each remaining tunnel corridor is tested for structural necessity. Let:

$$d_{ij}^{cor} = \text{shortest path between } i \text{ and } j \text{ with } \mathcal{T}_{cor} \text{ removed} \quad (13)$$

Tunnel $\mathcal{T}_{cor}$ is then classified as critical if for nodes i and j :

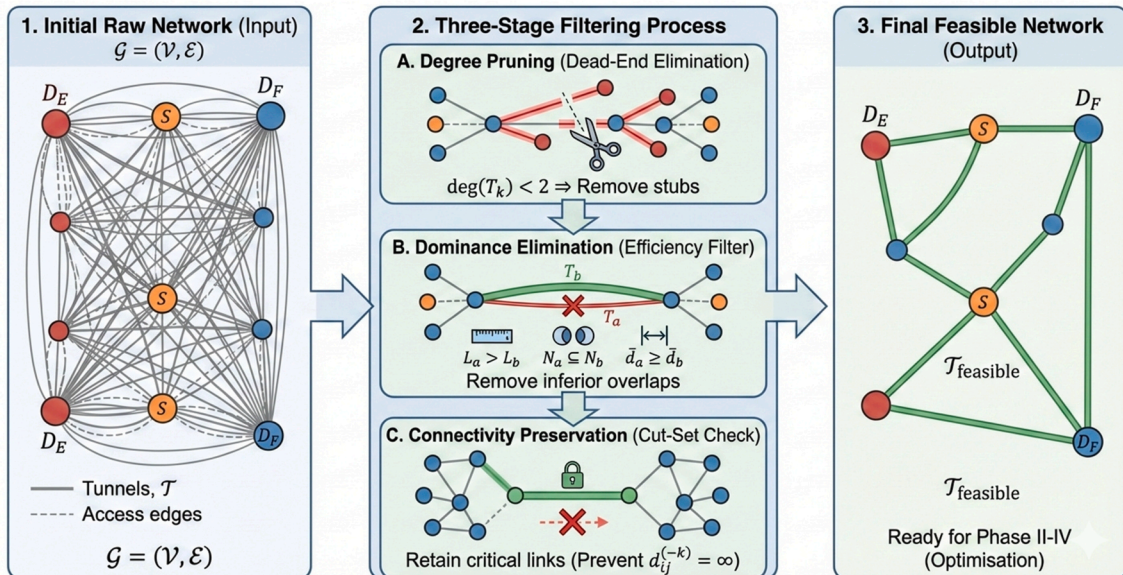


Fig. 4. Flowchart of the sub-phase in phase I for corridor network preprocessing.

$$d_{ij}^{cor} = \infty \text{ or } d_{ij}^{cor} > d_{ij}^{cor} \quad (14)$$

Such tunnels belong to the network cut-set and are retained to prevent disconnection or excessive distance escalation. After applying degree pruning, dominance elimination, and connectivity preservation, the feasible tunnel set is obtained as:

$$\mathcal{T}_{cor\text{feasible}} \subseteq \mathcal{T}_{cor} \quad (15)$$

This approach as part of phase I illustrated in Fig. 4 reduces set required to define the structural backbone used in the subsequent phases.

The graph-theory stage above (Phase I) functions primarily as a search-space reduction and route-generation mechanism. Rather than determining the final network topology directly, it identifies the set of technically feasible corridor alternatives available for interconnecting heat sources, existing district-heating systems, and future demand zones. These candidate routes are subsequently transferred to the gravity-model stage, where source-demand interactions are evaluated, and then to the MCDA stage, where thermodynamic, environmental, spatial, and economic criteria are assessed. Only configurations satisfying the Phase III screening criteria are passed to the MILP optimization model. As it is shown in Phase IV, within the final optimization stage, the MILP evaluates the surviving route-source-demand combinations simultaneously and determines the network configuration that minimizes the overall objective function. Consequently, graph theory establishes the feasible routing structure, while the subsequent gravity-model, MCDA, and MILP stages progressively identify the technically, environmentally, and economically optimal district-heating backbone.

2.2. Phase II: Thermal resource and demand mapping

At each node and time step the energy balance enforces conservation. For node i at time t , all incoming heat plus any local generation must equal the node's demand plus outgoing flows and losses. Formally, one can write for each time t :

$$\sum_{j:(i,j) \in \mathcal{N}} \dot{Q}_{ji,t} + \dot{Q}_{i,t}^{gen} = \dot{Q}_{i,t}^{dem} + \sum_{k:(i,k) \in E} \dot{Q}_{ik,t} + \dot{Q}_{i,t}^{loss} \quad (16a)$$

$$\dot{Q}_{i,t}^{dem} = \dot{Q}_{i,t}^{DH,exist} + \dot{Q}_{i,t}^{DH,plan} \quad (16b)$$

where $\dot{Q}_{ji,t}$ is the heat flow from node j to i , $\dot{Q}_{i,t}^{gen}$ is heat produced at i (e.g. by a boiler or heat pump), $\dot{Q}_{i,t}^{dem}$ is the heat required by the building at i , and $\dot{Q}_{i,t}^{loss}$ captures network losses. The $\dot{Q}_{i,t}^{dem}$ consists of candidate existing DHs and planned DHs. ones Variables $\dot{Q}_{i,t}^{gen}$ and $\dot{Q}_{i,t}^{dem}$ are evaluated based on the waste heat/renewable heat source GIS map and city demand maps, respectively. To calculate $\dot{Q}_{i,t}^{loss}$, a single pipe segment carrying mass flow $\dot{m}$, perimeter $\mathcal{L}$, and overall loss coefficient U is assumed. The one-dimensional continuous model results in Ref. [85]:

$$\frac{dT(x)}{dx} = -\frac{U\mathcal{L}}{\dot{m}C_p} (T(x) - T_{un}) \quad (17a)$$

For tunnel routes. For street routes, it results in Ref. [85]:

$$\frac{dT(x)}{dx} = -\frac{U\mathcal{L}}{\dot{m}\zeta_{p,water}} (T(x) - T_{env}) \quad (17b)$$

Where $\dot{m}$ in each route/pipeline calculated based on the supply and return temperatures. The closed-form solution gives [85]:

$$T(i \rightarrow j) = T(0)e^{-M d_{ij}^{eff}} + T_{soil,un} \left(1 - e^{-M d_{ij}^{eff}}\right) \quad (18a)$$

$$M = \frac{U\mathcal{L}}{\dot{m}\zeta_{p,water}} \quad (18b)$$

$$\dot{m} = \frac{\dot{Q}_{ji,t}}{\zeta_{p,water} (T_{sup} - T_{ret})} \quad (18c)$$

For aggregated modeling, linearized approximation is used for small $M d_{ij}^{eff}$ in equation (18a):

$$\Delta T \approx M d_{ij}^{eff} [T(0) - T_{soil,un}] \quad (19)$$

Heat loss is then expressed per edge in terms of flow and edge properties for later coupling:

$$\dot{Q}_{i,t}^{loss}(\dot{m}) \approx U_i \mathcal{L}_i d_{ij}^{eff} (T_{sup} - T_{soil,un}) \quad (20)$$

If $M d_{ij}^{eff}$ is not small, M is computed explicitly and solved using the closed form or approximated with piecewise-linear functions in the Mixed Integer Linear Programming (MILP). Pressure drops on edge e follows Darcy-Weisbach equation [86]:

$$\Delta P_e = f_e \frac{d_{ij}^{eff}}{D_e} \frac{\rho_{water}}{2} \left(\frac{\dot{m}_e}{\rho_{water} A_e} \right)^2 \quad (21)$$

Pumping power for a path ij is calculated by Ref. [86]:

$$\dot{W}_{pump,ij} = \sum_{e \in ij} \frac{\dot{m}_e \Delta P_e}{\rho_{water} \eta_{pump}} \quad (22)$$

Since $\dot{W}_{pump,ij}$ is quadratic in $\dot{m}_e$, the piecewise-linear segments of $\dot{m}_e$ is approximated and an incremental formulation is applied. To pre-evaluate $\dot{Q}_{i,t}^{DH,planned}$, the urban heat demand GIS area is discretized into spatial units:

$$\sigma_e = \sum_{e \in E} \frac{Q_e^{ann}}{A_e} \quad (23)$$

Where Q_e^{ann} is the annual heat demand, and A_e is the spatial area. Then, each demand unit is assigned a normalized temporal profile $\delta_e(t)$, with a defined peak demand is defined as:

$$Q_e(t) = Q_e^{ann} \delta_e(t) \quad (24)$$

$$Q_e^{peak} = \max_t Q_e(t) \quad (25)$$

Unserved demand units are grouped into candidate expansion clusters using density-based clustering algorithms. A cluster c is retained if both following conditions are satisfied:

$$\sum_{e \in c} Q_e^{ann} \geq Q_{min} \quad (26)$$

$$\frac{\sum_{e \in c} Q_e^{ann}}{A_c} \geq \sigma_{min} \quad (27)$$

where Q_{min} and σ_{min} are minimum viability thresholds.

2.3. Phase III: Strategic pairing and corridor filtering

A directed spatial interaction score is defined between thermal source $i \in \mathcal{S}$ and demand cluster $j \in \mathcal{D}$ as gravity model [87]:

$$G_{ij} = \frac{\mathcal{S}_i^\alpha \mathcal{D}_j^\beta}{(d_{ij}^{eff})^\gamma} \quad (28)$$

where $\mathcal{S}_i$ denotes available thermal capacity at source i , $\mathcal{S}_j$ denotes aggregated annual or peak demand of cluster j , d_{ij}^{eff} denotes effective GIS-derived corridor distance between nodes i and j , and α, β, γ are calibration exponents. Following the Phase I corridor screening process, the retained candidate routes are represented using their actual GIS-derived lengths. Therefore, the effective corridor distance used in the gravity model in equation (28) is defined as:

$$d_{ij}^{eff} = \sum_{(u,v) \in (i,j)_{retained}} L_{uv} \quad (29)$$

where summation is done over the retained corridor connecting nodes i and j , and L_{uv} is the actual GIS length of edge (u,v) . The route preference multiplier introduced in Equation (1) is used only during the preliminary corridor screening stage and is not used in the gravity-model calculations. In equation (28), demand cluster $\mathcal{S}$ consists of the heat demand for existing DHs as well as the candidate expansion clusters identified in phase II for the future planned DH:

$$\mathcal{S}_j = \begin{cases} Q_j^{ann, exist}, & \text{if DH exists} \\ Q_j^{ann, plan} e^{-\nu t_{plan}}, & \text{if DH not exists} \end{cases} \quad (30)$$

In equation (30), a temporal discount factor based on planning discount parameter ν is introduced to facilitate expansion of the current large-scale DH in expected realization year t_{plan} . This gravity formulation captures two key effects: (1) attraction proportional to thermal scale and (2) spatial friction proportional to actual GIS-derived corridor length. To ensure thermal feasibility, a temperature compatibility factor is introduced:

$$\Theta_{ij} = \exp\left(-\kappa \left|T_i^{source} - T_j^{dem}\right|\right) \quad (31)$$

where T_i^{sup} is source supply temperature, T_j^{req} is demand-side required supply temperature, κ is a sensitivity parameter. The final strategic interaction score becomes:

$$\Phi_{ij} = G_{ij} \Theta_{ij} \Psi_{policy} \Psi_{carbon} \quad (32)$$

where policy and carbon multipliers allow integration of regulatory priority and emissions reduction potential, however, there both considered as 1 in this study.

Interconnection of existing DHs is also analyzed based on gravity model similar to supply-demand model above. A reserve margin of each DH is defined as:

$$RM_{DH} = Cap_{DH} - Peak_{DH} \quad (33)$$

Only DH systems with $RM_{DH} > 0$ can support others. Therefore, for coalition $\mathcal{S}$:

$$RM_{\mathcal{S},r} = \sum_{DH \in \mathcal{S}} \max(0, RM_{DH}) \quad (34)$$

This is total available surplus capacity. To evaluate whether coalition $\mathcal{S}$ can help DH system r :

$$\Lambda_{\mathcal{S},r} = \frac{RM_{\mathcal{S}}}{Peak_r} \quad (35)$$

In equation (35), if $\Lambda_{\mathcal{S},r} > 1$, the coalition can fully cover peak demand of DH at point r , while if $\Lambda_{\mathcal{S},r} < 1$, it only partially supports. Based on equation (34) and gravity model, DH coalition interconnection score is then defined as:

$$\Pi_{\mathcal{S},r} = \frac{RM_{\mathcal{S}}^{\alpha} Peak_r^{\beta}}{\left(d_{\mathcal{S},r}^{eff}\right)^{\gamma}} \quad (36)$$

To avoid combinatorial explosion, coalition size is limited to pairwise coalitions ($|\mathcal{S}| = 1$), dual-support coalitions ($|\mathcal{S}| = 2$), triple-support coalitions ($|\mathcal{S}| = 3$). Moreover, only coalitions satisfying $\Pi_{\mathcal{S},r} \geq \Pi_{max}$ or belonging to the top ranked configurations are retained for Phase IV optimization. Based on equation (36), a criterion can be added to analyze interconnection between the DHs. This criterion evaluates how well a candidate transmission route r enables coalitions of DH systems to support other DH systems through gravity-type interaction:

$$\Pi^{route\ r} = \frac{\text{Total coalition potential of route } r}{\text{Maximum across all routes}} \quad (37a)$$

Which can be rewritten as:

$$\Pi_r = \frac{\sum_{(\mathcal{S},j) \in (\mathcal{S},r)} \Pi_{\mathcal{S},j}}{\max_r \sum_{(\mathcal{S},j) \in (\mathcal{S},r)} \Pi_{\mathcal{S},j}} \quad (37b)$$

When interconnecting DH or integrating DH with sources of different temperature levels, high-temperature DH or source supporting low-temperature DH or source may destroy exergy. Moreover, low-temperature waste heat cascaded properly improves exergy utilization and return-to-supply recovery increases second-law efficiency. Therefore, a new criterion is required to evaluate exergy based on second law of thermodynamics [88]. Assuming soil or tunnel air temperatures as the ambient temperature $T_{soil/air}$, for a heat stream delivered from a heat source or DH at temperature $T_{DH/source}$, the specific thermal exergy factor is [89]:

$$\varepsilon_{DH/source} = 1 - \frac{T_{soil/air}}{T_{DH/source}} \quad (38a)$$

The thermal exergy flow for heat flow between i and j is defined as (see equation (16a)) [89]:

$$\dot{\Psi}_{ij,t} = \dot{Q}_{ij,t} \varepsilon_{DH/source} \quad (38b)$$

A single, route-level scalar that captures how well route r preserves and uses exergy when enabling flows between sources and demand nodes i.e. existing and future/planned. A seasonally/annually aggregated heat transfers can be used similar to the annual aggregation in equation (30). Based on the source/DH outlet temperature T_i and delivered temperature at the demand i.e. existing or future DH T_j , the route exergy utilization ratio (unnormalized) $0 \leq \psi_{exergy,r} \leq 1$ is then defined as:

$$\psi_{ex,r} = \frac{\sum_{j \in \mathcal{D}} \sum_{i \in \mathcal{S}} \dot{Q}_{i-j,t} \varepsilon(T_j)}{\sum_{j \in \mathcal{D}} \sum_{i \in \mathcal{S}} \dot{Q}_{i-j,t} \varepsilon(T_i)} \quad (39)$$

Higher values provide better use of exergy i.e. less destruction or waste) while small values mean that the route causes big exergy loss for example because of high-temperature source feeding low value demand or long losses. The criterion is then defined as:

$$\psi_r = \frac{\psi_{ex}(r)}{\max_r \psi_{ex}(r)} \quad (40)$$

A single economic cost criterion is defined that fully internalizes piping costs, pumping electricity and the energy value of heat losses along the candidate routes. A levelized annual cost per energy (LCOE) delivered along route r is defined as [90]:

$$LCOE_r = \frac{C_r^{tot}}{Q_r^{tot}} = \frac{C_{pump}^{tot} + C_{heat}^{tot} + C_{pipe}^{tot}}{Q_r^{tot}} \quad (41)$$

Annual O&M costs is calculated as a portion of total cost and added to the total cost. According to equation (22) for circulation pump, for the annual period of H hours:

$$C_{pump}^{tot} = C_{elec} H \sum_{ij} \dot{W}_{pump,ij} \quad (42)$$

Total annual heat loss along route is calculated based on equation (20) mentioned above as:

$$C_{heat}^{tot} = C_{heat} H \sum_{ij} Q_{ij,t}^{loss} \quad (43)$$

Total annualized cost for piping capex for the candidate route r is calculated by rewriting equation (1) [91]:

$$C_{pipe}^{cap} = C_{pipe} \sum_{ij} d_{ij}^{eff} \quad (44a)$$

$$C_{pipe}^{tot} = C_{pipe}^{cap} \frac{\mathcal{R}(1 + \mathcal{R})^{years}}{(1 + \mathcal{R})^{years} - 1} \quad (44b)$$

Finally, equation (41) is normalized for MCDM to create a criterion:

$$LCOC_r = \frac{LCOE_r}{\max LCOC_r} \quad (45)$$

For each candidate corridor, a criteria vector is defined and then all criteria as well as the weighting factors are normalized for each route:

$$\mathcal{C}_r = \{\Phi_{ij}, \Pi_r, \psi_r, LCOC_r\} \quad (46a)$$

$$\sum_{\mathcal{C}_r} \mathcal{W}_{\mathcal{C}_r} = 1 \quad (46b)$$

To account for disparate physical units (e.g., Euros, Megawatts, Celsius, and dimensionless scores), a min-max normalization proxy is applied via Equation (46c) to bring all metrics into a unified [0,1] scale:

$$\tilde{\mathcal{C}}_r^k = \frac{\mathcal{C}_r^k - \mathcal{C}_{min}^k}{\mathcal{C}_{max}^k - \mathcal{C}_{min}^k} \quad (46c)$$

Where k shows the index for each criterion ($k = 1, 2, 3, 4$). A TOPSIS-based ranking is then performed. The positive and negative ideal solutions are defined as [92]:

$$\mathcal{B}_+^k = \max \tilde{\mathcal{C}}_r^k \quad (47a)$$

$$\mathcal{B}_-^k = \min \tilde{\mathcal{C}}_r^k \quad (47b)$$

The ideal solution is the alternative that maximizes all beneficial criteria in equation (46a), while the negative ideal solution is the alternative that minimizes all undesirable criteria. Once the ideal and negative ideal solutions are defined, the Euclidean distance between each alternative and both the ideal and negative ideal solutions is calculated. This distance measures how far each alternative is from the best (ideal) and worst (negative ideal) possible solutions [92]:

$$d_r^+ = \sqrt{\sum_k (\tilde{\mathcal{C}}_r^k - \mathcal{B}_+^k)^2} \quad (48a)$$

$$d_r^- = \sqrt{\sum_k (\tilde{\mathcal{C}}_r^k - \mathcal{B}_-^k)^2} \quad (48b)$$

where d_r^+ is the distance between the k -th alternative (criterion) and the ideal solution. d_r^- is the distance between the k -th alternative and the negative ideal solution. The final step is to compute the relative closeness of each route (network) to the ideal solution. This is done by calculating the ratio of the distance to the negative ideal solution to the sum of the distances to both the ideal and negative ideal solutions:

$$\text{Score}_r = \frac{d_r^-}{d_r^+ + d_r^-} \quad (49)$$

The higher the value of score for each route or network, the closer the alternative is to the ideal solution, and thus, the better it is in terms of the selected criteria. The alternatives are then ranked according to their relative closeness to the ideal solution. The alternative with the highest score value is considered the best choice for integration into the DH distribution network as summarized in Fig. 5.

The four criteria vector components defined in Equation (46a) are assigned equal baseline weights $\mathcal{W}_{\Phi} = \mathcal{W}_{\Pi} = \mathcal{W}_{\psi} = \mathcal{W}_{LCOC} = 0.25$. This approach prevents early-stage subjective bias, treating spatial

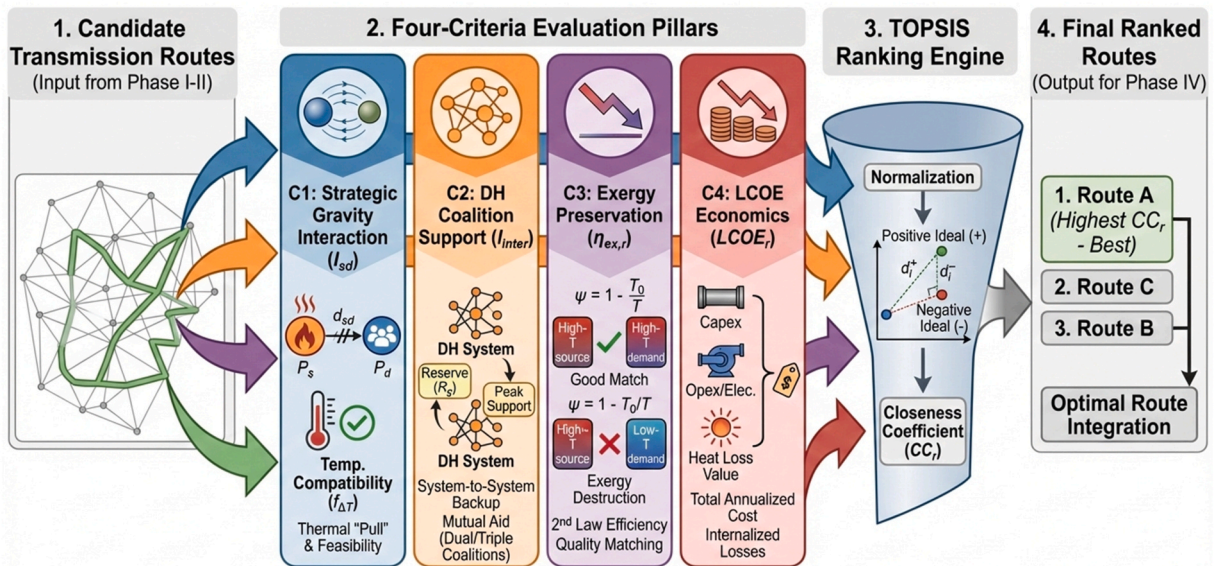


Fig. 5. Flowchart for evaluation of criteria in phase III.

attraction, network cooperation, thermodynamics, and economic efficiency with equal merit prior to optimization. In the sensitivity analysis, each criterion weight will perturb within a 15% interval of its baseline value while maintaining the normalization constraint in Equation (46b): $\mathcal{W}_\Phi + \mathcal{W}_\Pi + \mathcal{W}_\Psi + \mathcal{W}_{LCOC} = 1$. A large set of feasible weight combinations will be generated across the admissible weight space, and the complete Phase III–IV optimization sequence was repeated for each run (see Section 4.6 for the analysis and results).

2.4. Phase IV: Techno-economic optimization

The optimization framework is driven by a single-objective synthesized proxy that internalizes economic, environmental, and thermodynamic penalties, or evaluates them through a weighted sum approach. The comprehensive objective function (Z) is as the total annualized operational and capital costs alongside penalties:

$$Z = C^{tot,ann} + \tau_{CO_2}(CO_2)^{tot,ann} + \tau_{ex}\psi_{ex}^{des,ann} \quad (50a)$$

Equation (50a) has three main elements:

Annualized Economic Cost ($C^{tot,ann}$): It accounts for the annualized capital expenditures (CAPEX) of new pipeline installations (adjusted by whether they leverage the low-impedance tunnel network or require street-level excavation) and the variable operating expenditures (OPEX) including electricity for circulating pumps and primary heat procurement (defined by Equation (51)).

CO₂ Emissions Penalties ($\tau_{CO_2}(CO_2)^{tot,ann}$): It explicitly quantifies the carbon footprint of the network by multiplying individual heat source conversion efficiencies and fuel carbon intensities by active time-slice weights (defined by Equation (52)).

Exergy Destruction ($\tau_{ex}\psi_{ex}^{des,ann}$): It captures the thermodynamic irreversibilities of the network, penalizing low exergy utilization and temperature mismatch when upgrading low-grade waste heat (such as data center exhaust at 60–75°C) using heat-pump boosting (defined by Equation (53)).

The MILP optimization simultaneously minimizes annualized system cost, carbon emissions, and exergy destruction by considering multipliers τ as:

$$\min Z = \min(C^{tot,ann} + \tau_{CO_2}(CO_2)^{tot,ann} + \tau_{ex}\psi_{ex}^{des,ann}) \quad (50b)$$

where annualized system cost is defined based on Equation (41) in previous section as:

$$C^{tot,ann} = \sum_r \left(C_r^{tot,cap} \frac{\mathcal{R}(1+\mathcal{R})^{years}}{(1+\mathcal{R})^{years}-1} + C_r^{tot,O\&M} \right) y_r + \sum_t C_{elec} w_t (\dot{W}_{pump} + \dot{W}_{HP}) + \sum_t C_{fuel} w_t \dot{Q}_t^{gen} \quad (51)$$

in Equation (51), y_r is a binary decision variable for route (corridor) connection. A time-weighting factor w_t for representative periods based on the operational time of pumps and heat pumps. Annual carbon emission is defined by:

$$(CO_2)^{tot,ann} = \sum_t w_t \left(\sum_r (\dot{W}_{pump} + \dot{W}_{HP}) w_{em,elec} + \sum_e \dot{Q}_e^{gen} w_{em,fuel} \right) \quad (52)$$

The annual exergy destruction in equation (50) for each route is defined based on the supply and return temperatures of the route:

$$\psi_{ex}^{des,ann} = \sum_t w_t \left[\left(1 - \frac{T_{env}}{T_{sup,r}} \right) - \left(1 - \frac{T_{env}}{T_{ret,r}} \right) \right] \dot{Q}_{r,t} \quad (53)$$

In the exergy destruction calculation in Eq. (53), the environmental

reference temperature (T_{env}) corresponds to the monthly average ambient air temperature obtained from long-term meteorological observations [93]. For the case study in Section 3, the monthly values ranging from approximately 5°C to 16°C were used (Table 1), allowing the exergy factor to reflect seasonal variations in environmental conditions. This reference temperature is distinct from the soil temperature parameter used in the buried pipe heat-loss calculations.

To guarantee physical and thermodynamic feasibility, the MILP model enforces a rigorous set of structural and operational constraints.

Node-level energy balance: It was already introduced by Equations (16a) and (16b) which Enforce that the net thermal energy entering a node (from candidate routing corridors and local heat sources) must strictly balance the heat delivered to substations, network losses, and downstream mass flows.

Edge activation and capacity: Edge activation and capacity is applied as one of the optimization constraints at this step:

$$-y_e \dot{Q}_{ij,max} \leq \dot{Q}_{ij,t} \leq y_e \dot{Q}_{ij,max} \quad (54a)$$

in equation (54a), y_e is a binary decision variable for activation/deactivation of the edge.

Node capacity: The production from each source cannot exceed its useable capacity:

$$0 \leq \dot{Q}_e^{gen} \leq \dot{Q}_{max}^{gen} \quad (54b)$$

4th-Generation Supply Temperature: To ensure compatibility with fourth-generation district heating (4GDH) principles, supply temperatures at each network node are constrained within a predefined temperature range:

$$T_{min} \leq T_r^{sup} \leq T_{max} \quad (54c)$$

Heat-Pump Bounds: The heat generation output of each heat pump (if available) is bounded by its capacity.

$$\dot{Q}_{min}^{HP} \leq \dot{Q}_{i,t}^{HP} \leq \dot{Q}_{max}^{HP} \quad (54d)$$

Thermal dissipation: As already introduced by Equation (20), thermal heat losses along the underground corridors are dynamically constrained based on pipe dimensions, insulation coefficients, and the thermal properties of the ambient environment.

Mass flow rate continuity: Similar to node-level energy balance mentioned above, the continuous fluid mass flow rate of the heating water entering and exiting any given node i must maintain absolute structural equilibrium:

$$\sum_{j:(i,j) \in \mathcal{V}} \dot{m}_{ji,t} + \dot{m}_{i,t}^{gen} = \dot{m}_{i,t}^{dem} + \sum_{k:(i,k) \in \mathcal{E}} \dot{m}_{ik,t} + \dot{m}_{i,t}^{loss} \quad (55a)$$

Network hydraulics: As already introduced by Equation (21), frictional momentum losses across the network create a pressure gradient over candidate routing corridor paths is considered as another constraint.

Unidirectional Flow Restriction: Each pipe (supply or return) requires fixed hydraulic flows per time slice. The binary variables must prevent simultaneous conflicting flows on an edge:

$$y_{ji,t} + y_{ij,t} \leq 1 \quad (55b)$$

Source-demand temperature compatibility: A source can only supply a demand node when the required supply temperature can be achieved directly or through available heat-pump upgrading:

$$T_{gen} + \Delta T_{HP} \geq T_{sup} \quad (55c)$$

Heat-demand satisfaction: The total thermal energy supplied to

each demand node must satisfy the annual heat demand requirement at any time:

$$\mathcal{D}_{i,t} \leq \dot{Q}_{i,t}^{dem} \quad (55d)$$

Two mechanisms are incorporated into the framework to reduce prolonged part-load heat-pump operation at the city scale. First, when thermal demand decreases, the interconnected network can redistribute loads among available heat sources and heat pumps through the coalition and routing framework described in Phase III. This allows selected units to operate closer to their preferred capacity ranges while other units remain temporarily inactive. Second, Equation (54d) imposes minimum and maximum operating capacity constraints on each heat pump. Thereby preventing unrealistically low operating levels. Together, these mechanisms reduce the occurrence of prolonged low-load operation and provide a more realistic representation of large-scale district-heating system operation. Although detailed compressor part-load performance is not explicitly modeled, the optimization preferentially allocates thermal demand across available sources and heat pumps, thereby maintaining operation closer to practical capacity ranges.

2.5. Phase V: Integration and impact assessment

Baseline emissions typically individual gas boilers or decentralized heating in the existing DH are calculated as:

$$(\text{CO}_2)^{ann,baseline} = \sum_t \sum_e \dot{Q}_{e,baseline}^{gen} w_{em,fuel} w_t + \sum_t \sum_e \dot{W}_{e,baseline} w_{em,elec} w_t \quad (56a)$$

System emissions under the optimized backbone are:

$$(\text{CO}_2)^{ann,opt} = \sum_t \sum_e \dot{Q}_{e,opt}^{gen} w_{em,source} w_t + \sum_t \sum_e (\dot{W}_{e,HP} + \dot{W}_{e,pump}) w_{em,elec} w_t \quad (56b)$$

Total relative annual emission reduction is then calculated by:

$$\text{Emission savings (\%)} = \frac{(\text{CO}_2)^{ann,baseline} - (\text{CO}_2)^{ann,opt}}{(\text{CO}_2)^{ann,baseline}} \quad (57)$$

The thermodynamic quality of the interconnected district heating system is evaluated using an exergy-based environmental indicator. The useful exergy delivered to all demand nodes over the simulation horizon is calculated based on equation (38a) as:

$$\psi_{ex}^{use} = \sum_t \sum_e \dot{Q}_{e,t} \epsilon_{DH} w_t \quad (58a)$$

$$\psi_{ex}^{input} = \sum_t \sum_e \dot{Q}_{e,t}^{gen} \epsilon_{source} w_t + \sum_t \sum_e (\dot{W}_{e,HP} + \dot{W}_{e,pump}) w_t \quad (58b)$$

The overall exergy efficiency of the system is then defined as:

$$\eta_{ex} = \frac{\psi_{ex}^{use}}{\psi_{ex}^{input}} \quad (59)$$

This indicator is calculated for both the optimized interconnected district heating system and the baseline non-connected heating configuration, yielding $\eta_{ex}^{baseline}$ and $\eta_{ex}^{optimized}$, respectively. The comparison of these values provides a thermodynamic measure of how effectively each system utilizes high-quality energy resources to meet low-temperature heating demands, thereby complementing the economic and CO₂-based performance metrics.

Finally, the System Cost Ratio (SCR) is introduced to provide a normalized lifecycle comparison between the optimized large-scale DH

and the baseline non-connected DH configuration:

$$\text{SCR} = \frac{\sum_{y=0}^N \frac{C_{DH}^{tot,y}}{(1+r)^y}}{\sum_{y=0}^N \frac{C_{baseline}^{tot,y}}{(1+r)^y}} \quad (60)$$

where top and bottom of the ratio in equation (60) denote the total annual costs of the optimized large-scale DH and the baseline non-connected DH system in year y , respectively; r is the real discount rate; and N represents the project evaluation horizon (years). By expressing the ratio of total discounted costs rather than absolute differences, the SCR provides a scale-independent measure of economic competitiveness.

3. Methodology: GIS layers for the case study

In this section, we assess available input GIS data and waste/renewable heat sources for the case study of Dublin including data centers, surface water, CHP plants, industrial waste heat, power stations waste heat, and wastewater treatment and quantify their thermal useable capacity $\dot{Q}_{i,t}^{gen}$ as part of the input to the methodology.

3.1. Underground corridor network

Although the term “tunnel” is used as a general descriptor in this study, the layer integrates a wide range of underground corridors, including transport tunnels, disused rail corridors, utility galleries, sewer and stormwater culverts, and service ducts. For example, the Dublin Port Tunnel, a key road transport corridor extending several kms with internal clearances of approximately 4.6 to 4.9 m, differs substantially from smaller utility ducts or historic sewer systems. Consequently, the GIS dataset shown in Fig. 6 extracted from OpenStreetMap (OSM), Irish government data [94], and Dublin City Council incorporates a range of relevant attributes, including tunnel type, internal clearance, depth, length, managing authority, access points, and operational or legal restrictions.

3.2. Heat demand

This layer as shown in Fig. 7 quantifies the estimated space-heating and domestic hot-water demand within defined spatial units - such as building parcels, urban blocks, or grid cells - derived from building stock data and energy consumption statistics. Heat demand density is a critical determinant of phases II and III of the proposed frameworks as it facilitates the identification of optimal connection points for integrating existing small-scale DH networks into a unified city-scale system. Areas exhibiting high annual or peak thermal loads expressed as kWh/m² in equation (27) are more likely to support cost-effective heat distribution networks, as they allow for shorter pipe lengths per unit of demand and lower heat losses. According to analyses conducted by the Sustainable Energy Authority of Ireland (SEAI), the baseline scenario for potential district heating supply in Ireland exceeds 2.7 TWh per year, with Dublin representing a significant proportion of this potential [95]. Furthermore, GIS-based mapping by Codema indicates that approximately 75% of Dublin's built environment demonstrates conditions favorable to DH deployment, including sufficient load densities and proximity to heat sources [96].

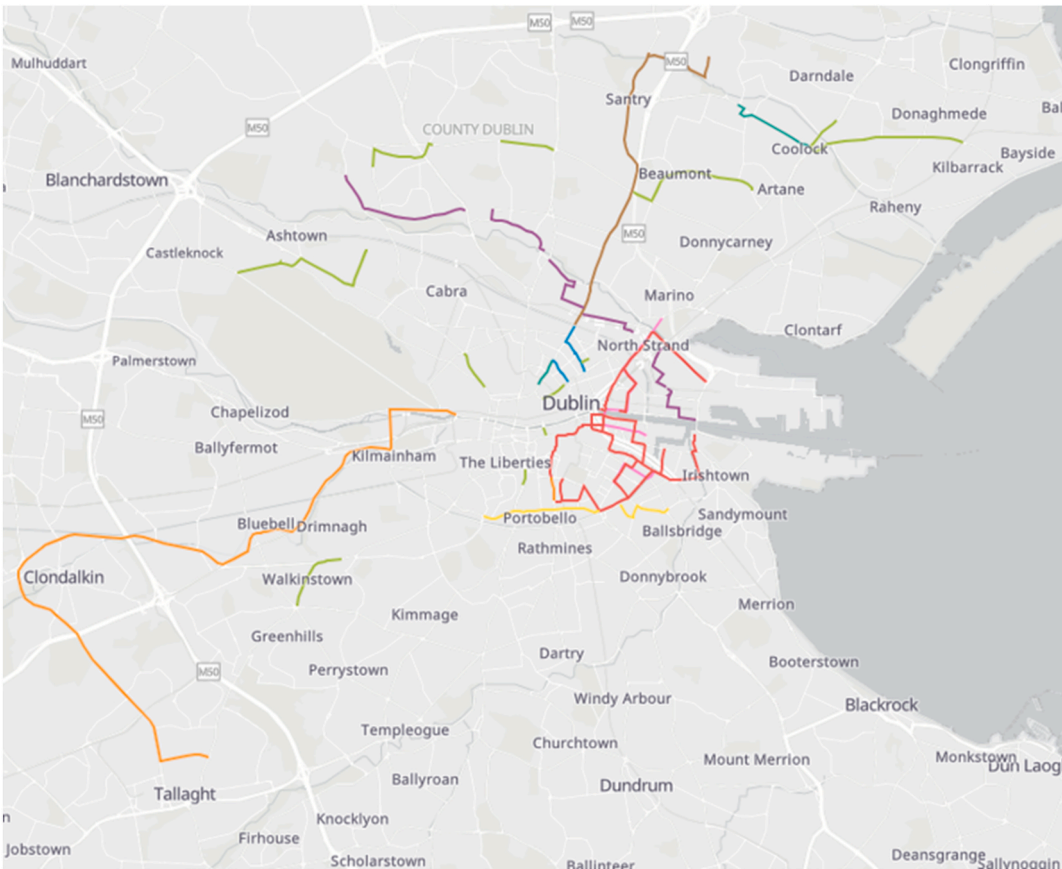


Fig. 6. GIS layer of underground corridor in Dublin.

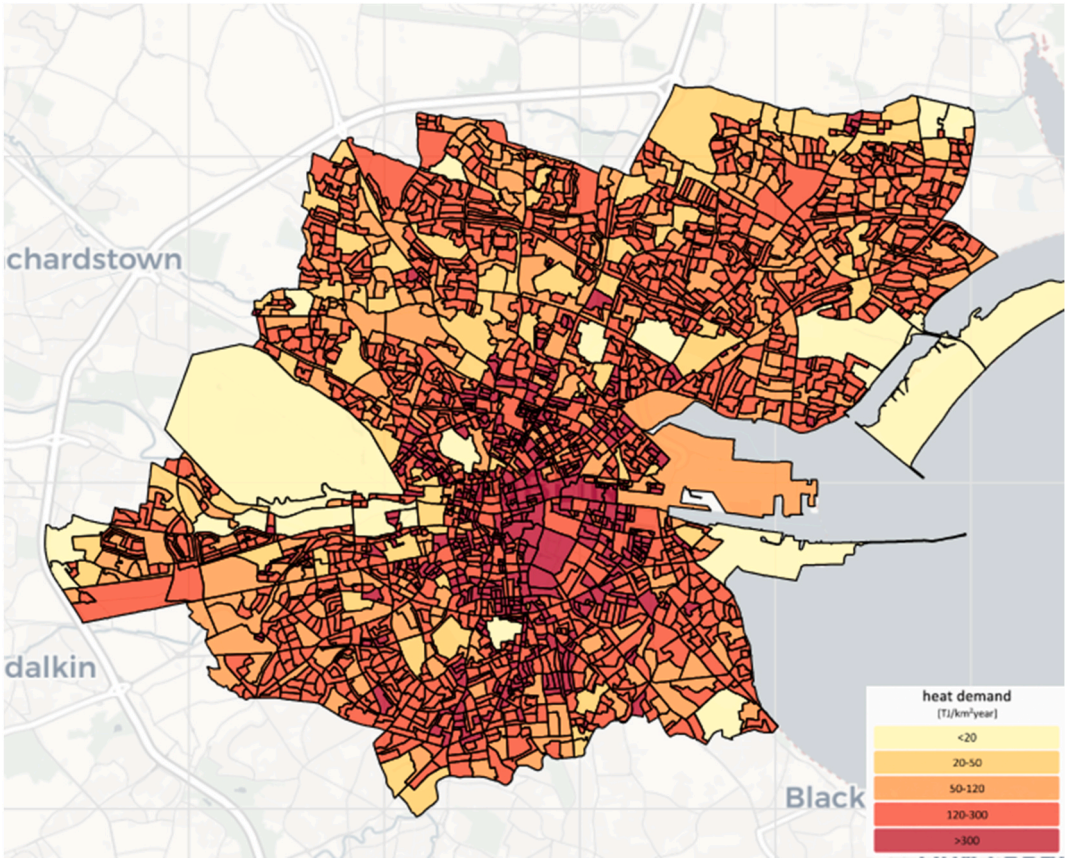


Fig. 7. GIS layer of heat demand in Dublin [96].

3.3. Data centers

The GIS layer in Fig. 8 representing datacenters (dark blue markers) highlights their spatial concentration primarily in the western and southwestern parts of Dublin, notably around Blanchardstown, Clondalkin, and Tallaght. Data centers represent continuous and predictable low-temperature waste heat sources whose recoverable thermal

potential is primarily governed by their electrical power consumption and cooling system configuration. Since nearly all consumed electrical energy is ultimately dissipated as heat, the raw thermal output of a data center dc can be approximated as:

$$\dot{Q}_{raw,dc}^{gen} = \eta_{conv,dc} \dot{W}_{elec,dc} \quad (61)$$

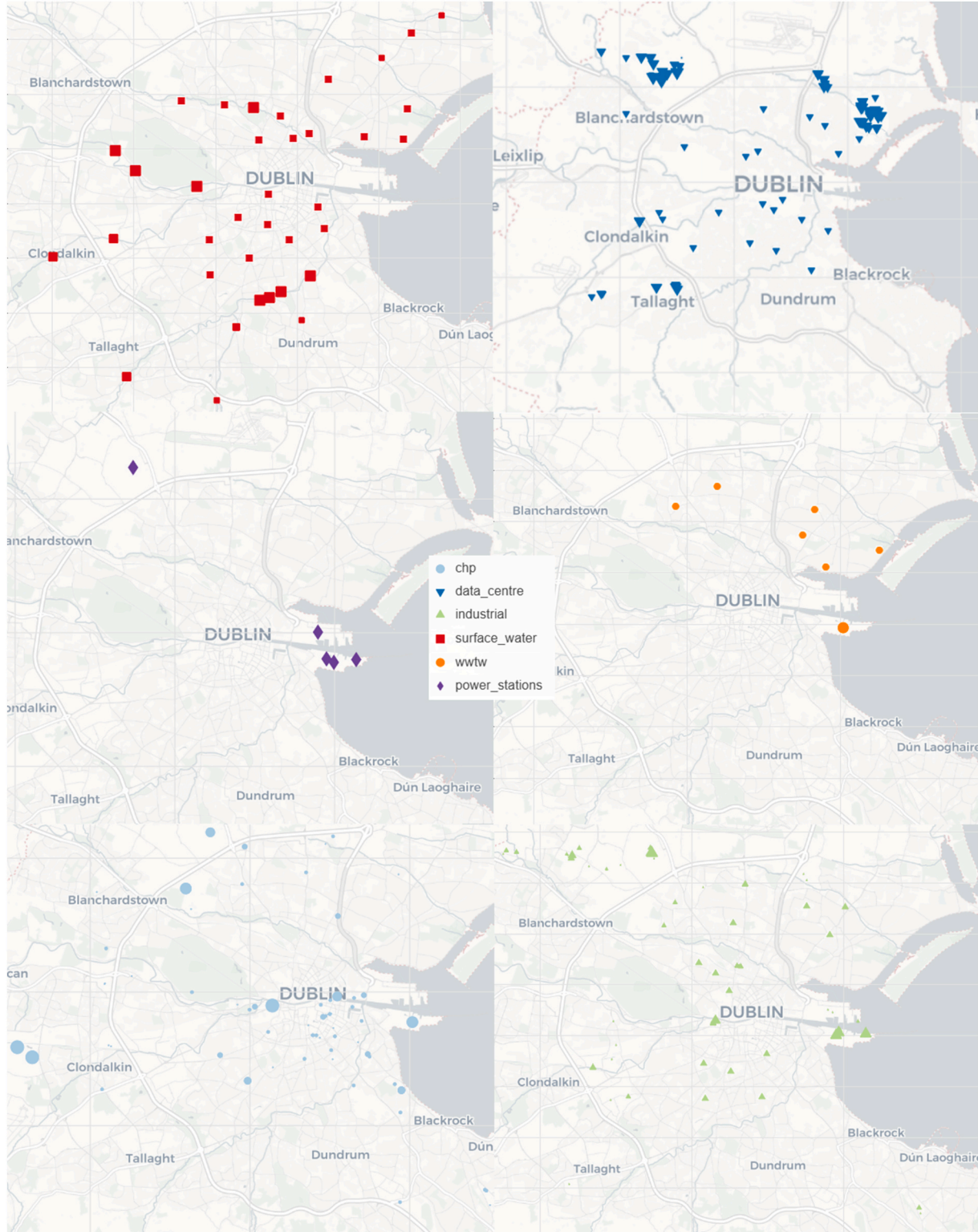


Fig. 8. GIS layer of locations for various waste heat in Dublin: data centers (top right), surface water (top left), waste water treatment (middle right), powerplant (middle left), industrial waste heat (bottom right), and combined heat and power (bottom left).

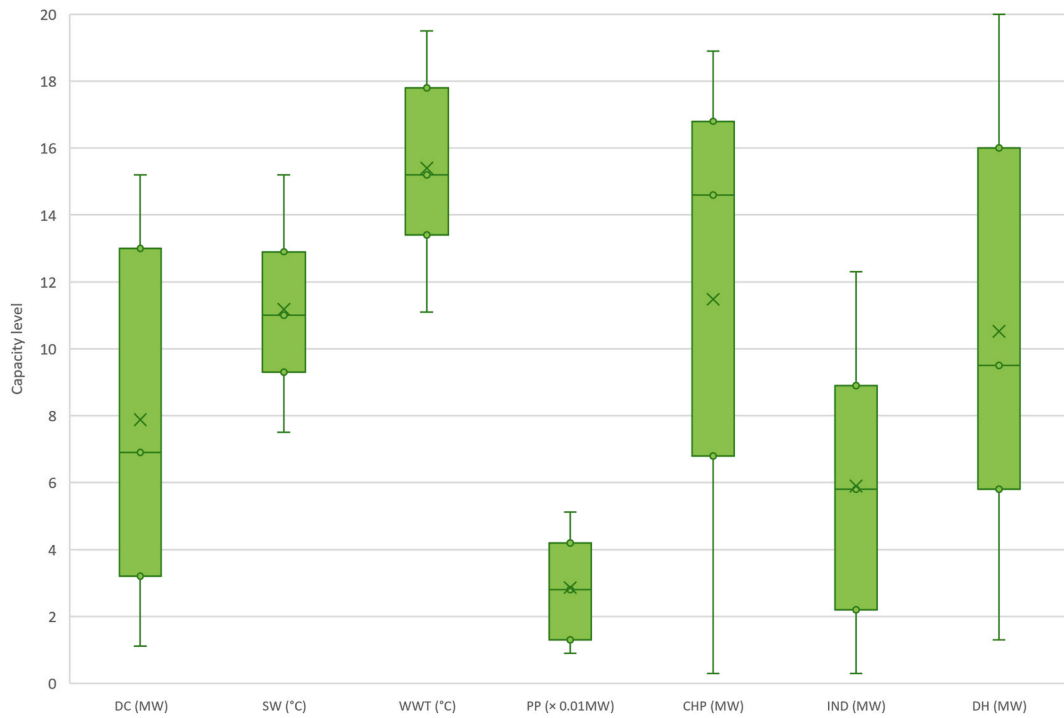


Fig. 9. Distribution of GIS data for potential waste heat sources and existing DHs.

Where $\dot{W}_{e,dc}$ is the data center electrical load (MW) and η_{conv} is the electricity-to-heat conversion efficiency, typically ranging between 0.95 and 0.99 [55]. The outlet temperature of the rejected heat T_i depends on the cooling technology and commonly lies between 25 and 40°C for air-cooled systems and up to 50–65°C for liquid-cooled configurations [68]. As these temperatures are generally below the required district heating supply temperature T_{sup} , heat upgrading through heat pumps is necessary. The theoretical coefficient of performance (COP) of the heat pump can be estimated using a Carnot-based approximation:

$$COP_{ideal} = \frac{T_{sup}}{T_{sup} - T_{dc}} \quad (62)$$

In practical applications, real COP values are lower due to system losses

and are typically assumed in the range of 4 to 7 [97]. With $\mathcal{A}$ as the system efficiency factor:

$$COP_{real} = \mathcal{A}(T_{source}, \Delta T_{upgrade}, Source) COP_{ideal} \quad (63)$$

$$\eta_{HP} = \frac{COP_{real}}{COP_{real} + 1} \quad (64)$$

In practical applications, real COP values are lower than the theoretical Carnot limit due to compressor inefficiencies, heat exchanger losses, control strategies, and operating conditions. Therefore, the system efficiency factor $\mathcal{A}$ is not treated as a constant but varies according to heat source characteristics and required temperature lift. In the present study, operational COP values were obtained from source-specific COP performance maps (Fig. 10), developed from representative literature

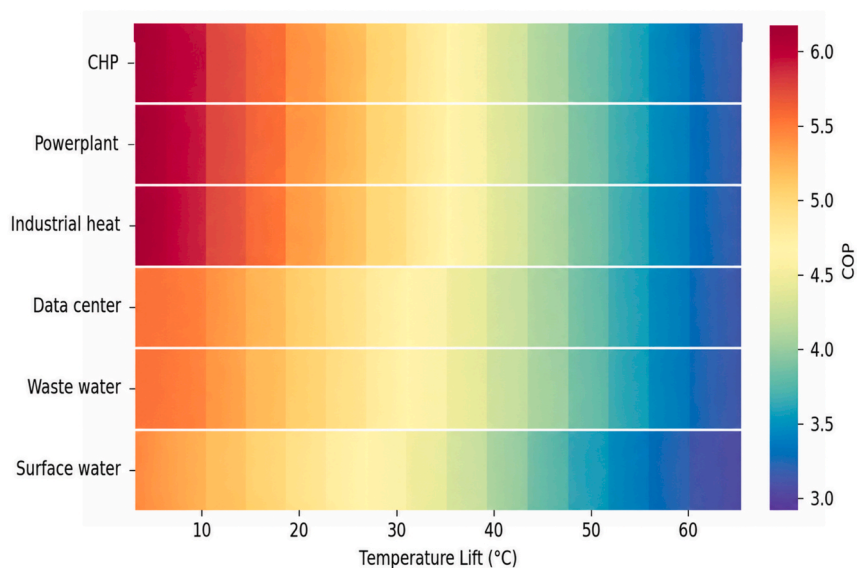


Fig. 10. COP for various technologies to extract heat from available sources.

data and implemented as a function of source type and temperature lift. Consequently, COP varies spatially and operationally throughout the GIS-based assessment rather than being represented by a single fixed value.

The useable upgraded thermal energy delivered to the DH network is therefore approximated by:

$$\dot{Q}_{dc,usable}^{gen} = \dot{Q}_{raw,dc}^{gen} \eta_{HP} \quad (65)$$

Where η_{HP} represents the effective heat pump utilization efficiency accounting for performance degradation and operational constraints, generally between 0.7 and 0.9. To reflect the high operational reliability of data centers, an availability factor α_{dc} is introduced, commonly exceeding 0.95 due to near-continuous operation [57]. The final technically recoverable heat potential becomes:

$$\dot{Q}_{dc}^{gen} = \dot{Q}_{dc,usable}^{gen} \alpha_{dc} \quad (66)$$

Subject to the feasibility condition

$$T_{dc} + \Delta T_{upgrade} \geq T_{sup} \quad (67)$$

In eq. (67), $\Delta T_{upgrade}$ represents the achievable temperature lift of the heat pump system. This formulation enables consistent spatial integration of data center waste heat into the district heating planning framework, capturing thermodynamic limits, temperature compatibility, and operational reliability.

3.4. Surface water

The GIS surface water layer shown in Fig. 8 (red markers) provides spatially explicit information on Dublin's rivers, canals, and engineered watercourses with identified potential for low-temperature geothermal energy extraction, serving as a strategic component in the transition towards a 5th-generation district heating and cooling (5GDHC) network. This dataset consists of georeferenced points and segments where flow rate, temperature, and volume data indicate the technical feasibility of extracting and exchanging heat. Surface water bodies - such as the River Liffey, River Tolka, Grand Canal, and smaller engineered channels - represent stable, locally available reservoirs of low-grade thermal energy. Their natural temperature ranges (15°C under Irish climatic conditions [68]) are below traditional district heating supply temperatures; they are ideally suited for 5GDHC networks. The overall heat extracted for surface water can be written as:

$$\dot{Q}_{sw}^{gen} = \eta_{HP} \dot{m}_{HP} \zeta_{p,water} (T_{sw,in} - T_{sw,out}) \quad (68)$$

Heat pump performance for surface water was determined using the source-specific COP surface presented in Fig. 10.

3.5. Wastewater treatment (WWT) waste heat

The heat from wastewater treatment illustrated in Fig. 8 arises from two main sources: the thermal energy contained in wastewater itself and the waste heat produced by treatment processes such as anaerobic digestion and CHP generation. Because wastewater flows are continuous and relatively warm compared to ambient conditions (typically 15–25°C [68]), they provide a stable, year-round low-temperature heat source that is well suited to recovery using heat exchangers and heat pumps. The most important asset in Dublin is the Ringsend Wastewater Treatment Plant, the largest in Ireland, serving the Greater Dublin Area with a treatment capacity equivalent to over two million people once ongoing upgrades are complete. Ringsend already operates anaerobic digestion of sewage sludge, producing biogas that fuels CHP units. In addition to high-grade CHP heat, low-grade heat can be recovered directly from wastewater streams at treatment plants or within major sewer collectors. Heat exchangers installed on influent or effluent flows can extract thermal energy without affecting treatment performance. The

recoverable thermal power from wastewater is given by:

$$\dot{Q}_{ideal,ww}^{gen} = \dot{m}_{ww} \zeta_{p,ww} (T_{in} - T_{out}) \quad (69)$$

In this equation, $\dot{m}_{ww}$ is the mass flow rate of wastewater, ζ_p is the specific heat capacity of wastewater, T_{in} is the influent wastewater temperature, and T_{out} is the wastewater temperature after heat extraction. If plant data is unknown, flow can be estimated from population P_o , and wastewater per capita q_{pc} (m³/person/day) which is typically 0.12–0.20 m³/day [58]:

$$\dot{m}_{ww} = \rho_{ww} \frac{P_o q_{pc}}{86400} \quad (70)$$

In practice, only a fraction of the ideal heat can be captured due to heat exchanger efficiency, fouling, operational constraints, and seasonal effects. This is accounted for using a recovery factor η_{rec} , typically between 0.5 and 0.75 [59], such that:

$$\dot{Q}_{usable,ww}^{gen} = \eta_{rec} \dot{Q}_{ideal,ww}^{gen} \quad (71)$$

The delivered thermal output is therefore governed by the heat pump coefficient of performance, generally ranging from 3.5 to 5.5 for WWT-based systems, enabling several units of heat to be supplied for each unit of electricity consumed:

$$\dot{Q}_{ww}^{gen} = \frac{\dot{Q}_{usable,ww}^{gen}}{1 - \frac{1}{COP_{HP}}} \quad (72)$$

3.6. Powerplants waste heat

The power plant GIS layer in Fig. 8 (purple markers) shows a different but complementary spatial pattern, with most facilities located near the Dublin Port area and along major energy corridors. Their proximity to coastal zones suggests potential synergies with CHP or waste-to-energy systems that already benefit from efficient cooling and logistical access. For a plant with electrical capacity $\dot{W}_{elec,pp}$ and conversion efficiency $\eta_{elec,pp}$, the total waste heat power can be expressed as:

$$\dot{Q}_{rej,pp}^{gen} = \eta_{pp} \dot{W}_{elec,pp} \left(\frac{1}{\eta_{elec,pp}} - 1 \right) \quad (73)$$

Where η_{pp} is the recovery factor depending on cooling system and integration feasibility. For plants with once-through cooling systems, it is typically in the range of 0.7–0.8, due to the direct availability of large quantities of cooling water at moderate temperatures [60]. For plants equipped with cooling towers, the recoverable portion is lower, generally between 0.4 and 0.6, as part of the heat is dissipated through evaporation and cannot be economically captured [60]. In the case of air-cooled condensers, the recoverable fraction is typically limited to 0.2–0.4, because the heat is rejected to ambient air at lower temperature levels, significantly constraining practical extraction [60]. Not all of this heat is directly useable in a district heating network, because much of it may be at low temperature (e.g., cooling water returning at 30–40°C) below typical DH supply requirements (often 70–90°C) [68]. To bridge this gap, heat pump systems can be integrated, where the coefficient of performance (COP) governs how much additional electrical input is needed to elevate the waste heat to distribution temperature. A realistic heat pump performance factor η_{HP} captures system losses and results in a useable upgraded heat quantity:

$$\dot{Q}_{pp}^{gen} = \dot{Q}_{rej,pp}^{gen} \eta_{HP} \quad (74)$$

Heat pump performance was determined using the source-specific COP surface presented in Fig. 10.

3.7. Industrial waste heat

Industrial waste heat is the surplus thermal energy generated as a byproduct of manufacturing, chemical refining, or data processing that is traditionally vented into the atmosphere or water as thermal pollution [98]. The map in Fig. 8 (green markers) suggests the potential for a multi-nodal system where these diverse hubs are interconnected; for instance, capturing the massive surplus at the Dublin Port could decarbonize the high-density city center areas through relatively short-distance transmission. The spatial distribution shows high-intensity heat sources, represented by larger triangles, concentrated in key industrial zones like Dublin Port, Clondalkin, and Blanchardstown, which are ideally positioned in close proximity to high-density residential and commercial demand centers. Since the annual useful heat consumption of the industrial facility is available, the annual fuel input is estimated indirectly using a realistic seasonal boiler efficiency. Let $\dot{Q}_{ind}^{input}$ denote the measured annual useful heat delivered to the industrial process. The corresponding annual fuel input is calculated as:

$$\dot{Q}_{ind}^{fuel} = \frac{\dot{Q}_{ind}^{del}}{\eta_{boiler}} \quad (75)$$

Where η_{boiler} represents the practical seasonal efficiency of industrial natural gas boilers. Based on operational performance reported for industrial systems, a conservative efficiency range of 0.85–0.92 is adopted to reflect real operating conditions rather than nameplate values [81]. The total annual thermal losses generated by the boiler are therefore obtained from the energy balance:

$$\dot{Q}_{ind}^{loss,ideal} = \dot{Q}_{ind}^{del} \left(\frac{1}{\eta_{boiler}} - 1 \right) \quad (76)$$

However, the majority of losses occur through the flue gas stream. To account for this, a flue-gas loss fraction γ_{flue} is introduced based on a conservative range of 0.75 to 0.90 for typical industrial boilers. Moreover, to represent the temperature constraints i.e. acid dew point limitations, minimum allowable stack temperature, corrosion prevention, a recoverable temperature fraction γ_{temp} is introduced [75] [76]. This parameter represents the share of flue gas heat available above the minimum technically useable temperature level with a conservative practical range of 0.50 to 0.75 [75] [76]. The annual waste heat contained in the flue gas stream is therefore estimated as:

$$\dot{Q}_{ind}^{gen} = \gamma_{temp} \gamma_{flue} \dot{Q}_{ind}^{del} \left(\frac{1}{\eta_{boiler}} - 1 \right) \quad (77)$$

3.8. Combined heat and power (CHP)

The spatial distribution of CHP plants across Dublin provides a valuable basis for evaluating potential waste heat recovery for district heating networks. As observed in Fig. 8 (light blue markers), the CHP installations are concentrated predominantly in the central and eastern parts of the city, with additional smaller units scattered in suburban areas such as Clondalkin, Tallaght, and Blackrock. This distribution suggests that a centralized or semi-centralized district heating network could leverage high-density CHP clusters in the city center while considering strategic pipeline extensions to serve peripheral neighborhoods. A convenient parameter in evaluation of available heat for integration is the heat-to-power ratio:

$$\dot{Q}_{CHP,ideal}^{gen} = \gamma_{CHP} \dot{W}_{elec,CHP} \quad (78)$$

For gas-engine CHP 80% to 90% of $\dot{Q}_{CHP,ideal}^{gen}$ is useable directly while for condensing steam turbine up to 20% of that can be used directly without heat pump [99] [100].

3.9. Summary of GIS inputs, spatial characterization, and model parameters

The GIS-based spatial analysis was implemented by integrating three spatial datasets: (1) building-based heat-demand layers derived from building stock data and energy statistics, (2) georeferenced renewable and waste-heat source locations including data centers, surface water bodies, wastewater treatment assets, power plants, industrial facilities, and CHP plants, and (3) underground corridor layers extracted from OpenStreetMap, Irish government datasets, and Dublin City Council records:

Heat demand zones: Heat-demand zones were identified using the GIS-based clustering in Section 3.2 (Fig. 7 as the input data). Existing district-heating systems were represented directly using their reported capacities and service areas, while future district-heating development zones were derived from spatial demand-density analysis (Equations (23)–(25)) and gravity-based source-demand (Equation (28)) matching procedures. This approach enabled the identification of geographically concentrated demand clusters suitable for future network expansion while preserving consistency with existing district-heating infrastructure.

Underground corridors: Underground corridors were incorporated as candidate thermal transmission pathways through the GIS pre-processing framework described in Section 2.1 with the input data shown in Fig. 6 and explained in Section 3.1. Corridor selection was subject to multiple spatial constraints including accessibility, connectivity, network continuity, and routing feasibility. Redundant, isolated, or non-contributing corridor segments were removed through the graph-theory filtering procedures presented previously (Equations (1)–(15)). The resulting corridor network formed the candidate backbone used during the subsequent routing and optimization stages.

Renewable and waste heat resources: Renewable and waste-heat resources were spatially identified and quantified using a GIS database shown in Fig. 8 for all six candidate sources while the capacity of each source type is shown in Fig. 9 based on statistical analysis. Each source was represented as an individual georeferenced node with the given locations in Fig. 8. It is associated with technical attributes including available thermal capacity, source temperature, operational characteristics, and recovery potential (Shown in Table 1 and Fig. 9). Thermal capacities were estimated using source-specific methodologies (Equations (61)–(78)) described in Section 3.3 to Section 3.8 (based on the source type). To ensure conservative resource assessment, the optimization framework employed source-specific minimum annual available capacities for industrial, data-center, CHP, and power-generation assets, while minimum annual source temperatures were adopted for wastewater and surface-water resources when evaluating heat-pump performance. These attributes formed the basis for the subsequent gravity-model screening, MCDA ranking, and MILP optimization stages.

GIS resolution: The study area was discretized into 200 m × 200 m grid cells, representing a compromise between capturing urban heat-demand heterogeneity and maintaining computational tractability for the city-scale GIS-MCDA-MILP framework.

The box plot in Fig. 9 illustrates the distribution of GIS data for the six primary heat source categories as well as the existing DHs utilized in the Dublin-based model, highlighting the variability in capacity levels across different sources. Waste Water Treatment (WWT) temperatures and Surface Water (SW) temperatures represent thermal baselines, with WWT showing the highest overall values (median 15 °C) and a narrower range compared to power-based metrics. In contrast, Combined Heat and Power (CHP) heat consumption and Data Center (DC) electricity consumption exhibit the greatest variability; CHP, in particular, shows a wide interquartile range and the largest overall spread, reflecting diverse scales of electricity output. Powerplant (PP) outputs, scaled down by a factor of 0.01, represent the highest relative capacity levels in the dataset, while Industrial (IND) heat demand shows a moderate distribution centered around a median of 6 MW. The inclusion of both the

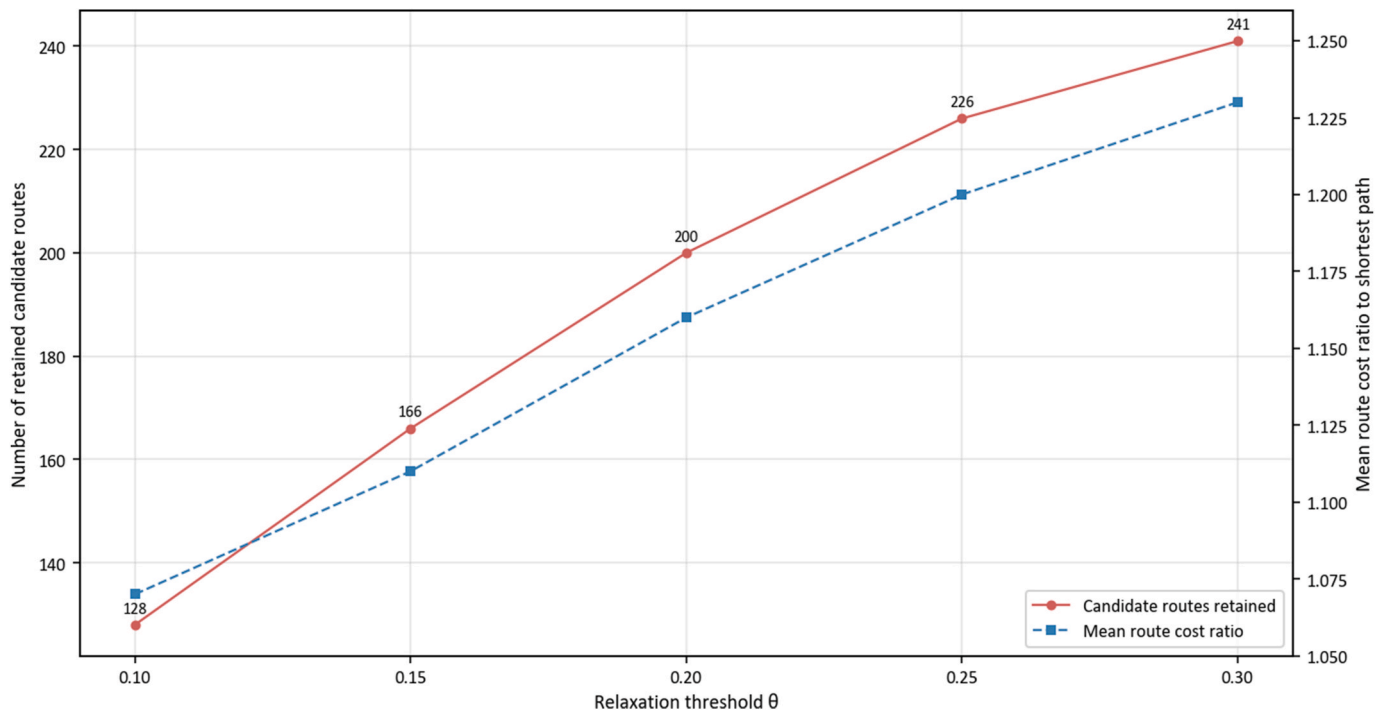


Fig. 11. Corridor screening sensitivity as a function of relaxation threshold (θ).

median (horizontal line) and mean (X marker) within each box highlights the skewness in distributions, particularly in the CHP and DC categories, which serves as a critical stochastic foundation for the subsequent modeling phases. DH capacities in the study area range from 1.3 to 20 MW indicating substantial variability in system size. The wider spread above the median suggests a moderately right-skewed distribution, reflecting the presence of several higher-capacity systems alongside predominantly small-to medium-scale installations. To avoid overestimation of recoverable waste heat, source capacities were defined using conservative availability assumptions. For industrial facilities, data centers, CHP plants, and power-generation assets, the available thermal capacity supplied to the optimization corresponded to the minimum annual observed thermal output rather than nominal or peak values. For environmental heat sources such as wastewater and surface water, the minimum measured source temperature was adopted when evaluating heat-pump performance. These assumptions ensure that all modeled heat supplies represent guaranteed minimum availability levels throughout the year.

By consolidating all modelling assumptions in a structured format, Table 1 provides the parametric foundation for the GIS-MCDA-optimization framework and enables systematic sensitivity analysis of the large-scale DH integration results. The baseline economic assessment is based on the parameter ranges reported in Table 1, including electricity prices, CO₂ penalties, discount rates, and infrastructure cost assumptions. Specifically, the optimization uses annualized cost formulations with representative electricity and heat-price assumptions, a CO₂ penalty term, a real discount rate of 4%, and a 25-year project evaluation horizon. Pipe installation costs, heat-pump CAPEX, pumping costs, and other capital items are therefore evaluated consistently within a life-cycle framework rather than as single-year expenditures. To assess the robustness of the economic results, uncertainty ranges for the principal techno-economic parameters are provided in Table 1 and are subsequently evaluated through phased-deployment and sensitivity analyses presented in the Results section.

Fig. 10 illustrates the continuous COP surface used in the model, obtained through interpolation of representative performance values from literature [54]. The heat map supports comparative assessment of temperature-lift sensitivity across different waste heat sources.

4. Results and discussions

To assess the robustness of the integrated GIS-gravity-MCDA-MILP framework, a two-stage sensitivity analysis was performed across Phase I corridor screening and Phase IV optimization. Fig. 11 illustrates the effect of the relaxation threshold (θ) on the size and quality of the candidate corridor pool. As θ increases from 0.10 to 0.30, the number of retained routes grows from 128 to 241, while the mean route cost ratio relative to the shortest-path baseline increases moderately from 1.07 to 1.23. This confirms that the Phase I screening mechanism progressively expands the feasible solution space without introducing excessive path inefficiency, thereby maintaining a controlled trade-off between diversity and cost quality of candidate corridors.

Fig. 12 evaluates the impact of the screened corridor set on the final MILP solution. The results indicate a rapid reduction in the optimality gap as the number of candidate routes increases, stabilizing at approximately 0.2% beyond 200 routes. This demonstrates that the optimization framework achieves near-convergence with respect to the candidate network size, and that further expansion of the corridor pool does not significantly improve the objective function Z . Importantly, the CO₂ emission reduction metric also converges to a stable range of approximately 68–69%, confirming that the decarbonization performance of the system is insensitive to further increases in solution space once a sufficient diversity of feasible routes is available. This joint convergence of both the optimization gap and the environmental performance metric provide strong evidence that the adopted θ threshold yields a near-optimal and physically consistent network design while maintaining computational efficiency.

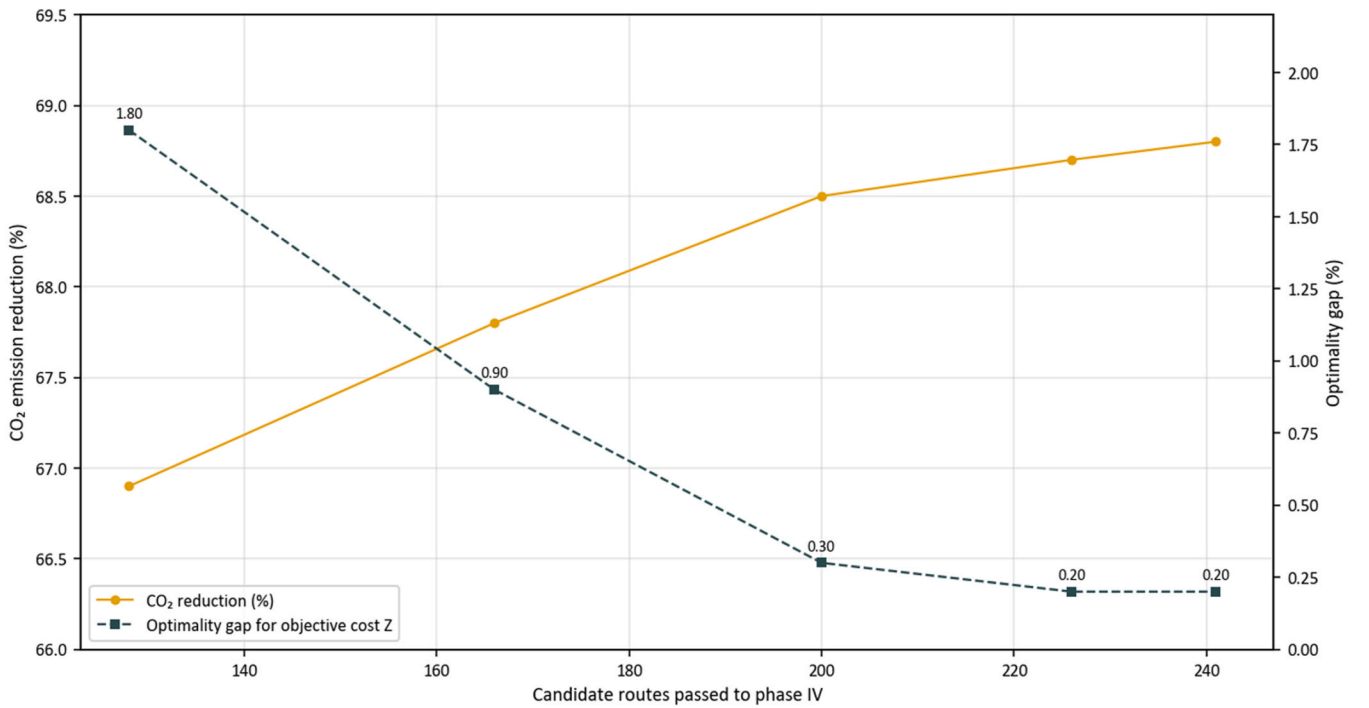


Fig. 12. Final MILP solution robustness with respect to candidate route pool size.

4.1. Optimal distribution network

Fig. 13 illustrates the global optimum for the proposed city-scale thermal grid, representing the optimized network topology that interconnects existing DH systems with newly identified consumer zones.

The color-coded segments represent a sophisticated thermal grid spanning a total of 148 km of existing corridor and new routes. The Red lines, totaling approximately 42 km, act as the high-temperature primary arteries, likely carrying pressurized hot water directly from central heat plants or industrial waste-heat sources to the densest urban corridors.

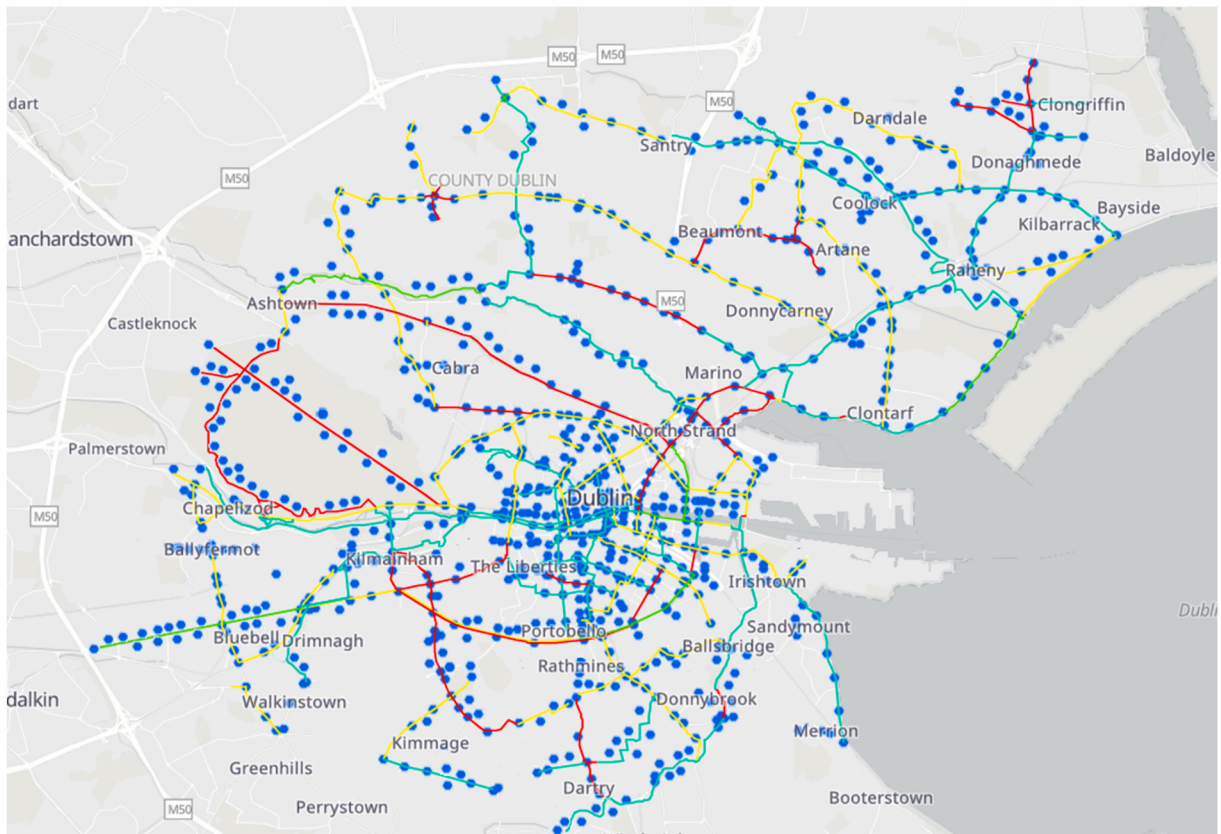


Fig. 13. Optimized distribution network for large-scale climate-neutral DH system.

These transition into the cyan and yellow networks - the largest portion of the grid at 58 km and 34 km respectively - which serve as the medium-to-low temperature distribution loops for residential and commercial heating. Finally, the 14 km of Light Green segments represent the lowest temperature lines or specialized ambient loops, ensuring thermal efficiency across the entire metropolitan footprint. The blue nodes distributed across the map signify the building clusters successfully connected to this large-scale DH infrastructure. These clusters were dynamically aggregated based on the spatial heat demand density and temporal profiles evaluated during Phase II. Specifically, only demand clusters satisfying the minimum viability thresholds for annual heat demand and spatial area density, governed respectively by Equation (26) and Equation (27), were retained for network integration. The dense concentration of these connected nodes in the central and eastern sectors of Dublin aligns robustly with the high-demand density zones previously mapped, validating the model's capacity to target areas with superior cost-benefit ratios. The varying colors of the distribution lines in Fig. 13 denote the distinct temperature levels of the supply networks, which are directly dictated by the innate temperature profiles of the connected heat sources or existing DHs. For instance, high-intensity sources such as power plants, CHP installations, and industrial facilities generally supply higher-grade waste heat. This allows specific transmission corridors originating from these hubs to operate at elevated temperatures, supplying legacy high-demand nodes directly without requiring extensive heat pump upgrading. This multi-temperature routing strategy is a direct mathematical consequence of the exergy preservation criterion ψ_r and the techno-economic optimization formulated in Phases III and IV. Rather than forcing a uniform, high-temperature distribution across the entire city, the mixed-integer linear programming (MILP) model minimizes annual exergy destruction $\psi_{ex}^{des,ann}$, by cascading temperatures throughout the network based on source availability. Consequently, primary transmission lines carrying this higher-grade heat from industrial and power generation hubs are routed toward high-density legacy districts, while secondary distribution branches integrating low-

temperature sources such as surface water or data centers operate at lower temperatures, characteristic of 4GDH and 5GDHC paradigms. This hierarchical temperature distribution ensures strict thermodynamic compatibility between specific heat sources and demand clusters, driven by the temperature compatibility factor Θ_{ij} calculated in Equation (31). In the western and southwestern peripheries - encompassing Blanchardstown, Clondalkin, and Tallaght - the network design predominantly captures continuous, low-temperature waste heat from the dense concentration of data centers. Because the rejected heat from these facilities typically ranges between 25 and 40°C for air-cooled systems, the model actively deploys heat pump upgrading logic to meet the localized supply temperature bounds dictated by Equation (56). Conversely, the eastern seaboard and Dublin Port area emerge in Fig. 13 as a high-capacity, high-temperature thermal hub. In this region, the strategic gravity interaction score Φ_{ij} calculated via Equation (32) heavily favors centralized routing due to the immense thermal "pull" of high-grade industrial waste heat, CHP units, and low-grade continuous flow from the Ringsend Wastewater Treatment Plant.

The physical trajectories of the pipeline network in Fig. 13 validate the techno-economic efficacy of utilizing existing underground infrastructure. The routing algorithm aggressively penalizes greenfield and street-level excavations through the route preference factor $\omega(r_e)$ in Equation (2), while balancing the thermal dissipation penalty λ accrued over longer transmission corridors via Equation (3). By heavily weighting established transport tunnels and utility corridors as low-impedance spatial pathways, the resulting topology successfully minimizes the annualized capital expenditure modeled in Equation (44a). This allows the large-scale network to bridge the spatial gap between decentralized suburban thermal sources and the dense urban core with minimal structural disruption to the city.

4.2. Heat source and DH matching

As Fig. 14 shows, the optimized city-scale source-demand matching

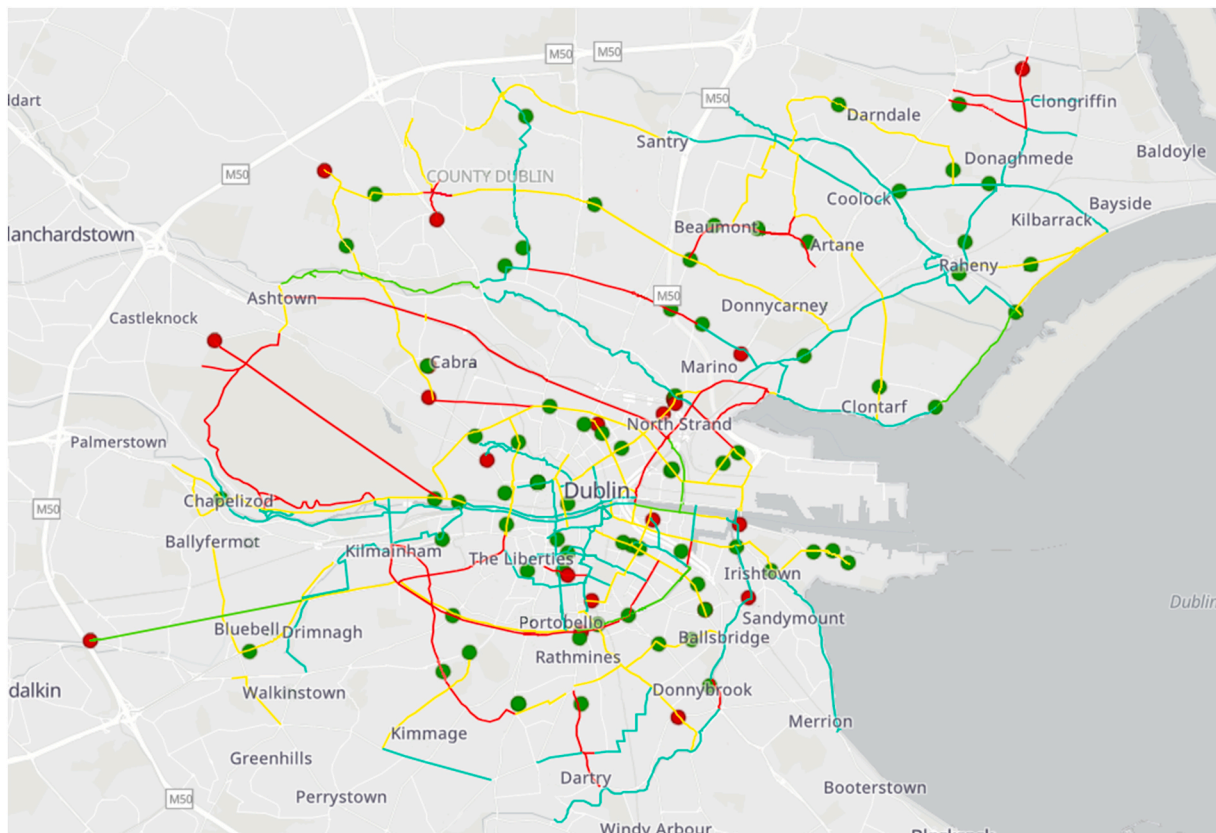


Fig. 14. Locations for optimized distribution substations.

aggregates 17 incumbent DHs (marked with red) and connects 66 mapped thermal sources (marked with green) across Dublin. Interconnection creates active coalitions among existing DH marked with red: interconnection allows pooling of 16% reserve margin effectively across the city. By routing high-exergy heat from the eastern port directly to high-demand legacy zones, and cascading low-grade heat from western data centers via heat-pumps into local low-temperature corridors, the topology reduces system exergy destruction while keeping transmission losses lower than a single high-temperature approach. The interconnected existing DH networks are no longer passive heat sinks but function as active prosumers within the grid. This connectivity improves load balancing and operational resilience across the city, allowing surplus heat from industrial hubs or wastewater treatment (e.g., the Ringsend WWTP) to be redistributed to satisfy peak demands in distant suburban nodes. This allows the system to satisfy the normalized reserve margin for other nodes, ensuring that a DH system at a specific point can receive support from the coalition when its own local sources are insufficient. This transformation from “thermal islands” to an interconnected coalition is the core of the “System Cost Ratio” improvement. The routes in your figure clearly gravitate toward the Dublin Port Tunnel and other utility corridors. This is because the model “aggressively penalizes” traditional street-level excavation, assigning a lower cost-weighting to established underground infrastructure. This hierarchical division is exactly the expected outcome when the optimization minimizes a combined annualized cost and exergy destruction objective while enforcing temperature compatibility constraints: higher-exergy sources serve higher-temperature sinks directly to minimize exergy destruction, while low-grade sources are cascaded downstream after upgrading where economically viable.

4.3. Spatial distribution of substations

The dominance of many small substations in the order of 2 to 5 MW class as shown with triangle sizes in Fig. 15 supports a procurement and operational strategy based on modular packaged substations and distributed small heat-pump boosters rather than a few very large conversion plants. Moreover, the hydraulic and pumping burden per substation is modest individually, but aggregated pump energy and electricity demand for heat pumps can be significant; therefore, routing choices that exploit low-impedance tunnel corridors i.e. reducing head and length materially lower LCOE and exergy penalties as described in Phase I and Phase IV of the methodology.

4.4. Impact assessment

Using spatial demand in Fig. 7, the study area corresponding to almost 43% of Dublin's buildings requiring approximately 2.4 TWh of heat per year for space and water heating. Practically, uncertainty in building stock, connection rates and future fabric upgrades mean ± 10 to 20% variance is reasonable; therefore, planners should test sensitivity around the 2.0 to 2.8 TWh/yr band when optimizing network layout or sizing central plant. An inventory of urban waste-heat anchors for the area indicates a credible recoverable range of roughly 2.0 to 2.8 TWh/yr, with data centers and CHPs heat as the dominant stream and wastewater and industrial/powerplant sources providing useful complements along with surface water. The lower bound reflects only higher-temperature streams that can be used directly while the upper bound assumes extensive capture and the application of heat-pump upgrades to low-grade flows. From a technical standpoint this range shows that the city's waste-heat resources, if properly aggregated and routed, are of the same order as the covered demand and therefore can form the backbone of a low-carbon district network. The principal practical challenges are temporal matching, routing losses and plant siting. If the system were limited to direct, high-temperature waste heat only, the network could meet roughly 23% to 38% of the demand. However, integrating electrically driven heat pumps with the seasonal performance factor of 3.1 to 3.5 to upgrade low-



Fig. 15. Locations for optimized distribution substations.

grade sources increases useable thermal output substantially: in realistic heat-pump-assisted cases the system can cover 60% to 90% of the area's demand. In best-case designs aggressive capture of anchors, substantial thermal storage and demand-side flexibility near-full coverage is achievable. In the central scenario, where the full thermal demand is delivered using heat pumps, total annual emissions fall to roughly 31% to 32% of the baseline, corresponding to a 68% to 69% reduction in CO₂ emissions relative to conventional system. Under more conservative, partial-capture scenarios where only a fraction of the demand is supplied by recovered heat, the reduction remains significant, typically in the range of 20% to 40% below baseline emissions, depending on the share of heat displaced. In contrast, optimistic near-zero-combustion configurations—maximizing direct waste heat use and minimizing fossil backup—can achieve reductions of 89% to 94% relative to the baseline, effectively approaching full decarbonization of operational heating emissions within the study area.

Using representative system values, the exergy efficiency rises from roughly 28% for distributed boiler systems to about 52% to 60% for an optimized low-temperature DH with heat-pump boosting which shows an absolute increase of 24% to 32%. The observed improvement in exergy efficiency is primarily driven by the transition from high-exergy fuel combustion at the building scale to a temperature-matched, low-temperature district-heating architecture. In the baseline configuration, natural-gas boilers typically generate water temperatures of 70–90°C to satisfy end-use heating demands that often require substantially lower temperatures. This mismatch destroys a significant fraction of the available exergy before useful heat reaches the consumer. In contrast, the proposed network utilizes a cascading temperature (i.e. four-level temperature) hierarchy that directly exploits high-temperature waste heat where available while upgrading low-temperature sources through centralized heat pumps. By matching source temperatures more closely to demand requirements, the network reduces unnecessary temperature lifts and therefore lowers thermodynamic irreversibility. Furthermore, the integration of multiple waste-heat streams allows heat to be recovered from sources that would otherwise reject thermal energy to the environment. Although heat pumps consume electricity, their high coefficient of performance enables the delivery of several units of useful heat per unit of electrical input, substantially improving the overall utilization of high-quality energy resources. The resulting increase in exergy efficiency from approximately 28% to 52–60% therefore reflects not only waste-heat recovery but also improved temperature matching, reduced exergy destruction throughout generation and distribution, and the adoption of low-temperature fourth-generation district-heating principles. Compared with conventional third-generation district-heating systems, which often operate with supply temperatures exceeding 80–100°C and rely

predominantly on centralized combustion-based generation, the proposed configuration operates at substantially lower temperatures and integrates a wider portfolio of low-grade renewable and waste-heat resources. This thermodynamic shift is the principal reason for the higher exergy efficiency achieved by the optimized network.

In terms of cost, the large-scale DH operator's fuel and electricity bill can fall by 75% to 90% in realistic and optimistic designs compared with a baseline. With modest additional tunnel reuse to lower trenching costs the project can reach simple payback in the order of two decades (18 to 24 years) in a realistic heat-pump assisted scenario. Because the exergy factor depends on the ratio between the reference temperature and the thermal stream temperature, seasonal variations in ambient conditions influence the absolute magnitude of both input and useful exergy. However, both the baseline and optimized configurations are evaluated using the same monthly reference temperatures. Consequently, seasonal fluctuations affect both systems in a similar manner and have only a limited influence on the relative exergy improvement. The reported increase in exergy efficiency is therefore primarily attributable to the transition toward lower-temperature district heating operation, improved temperature matching between sources and demands, and reduced exergy destruction throughout the network rather than to the specific choice of environmental reference temperature.

Quantitative evaluation of the gravity interaction, temperature compatibility, exergy utilization, and economic criteria confirms the structural logic of the optimized large-scale district heating backbone. High-capacity eastern power plant and CHP sources exhibit gravity interaction scores exceeding 58, almost five times higher than medium-grade industrial or upgraded data center connections. This dominant

spatial attraction numerically justifies the formation of high-temperature primary corridors linking eastern anchors to central demand clusters. Temperature compatibility factors further reinforce this hierarchy. High-grade 90°C sources yield compatibility values near 1.8, while upgraded low-grade streams provide values below 1.0, indicating mild thermodynamic penalties. Exergy analysis shows a clear gradient in thermodynamic quality: high-temperature sources preserve approximately 0.221 specific exergy factor compared with 0.163 for upgraded low-grade flows, representing a 35% reduction in thermodynamic usefulness when relying solely on cascaded heat-pump sources. Economic analysis highlights the decisive role of tunnel utilization. High-grade connections routed through existing underground corridors achieve levelized delivery costs near €20/MWh, while street-based medium-distance connections rise above €80/MWh. Heat-pump-supported low-grade routes remain competitive i.e. around €77/MWh, but are constrained by electricity costs and COP limitations. The combined criteria demonstrate that the optimized network naturally evolves into a multi-temperature hierarchical structure: high-exergy eastern anchors supply dense legacy zones through cost-efficient tunnel corridors, while lower-grade western and suburban sources are integrated via localized heat-pump upgrading and shorter loops. This confirms that minimizing annualized cost and exergy destruction simultaneously leads to thermodynamically coherent and economically rational city-scale thermal infrastructure.

4.5. Decarbonization

Fig. 16 presents the spatial distribution of decarbonization achieved after integration into the optimized large-scale DH network. The legend

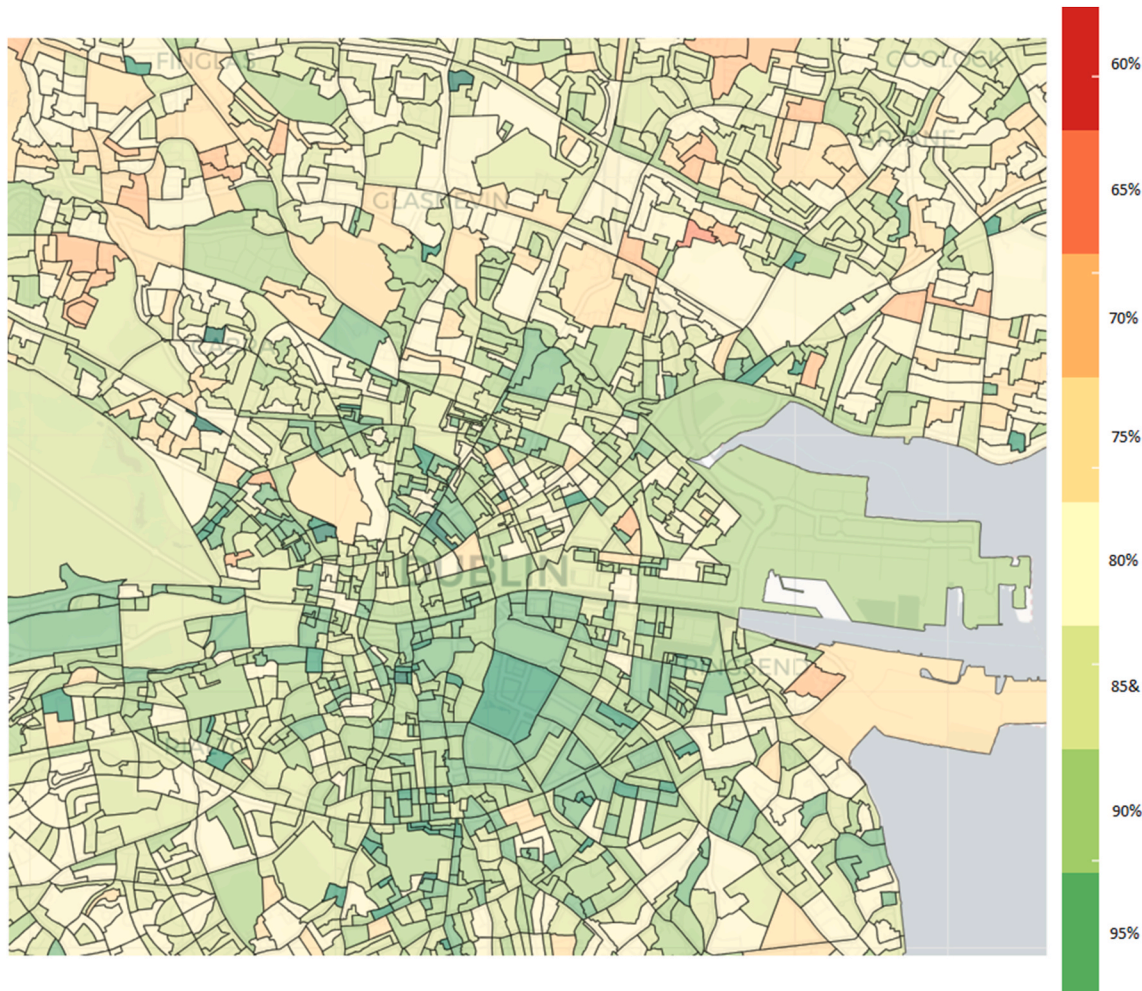


Fig. 16. Spatial distribution of decarbonization based on identified regions.

indicates a performance range from approximately 60% (red zones) to 95% (dark green zones) CO₂ reduction relative to the baseline individual boiler-based heating systems. The results demonstrate clear spatial stratification consistent with the temperature-layered routing and source–demand matching logic described in Sections 4.1–4.4. The highest decarbonization levels (90–95%) are concentrated in the inner-city core and docklands corridor, extending west–east from The Liberties through the city center toward Dublin Port. These areas correspond to high heat-density clusters retained after Equations (26) and (27), direct connection to high-grade waste heat sources (CHP, industrial, power-plant), short transmission distances along low-impedance tunnel corridors, and reduced thermal losses and pumping penalties. Given that the study covered area demand is 2.4 TWh·yr^{−1}, and that high-temperature direct-use waste heat can cover roughly 13–28% of total demand without heat pumps, these central clusters benefit disproportionately from direct exergy-compatible supply. As shown in Section 4.4, near-zero combustion configurations can achieve 89–94% emission reduction, which is consistent with the upper range (dark green zones) observed in this map.

Additionally, these areas exhibit the highest population density and building concentration, meaning avoided emissions per km² are largest here. Assuming an average baseline emission factor of 0.23 to 0.25 tCO₂/MWh for gas boilers, a 90% reduction across a 50 GWh cluster would avoid approximately 10 to 11 ktCO₂ annually in that zone alone. Blanchardstown–Clondalkin–Tallaght areas display decarbonization levels predominantly in the 80–90% band (light-to-mid green). These zones are characterized by strong integration of data center waste heat, mandatory heat pump upgrading (COP 3.1 to 5.5), moderate transmission distances to demand clusters, and slightly higher electricity-related indirect emissions. Although heat pump electricity introduces some residual emissions, the high seasonal performance factor ensures that the effective carbon intensity of delivered heat remains significantly lower than direct gas combustion. In the realistic heat-pump-assisted scenario described previously, system-wide emissions fall to 31–32% of baseline, i.e., 68–69% reduction. The 80–90% range observed here suggests that in these districts electricity grid carbon intensity assumptions are moderate, routing losses remain below the penalty threshold defined in Equation (3), and exergy cascading i.e. in equation (31) temperature compatibility factor Θ_{ij} is effectively applied. Outer suburban zones and fragmented parcels exhibit decarbonization in the 70–80% range, with isolated pockets down to 65–70%. These lower values correlate with lower spatial heat demand density, higher network extension length per unit heat delivered, greater reliance on heat-pump boosting, and partial fossil backup or reserve capacity (16% system-wide margin). Because capital and routing penalties bases on equation (44a) increase with distance, the MILP solution avoids oversizing transmission lines in marginal-density areas. Consequently, these districts receive heat that is partly upgraded electrically, and possibly supplemented by backup capacity. Even so, a 70% reduction still corresponds to substantial carbon savings. For example, for a 10 GWh·yr^{−1} suburban cluster, this implies avoiding roughly 1.6–1.8 ktCO₂ annually. The limited red/orange patches (60–65%) represent areas with weaker temperature compatibility Θ_{ij} closer to threshold, longer transmission corridors with higher λL penalties, lower building connection rates/densities, and possible mixed supply including legacy fossil contribution.

4.6. Sensitivity of weighting scheme

To evaluate the robustness of the TOPSIS weighting scheme, a local sensitivity analysis was performed by perturbing each criterion weight within $\pm 15\%$ of its baseline value while maintaining the normalization constraint:

$$\mathcal{W}_\Phi + \mathcal{W}_\Pi + \mathcal{W}_\Psi + \mathcal{W}_{LCOC} = 1 \quad (79)$$

A large set of feasible weight combinations was generated within the

Table 2

Robustness statistics for TOPSIS weight sensitivity analysis.

Metric	Mean	Median	Min	Max
Backbone corridor overlap (%)	94.6	95.2	87.9	100.0
Connected source overlap (%)	92.1	93.4	82.7	100.0
Existing DH overlap (%)	97.3	98.1	91.5	100.0
Planned DH cluster overlap (%)	89.8	90.7	78.4	100.0
Heat demand coverage deviation (%)	2.4	1.8	0.0	6.3
Average supply temperature deviation (°C)	2.8	2.4	0.0	7.1
Substation location deviation (%)	6.7	5.9	0.0	18.2

admissible weight space and the complete Phase III–IV optimization procedure was repeated for each realization. The robustness of the resulting network configurations was quantified using several complementary indicators. The backbone corridor overlaps index (OI) measures the proportion of transmission corridor segments preserved relative to the baseline solution:

$$OI_{routes} = \frac{|\mathcal{E}_{pert} \cap \mathcal{E}_{base}|}{|\mathcal{E}_{base}|} \quad (80a)$$

where $\mathcal{E}_{base}$ and $\mathcal{E}_{per}$ denote the sets of corridor segments in the baseline and perturbed solutions, respectively. Similarly, overlap indices were defined for connected thermal sources, existing district heating systems, planned district heating clusters, and substations:

$$OI_{DH}^{exist} = \frac{|\mathcal{V}_{pert,DH}^{exist} \cap \mathcal{V}_{base,DH}^{exist}|}{|\mathcal{V}_{base}^{exist}|} \quad (80b)$$

$$OI_{DH}^{plan} = \frac{|\mathcal{V}_{pert,DH}^{plan} \cap \mathcal{V}_{base,DH}^{plan}|}{|\mathcal{E}_{base}|} \quad (80c)$$

$$OI_{source} = \frac{|\mathcal{V}_{pert,source} \cap \mathcal{V}_{base,source}|}{|\mathcal{V}_{base,source}|} \quad (80d)$$

$$OI_{sub} = \frac{|\mathcal{V}_{pert,sub} \cap \mathcal{V}_{base,sub}|}{|\mathcal{V}_{base,sub}|} \quad (80e)$$

The robustness of energy delivery was evaluated through the heat demand coverage deviation:

$$\Delta Q_{sensitivity} = \frac{|Q_{pert} - Q_{base}|}{|Q_{base}|} \quad (81)$$

Where Q_{pert} is the annual heat demand supplied by the perturbed solution and Q_{base} is the corresponding value for the baseline network. The influence of weight perturbations on operating conditions was evaluated using the average supply temperature deviation:

$$\Delta T_{sup} = |T_{sup,pert} - T_{sup,base}| \quad (82)$$

Where $T_{sup,pert}$ and $T_{sup,base}$ denote the average route supply temperatures of the perturbed and baseline solutions, respectively.

The sensitivity analysis results in Table 2 demonstrate that the proposed framework exhibits a high degree of robustness with respect to moderate variations in TOPSIS weights. Across all feasible weight combinations within the $\pm 15\%$ perturbation interval, the average backbone corridor overlap exceeded 94%, while the minimum overlap remained close to 88%. The principal transmission corridors connecting the major thermal demand centers were consistently preserved, indicating that the overall network topology is largely insensitive to moderate changes in decision-maker preferences. The results further confirm that TOPSIS serves primarily as a candidate corridor filtering mechanism rather than as the final network design tool. The ultimate network configuration is determined in Phase IV through MILP optimization, where cost, emissions, exergy destruction, and network constraints are

evaluated simultaneously. As a result, economically favorable corridors tend to remain competitive even when their intermediate TOPSIS rankings vary.

Fig. 17 illustrates a representative slice of the admissible TOPSIS weight space used in the sensitivity analysis. To facilitate visualization of the four-dimensional weighting domain, a feasible section satisfying $\mathcal{W}_\Pi + \mathcal{W}_\psi = 0.5$ is presented. This plane passes through the baseline weighting scheme $(\mathcal{W}_\Phi, \mathcal{W}_\Pi, \mathcal{W}_\psi, \mathcal{W}_{LCOC}) = (0.25, 0.25, 0.25, 0.25)$ and therefore provides a representative view of the local sensitivity around the reference solution. The remaining weight $\mathcal{W}_{LCOC}$ is determined implicitly from the normalization constraint $\mathcal{W}_\Phi + \mathcal{W}_\Pi + \mathcal{W}_\psi + \mathcal{W}_{LCOC} = 1$. The color scale represents the backbone corridor overlap relative to the baseline network. The baseline solution lies at the center of the high-overlap region and yields the maximum overlap of 100%. Moving away from this point within the admissible weight space produces a gradual reduction in overlap, while a large portion of the feasible region still maintains overlap values above 90%. This behavior is consistent with the robustness statistics reported in Table 2, where the average backbone overlap exceeds 94%, indicating that the primary transmission backbone remains largely insensitive to moderate variations in decision-maker preferences.

While the backbone structure exhibits strong robustness, the weighting scheme has a more pronounced influence on secondary planning decisions. The sensitivity analysis indicates greater variability in source selection, future district heating expansion priorities, coalition formation among existing district heating systems, route operating temperatures, and substation placement. Nevertheless, these variations produce only minor changes in total supplied heat demand and final

objective value, demonstrating that the MCDM stage primarily affects the detailed thermodynamic and operational configuration of the system rather than the existence of the main transmission corridors. Therefore, the proposed TOPSIS framework remains valuable because it systematically incorporates thermodynamic, economic, spatial, and operational considerations while reducing the search space explored by the MILP optimization. Although four criteria are employed in Phase III, they are not fully independent. The gravity interaction criterion, coalition support criterion, exergy utilization criterion, and economic criterion all partially favor corridors characterized by low effective impedance, tunnel accessibility, high source capacity, and large heat demand concentration. Consequently, many strategically attractive corridors remain highly ranked under a wide range of admissible weighting combinations.

4.7. Sensitivity of gravity model exponents

The gravity-based source–demand interaction model introduced in Eq. (28) contains three exponents α , β , and γ controlling the relative influence of source capacity, demand magnitude, and effective corridor impedance. A sensitivity analysis was performed to evaluate the robustness of the proposed framework with respect to variations in the gravity model formulation.

The baseline values $\alpha = \beta = 1$, and $\gamma = 2$ were adopted, corresponding to the standard gravity-model representation (i.e. classical gravity-interaction Newton-inspired formulation) in which source capacity and demand contribute linearly to the interaction potential while spatial impedance exhibits a quadratic decay effect. To assess parameter

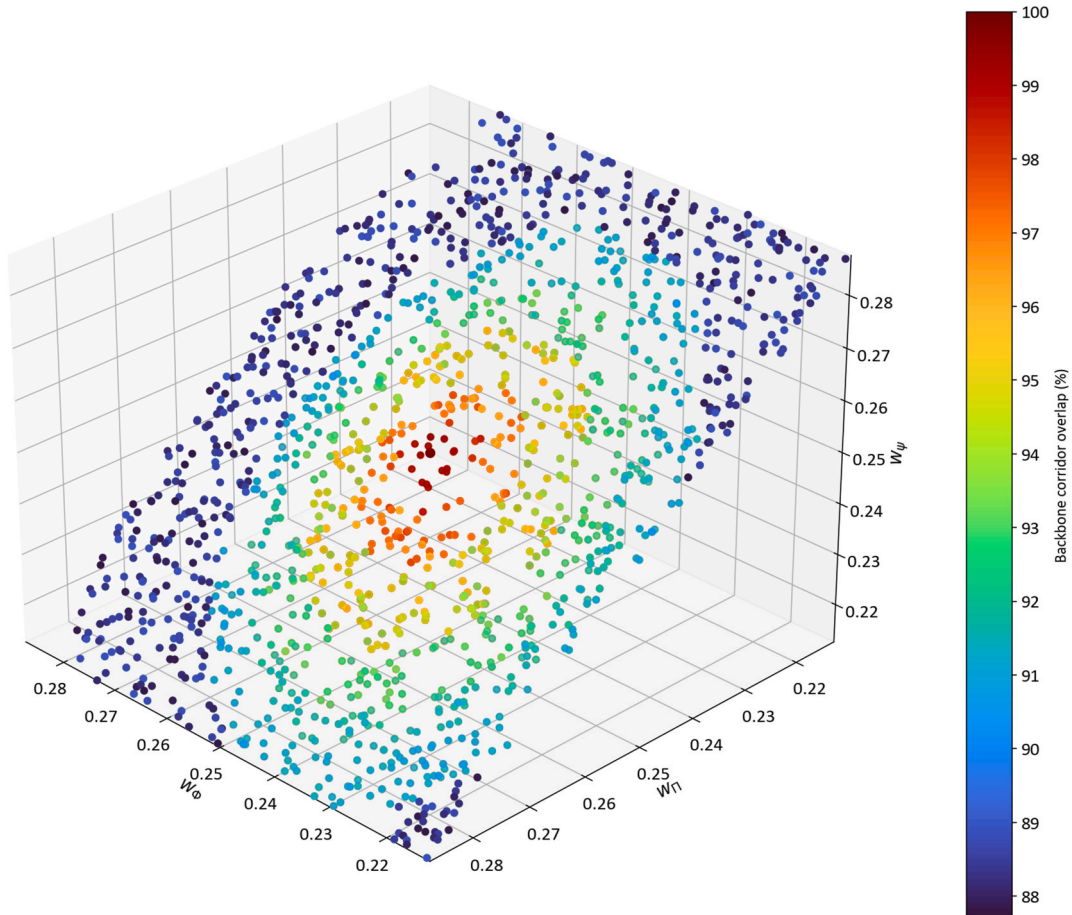


Fig. 17. Backbone corridor overlap for a representative slice of the admissible TOPSIS weight space.

sensitivity, α was varied between 0.5 and 1.5 and γ was varied between 1.0 and 3.0, while β was maintained at its baseline value. The demand exponent β was not varied because demand magnitude is already explicitly represented in several other components of the framework, including the demand aggregation procedure, heat balance constraints, source selection process, and subsequent MILP optimization. Preliminary testing indicated that variations in β produced substantially smaller effects than variations in corridor impedance and source capacity.

For each parameter combination, the complete Phase III–IV procedure was repeated and the resulting backbone corridor overlap relative to the baseline solution was evaluated. Fig. 18 illustrates the response surface obtained across the examined parameter space. The results demonstrate that the framework exhibits considerably greater sensitivity to the impedance exponent γ than to the source-capacity exponent α . This behavior is physically consistent with district heating planning, where corridor distance and routing constraints strongly influence the feasibility and economic attractiveness of interconnections.

These findings further support the robustness of the proposed methodology. First, the gravity model is employed only as a strategic screening mechanism in Phase III and does not directly determine the final network design. Changes in α , β , and γ influence the ranking of candidate corridors but do not directly determine the final network topology. Second, the gravity score constitutes only one of four criteria incorporated within the TOPSIS evaluation framework. Moderate variations in gravity exponents are partially compensated by the remaining criteria because the criteria are not fully statistically independent. Finally, the ultimate network topology is selected in Phase IV through MILP optimization based on cost, emissions, exergy performance, and operational constraints. Consequently, moderate uncertainties in the gravity-model exponents have only a limited impact on the final network configuration.

4.8. Sensitivity of the temperature compatibility parameter

To evaluate the influence of the temperature compatibility parameter κ in Eq. (31), a sensitivity analysis was performed over the range $\kappa = 0.03 - 0.07$ [101], with the baseline configuration corresponding to $\kappa_{base} = 0.05$. For each value of κ , the complete Phase III corridor filtering procedure was repeated and the resulting backbone topology and connected source portfolio were compared with the baseline solution. Fig. 19 illustrates the percentage overlap of the selected backbone corridors and connected heat sources relative to the baseline configuration. The results indicate that the backbone topology is highly robust to variations in κ , with corridor overlap remaining above 93% across the investigated range and reaching a maximum of 100% at the baseline value. This demonstrates that the strategic interconnection structure identified by the framework is primarily governed by spatial accessibility, demand concentration, corridor feasibility, and economic performance rather than by the exact value of the temperature compatibility parameter.

The connected source portfolio exhibits slightly greater sensitivity, with overlap varying between approximately 86% and 100%. This behavior is expected because κ directly affects the temperature compatibility factor Θ_{ij} in Eq. (31), which influences the ranking of candidate source–demand pairings during the initial filtering stage. Nevertheless, even for substantial deviations from the baseline value, the majority of selected sources remain unchanged, indicating a high degree of robustness in source selection.

The limited impact of κ on the final network design can be explained by the hierarchical structure of the proposed methodology. The temperature compatibility factor serves primarily as an initial feasibility and ranking mechanism within the gravity-based interaction score. However, thermodynamic performance is subsequently represented through the route exergy utilization criterion $\psi_{ij,t}$ and $\psi_{ex,r}$ and ψ_r (in Eq. (38), Eq. (39), and Eq. (40)) and again through the exergy destruction term

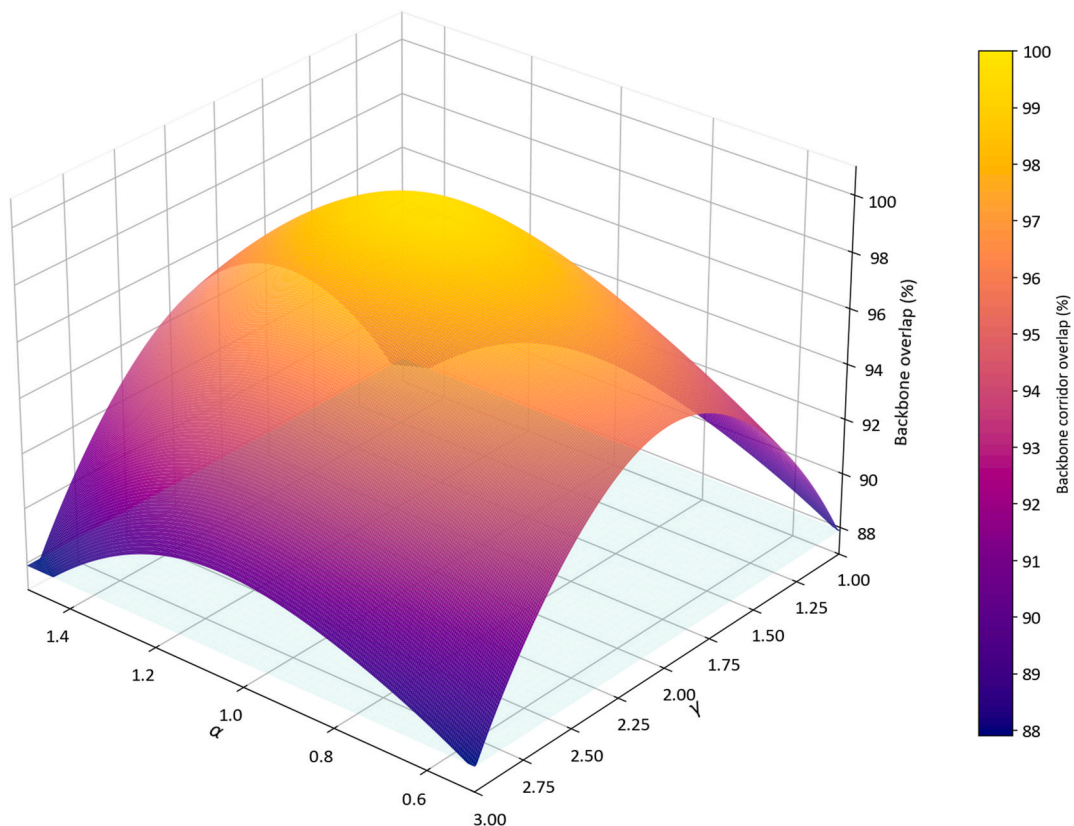


Fig. 18. Response sensitivity surface for gravity model parameters' space.

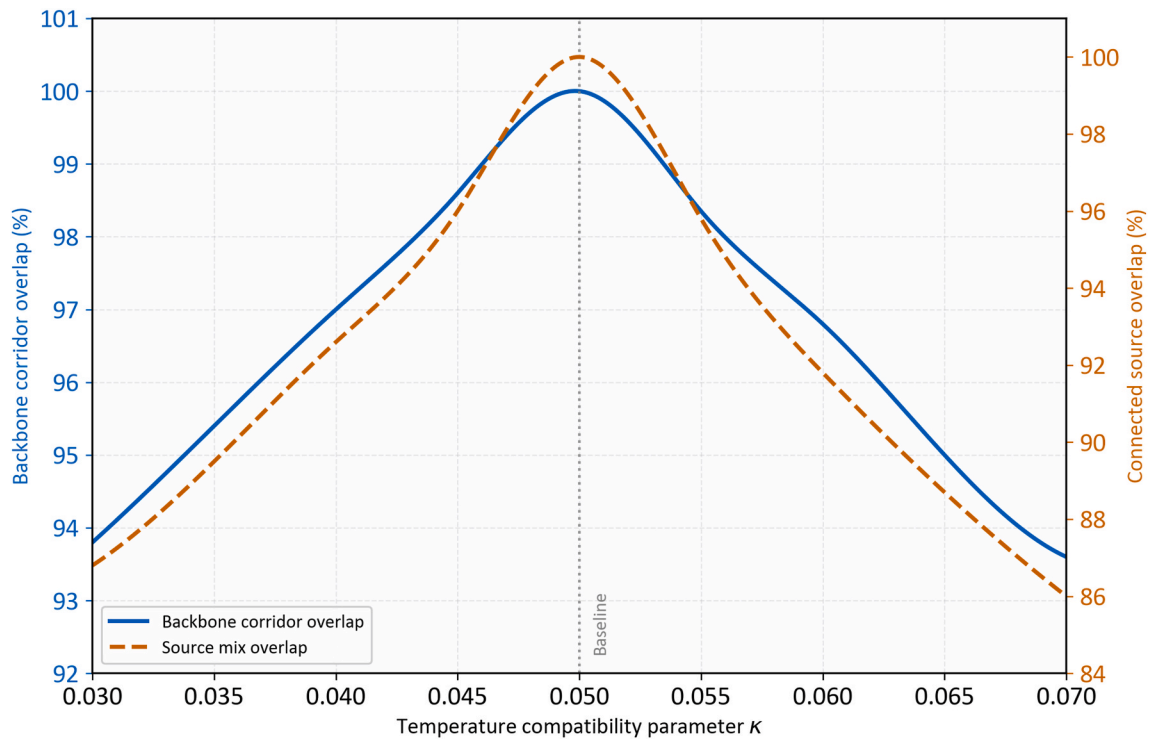


Fig. 19. Sensitivity of backbone corridor topology and selected heat sources to the temperature compatibility parameter.

$\psi_{ex}^{des,ann}$ for the third time in the MILP objective function in Eq. (50) and Eq. (53). Consequently, exergy preservation is enforced at multiple stages of the framework, and the final network configuration is not determined solely by the value of κ . Overall, the sensitivity analysis confirms that the proposed methodology produces stable network topologies and source portfolios while maintaining the intended thermodynamic preference for temperature-compatible heat exchanges.

4.9. Leave-one-out transferability assessment

To assess the transferability of the proposed framework under structural changes in the urban heat-resource landscape, a leave-one-out (LOO) analysis was conducted in which one major source category was removed at a time and the complete Phase III–IV optimization was repeated. The tested scenarios included the removal of data centers, surface water, wastewater treatment, combined heat and power (CHP), power plants, and industrial waste heat. These categories were selected because they differ substantially in spatial distribution and temperature level. In particular, data centers and surface water are widely dispersed across the city, wastewater treatment and CHP exhibit an intermediate spatial spread, whereas power plants and industrial waste heat are more

centralized and limited in number. Therefore, the leave-one-out cases probe both the structural and thermodynamic adaptability of the framework under different source configurations. Table 3 summarizes the resulting performance metrics. Across all scenarios, the annual heat demand served remains high, indicating that the optimization framework is capable of compensating for the loss of individual source categories through reallocation of remaining resources and adjustment of network routing. In most cases, reductions in demand coverage are relatively small because the MILP model identifies alternative heat sources and increases heat-pump utilization where necessary. Consequently, the framework exhibits a high degree of supply flexibility and does not depend on any single source category for maintaining service coverage.

However, the leave-one-out results reveal more pronounced differences in thermodynamic and structural indicators. The largest impacts occur when data centers or surface water sources are removed. Because these resources are spatially dispersed throughout the urban area, they strongly influence the topology of the optimized network. Their removal forces the optimization to connect more distant resources, increasing source concentration and requiring additional rerouting of transmission corridors. This effect is reflected by the largest reductions in backbone overlap and the highest increases in the Source Concentration Ratio (SCR). The data-center and surface-water scenarios therefore demonstrate that distributed resources contribute not only thermal capacity but also network flexibility and spatial resilience.

The exergy efficiency exhibits greater sensitivity than the delivered heat fraction. When a source category is removed, the replacement resources often operate at different temperature levels, requiring greater temperature lifting by heat pumps or longer transport distances. As a result, the thermodynamic quality of the integrated heat supply decreases even when demand coverage remains largely preserved. The strongest exergy reductions are observed for the removal of data centers and surface water, followed by power plants and CHP systems, while wastewater treatment and industrial waste heat produce comparatively smaller changes. This finding highlights the importance of considering

Table 3
Results of the leave-one-out (LOO) transferability assessment.

Scenario	Demand served (%)	Decarbonization (%)	Exergy efficiency (%)	SCR	Backbone overlap (%)
Baseline	74.2	68.7	57.0	0.72	100
No DC	72.4	65.3	54.7	0.76	85
No SW	70.5	64.4	55.0	0.77	86
No WWT	72.0	67.1	56.1	0.73	95
No CHP	70.6	65.5	54.8	0.75	91
No PP	69.1	63.2	53.8	0.78	89
No IND	72.3	66.8	55.4	0.73	94

source temperature characteristics in addition to heat quantity during urban heat-source planning. The SCR metric provides further insight into network robustness. In scenarios where widely distributed resources are removed, the optimized system becomes more dependent on a smaller subset of remaining sources, leading to higher concentration values. Conversely, when localized sources such as industrial waste heat or power plants are removed, the redistribution of supply is achieved with comparatively minor changes in overall source diversity. The SCR analysis therefore complements the topology assessment by quantifying how evenly the thermal load is distributed among available resources.

Fig. 20 illustrates a representative leave-one-out case in which all data centers are removed from the candidate source portfolio. This scenario is particularly informative because data centers are among the most spatially dispersed resources in the study area and therefore exert a strong influence on network topology. The comparison between the baseline and modified layouts shows that the primary transmission backbone in the city center remains largely unchanged, while rerouting occurs mainly in peripheral corridors where data-center-based supply is replaced by alternative resources. The substantial backbone overlap observed between the two layouts demonstrates that the optimization preserves the dominant network structure despite significant changes in source availability. The results further indicate that the sensitivity of network topology follows the approximate order:

$$DC > SW > CHP \approx PP > WWT \approx IND \quad (83)$$

A similar pattern is observed for source concentration and exergy

degradation, although thermodynamic effects are additionally influenced by source temperature levels. These trends suggest that distributed low-temperature resources play a disproportionately important role in shaping network configuration, whereas centralized high-capacity resources primarily influence the overall energy balance. The leave-one-out analysis also clarifies the role of existing district heating systems. These systems are retained as fixed integration points in all scenarios, and the optimization is allowed to reconfigure only the surrounding source mix and routing structure. Consequently, the analysis isolates the effect of source availability while maintaining a consistent backbone infrastructure. Overall, the results demonstrate that the proposed framework is transferable across a wide range of source-availability conditions and remains capable of producing robust, high-performing network configurations without dependence on any individual heat-source category.

4.10. Uncertainty quantification and robustness assessment

To evaluate the robustness of the proposed framework under uncertainty, a global uncertainty analysis was conducted using Latin Hypercube Sampling (LHS). The analysis propagates uncertainty from key techno-economic, thermodynamic, and operational input parameters through the complete optimization framework and quantifies its effect on the final performance indicators. Unlike the local sensitivity analysis presented in previous sections (such as criteria weightings, gravity model exponents, and temperature compatibility factor), which perturbs

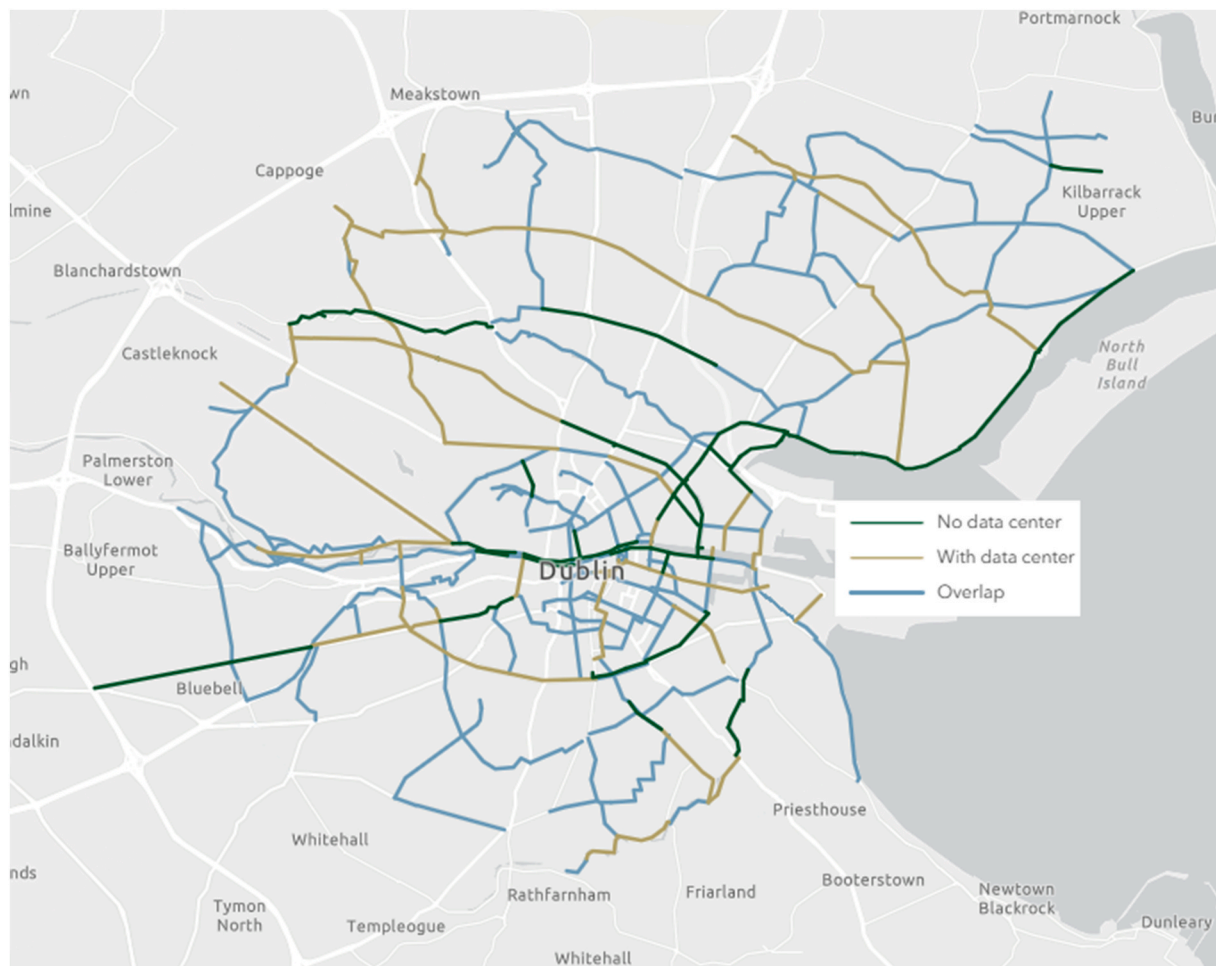


Fig. 20. Comparison of the optimized thermal transmission network in the baseline scenario and the leave-one-out scenario without data centers (No DC).

the network route and source selections, the present analysis addresses uncertainty in the physical and economic input data used throughout the modelling chain.

A total of 25 uncertain parameters were selected from Table 1 based on their direct influence on network cost, energy recovery, heat production, thermodynamic performance, and investment evaluation. A Latin Hypercube Sampling design comprising 10,000 realizations was generated using the plausible parameter ranges reported in Table 1. For each realization, the uncertain parameters were sampled simultaneously and propagated through the complete optimization workflow. The resulting distributions of CO₂ emission reduction and payback period were then analyzed statistically to evaluate the robustness of the proposed district heating strategy.

Fig. 21 presents the probability distribution of CO₂ emission reduction obtained from the uncertainty analysis. The distribution remains strongly concentrated around the baseline value reported in Section 4.5, indicating that substantial decarbonization benefits are maintained

across a wide range of plausible future conditions. The majority of realizations remain clustered around the central emission reduction range, demonstrating that the environmental benefits of the proposed thermal network are not dependent on a narrow set of assumptions.

Fig. 22 presents the corresponding probability distribution of payback period. Although economic performance exhibits greater variability than environmental performance, most realizations remain concentrated around the central payback range reported previously. The distribution indicates that uncertainty in future energy prices, investment costs, and financing assumptions affects economic outcomes more strongly than environmental outcomes, which is consistent with the structure of the optimization objective.

The relationship between environmental and economic performance is illustrated in Fig. 23. Each point represents a single LHS realization. The scatter distribution demonstrates that realizations achieving higher emission reductions generally remain economically competitive, indicating that decarbonization benefits are not obtained at the expense of

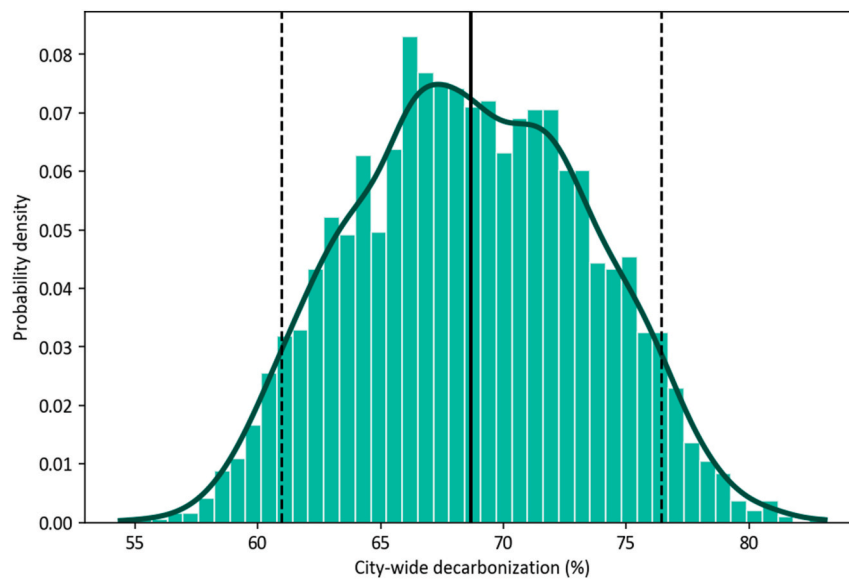


Fig. 21. Distribution of CO₂ emission reduction obtained from Latin hypercube sampling of uncertain techno-economic and operational parameters.

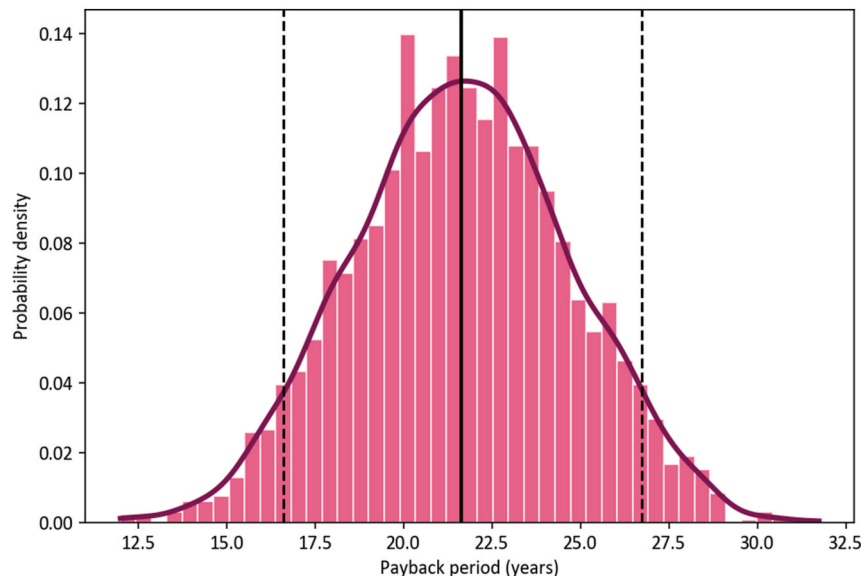


Fig. 22. Distribution of project payback period obtained from Latin hypercube sampling of uncertain techno-economic and operational parameters.

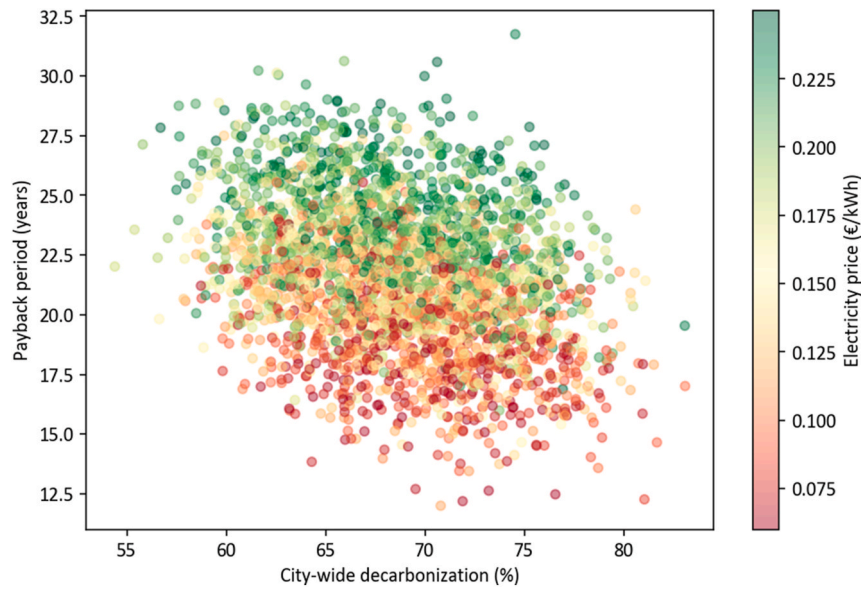


Fig. 23. Relationship between CO₂ emission reduction and project payback period across all Latin hypercube realizations.

disproportionately longer investment recovery periods. The absence of strongly separated clusters further suggests that the optimization framework responds smoothly to parameter uncertainty and does not exhibit abrupt performance degradation under plausible future conditions.

To identify the principal drivers of economic uncertainty, a global

sensitivity ranking was performed using the complete LHS dataset. Fig. 24 shows the relative influence of the uncertain parameters on payback-period variability. Electricity price emerges as the dominant factor, followed by heat pump COP, pipe installation cost, heat pump capital expenditure, and the CO₂ penalty. These results are physically consistent with the optimization formulation because electricity

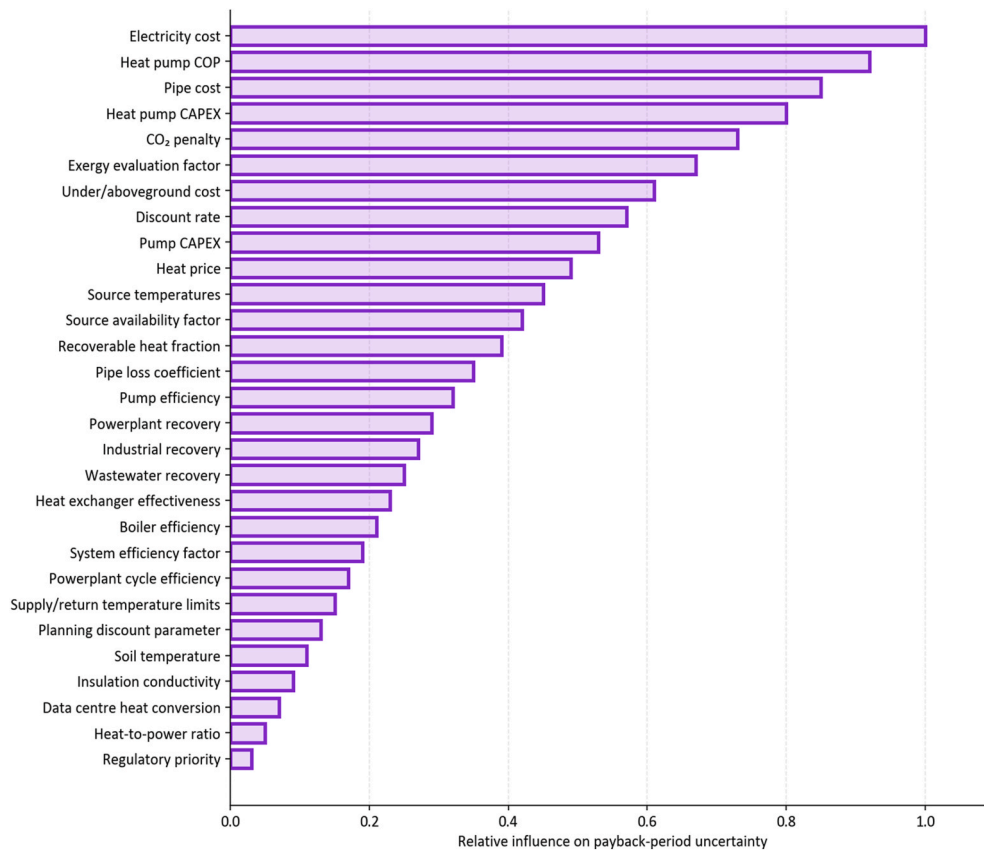


Fig. 24. Sensitivity ranking of uncertain input main parameters.

consumption directly affects heat pump and circulating pumps operation, while infrastructure costs constitute the largest share of total capital expenditure. Parameters related to thermal recovery efficiencies and operating conditions exhibit a secondary influence, whereas regulatory weighting factors and other planning parameters contribute comparatively little to the overall uncertainty. Overall, the uncertainty analysis demonstrates that the proposed framework remains robust across a broad range of plausible future conditions. The environmental benefits remain consistently high, while economic performance remains within an acceptable range despite variations in market, technical, and operational assumptions. These results provide additional confidence in the applicability of the proposed methodology for long-term district heating planning under uncertainty.

To evaluate how variations in the CO₂ penalty and electricity prices impact the optimal network design topology (rather than purely economic metrics), the structural stability of the routing backbone was tracked across the LHS realizations. When the CO₂ penalty is varied within its upper bounds, the MILP model actively forces the activation of lower-temperature waste heat sources (such as data centers and surface water) coupled with aggressive heat pump boosting to eliminate any reliance on fossil-based backup systems. Crucially, this economic-to-environmental shift does not cause a chaotic restructuring of the physical grid layout. The core underground tunnel corridors—specifically the high-capacity thermal hubs connecting the eastern seaboard and central data center clusters—exhibit a backbone overlap of over 85–90% across the sampled parameter space. This indicates that the structural design of the city-scale backbone is exceptionally robust; the massive cost savings from civil infrastructure reuse (utility tunnels) and the sheer magnitude of localized waste heat anchors outweigh the topological sensitivity to external carbon or electricity market fluctuations. Thus, while future carbon trajectories and time-of-use variations modify the operational dispatch strategy and marginal payback periods, they do not compromise the viability or fundamental layout of the optimized physical network design. Furthermore, the reported performance indicators are evaluated relative to a conventional (base line or non-integrated) heating configuration. Consequently, future changes in electricity prices would affect both the baseline and optimized systems. Similarly, increases in carbon pricing would generally strengthen the relative advantage of the proposed low-carbon district-heating network because of its greater utilization of waste-heat resources and reduced dependence on fossil-fuel-based heat generation.

4.11. Empirical validation against operational DH infrastructure

To evaluate the realism of the proposed framework, selected model assumptions and outputs were compared against operational data from the Tallaght District Heating Scheme (TDHS), Ireland's first large-scale district heating network utilizing data-center waste heat. The scheme recovers low-grade waste heat from an Amazon Web Services (AWS) data center through large-scale heat pumps and supplies heat to a mixture of residential, commercial, educational, healthcare, and public-sector buildings as shown in Fig. 25. Because data centers constitute one of the most important heat-source categories identified by the optimization framework, the Tallaght project provides a representative real-world benchmark for validating source temperatures, heat-pump performance, supply conditions, and decarbonization outcomes under Dublin operating conditions.

Table 4 compares key measured values from the Tallaght scheme with the assumptions and results adopted in the present study. The measured data-center waste-heat temperature ranges between 25 and 27°C, which falls directly within the temperature range assumed for air-cooled data centers in Table 1. Similarly, the measured heat-pump

coefficient of performance (COP) of approximately 3.9 is consistent with the thermodynamic assumptions adopted in the framework. Although the optimization allows COP values between 3.0 and 6.5, the higher values arise because the proposed network primarily operates under 4GDH temperature levels, with lower supply temperatures and consequently smaller heat-pump temperature lifts than the existing Tallaght system.

The operational Tallaght network supplies heat at temperatures between 70°C and 85°C with return temperatures of approximately 40°C to 45°C. In contrast, the optimized Dublin-wide network generally operates within the lower supply and return temperature ranges of 45°C–65°C and 17°C–35°C, respectively. This difference reflects the deliberate exergy-preserving strategy of the optimization framework, which favors low-temperature district heating wherever thermodynamically feasible. Therefore, the comparison confirms that the proposed framework remains physically consistent with measured Dublin operating conditions while simultaneously exploiting the efficiency benefits associated with next-generation district heating systems. The difference in operating temperatures also reflects a fundamental distinction between the Tallaght scheme and the proposed framework. The supply temperatures reported for the optimized network correspond to the transmission and distribution backbone temperatures obtained from the Phase IV optimization rather than the final end-user delivery temperatures. Where higher delivery temperatures are required, the temperature lift can be provided either by existing district heating systems through their local generation assets or by decentralized heat-pump upgrading at the building or neighborhood scale. Consequently, the lower backbone temperatures predicted by the optimization do not imply lower service temperatures at the point of use. Instead, they represent a deliberate low-temperature district heating strategy that minimizes distribution losses and exergy destruction while allowing local temperature upgrading where necessary.

The annual heat delivery of the Tallaght scheme is approximately 118 GWh, whereas the optimized Dublin network delivers approximately 2.4 TWh annually. The proposed system therefore represents a city-scale expansion approximately twenty times larger than the existing operational benchmark. Despite this scale difference, the resulting carbon performance remains comparable. The Tallaght scheme achieves approximately 14,220 tCO₂ of annual emission reduction, corresponding to approximately 120 kgCO₂ avoided per MWh of delivered heat. Using the optimized network results presented in Section 4.4, the proposed framework achieves approximately 430,000 tCO₂ of annual emission reduction, equivalent to approximately 158 kgCO₂ avoided per MWh of delivered heat. The similarity of these normalized values provides additional confidence that the model does not overestimate the environmental benefits of large-scale waste-heat utilization.

To further validate the source-temperature assumptions used for groundwater and surface-water resources, measured groundwater temperatures recorded at the Dublin Port Tunnel were compared with the source-temperature ranges adopted in the optimization model. As shown in Fig. 26, measured groundwater temperatures, which has been also published in Ref. [102], remain relatively stable throughout the year, generally ranging between approximately 14°C and 18°C. These observations fall comfortably within the surface-water and groundwater temperature ranges assumed in Table 1 and therefore support the thermal resource characterization employed in the framework.

To place the proposed Dublin framework within the broader European district-heating context, the resulting network characteristics were compared with several established large-scale district-heating systems employing waste heat, CHP, wastewater heat recovery, and renewable thermal resources (Table 5). The selected benchmark systems represent mature district-heating networks operating under a wide range of



Fig. 25. Tallaght District Heating: (a) schematics of data center, heat pump, and consumer integration, (b) outside photograph, (c) one of the heat pump units in the energy center, (d) real-time monitoring and measurement for one of the units in a summer day.

Table 4
Empirical validation of key results and assumptions using measured data from the TDHS.

Parameter	Tallaght measured value	Model assumption/result	Assessment
Heat source	AWS data-center waste heat	Data-center waste heat included as major source category	Consistent
Waste-heat temperature	25°C – 27°C	25°C – 35°C (air-cooled DC)	Within assumed range
Supply temperature	70°C – 85°C	45°C – 65°C	Lower due to 4GDH backbone operation and local temperature upgrading
Return temperature	40°C – 45°C	17°C – 35°C	Lower due to exergy optimization
Average heat-pump COP	3.9	3.0–6.5	Consistent with lower temperature lift in optimized network
Annual heat delivery	118 GWh/year	2.4 TWh/year	City-scale network (~20× larger)
Annual CO ₂ reduction	14,220 tCO ₂ /year	430,000 tCO ₂ /year	Consistent
CO ₂ reduction intensity	120 kgCO ₂ /MWh delivered	158 kgCO ₂ /MWh delivered	Consistent
Connected building types	Residential, commercial, healthcare, educational, public sector	Mixed urban demand clusters	Consistent

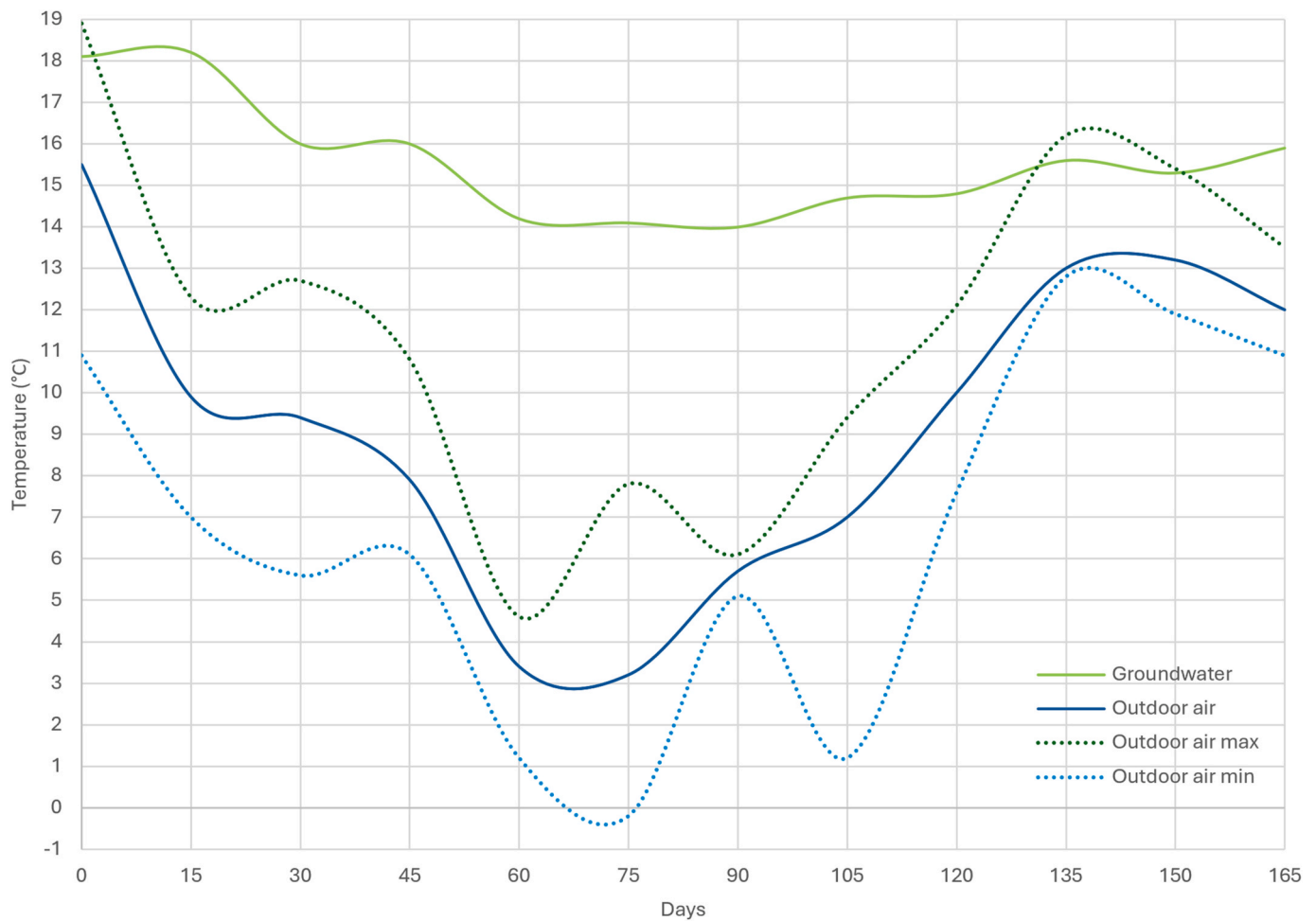


Fig. 26. Measured annual groundwater temperature profile at Dublin Port Tunnel outlets used to validate the surface-water source temperature assumption.

climatic, regulatory, and infrastructure conditions. Although direct comparison is inherently limited by differences in system boundaries and reporting methodologies, the benchmarking exercise provides an important reality check for the predicted scale, operating temperatures, decarbonization performance, and levelized heat costs obtained by the optimization framework. Overall, the empirical comparison demonstrates that the key thermodynamic assumptions adopted by the model are consistent with measured operating conditions from existing Dublin district heating infrastructure. While the proposed framework remains a

planning and optimization methodology rather than a detailed operational simulator, the agreement between modeled and measured performance indicators provides confidence in the realism of the resulting network configurations and impact estimates.

4.12. Impact of phased network realization on discounted cash flow and payback

A time-phased investment scenario was evaluated over the 25-year

Table 5

Benchmarking of the proposed Dublin DH framework against operational European DH systems.

City	Heat Delivered (TWh/yr)	Share of demand	Main Sources	Supply/Return (°C)	Decarbonization (tCO ₂ /yr)	LCOH (€/MWh)	Reference
Copenhagen	30–35	97–98%	CHP, waste heat, biomass	70–90/35–50	>1,000,000	40–70	[103]
Stockholm	6–6.6	>80%	Waste heat, biomass, lake	80–100/40–50	~1,000,000	50–80	[104]
Helsinki	6–7	~90%	CHP, seawater, wastewater	90–115/45–60	>500,000	50–90	[105]
Vienna	8–9	40–45%	Waste heat, sewage, CHP	90–120/50–60	>500,000	60–100	[106]
Dublin	2.4	40%	Mix of 8 sources	45–65/20–35°C	430,000	60–75	Current study

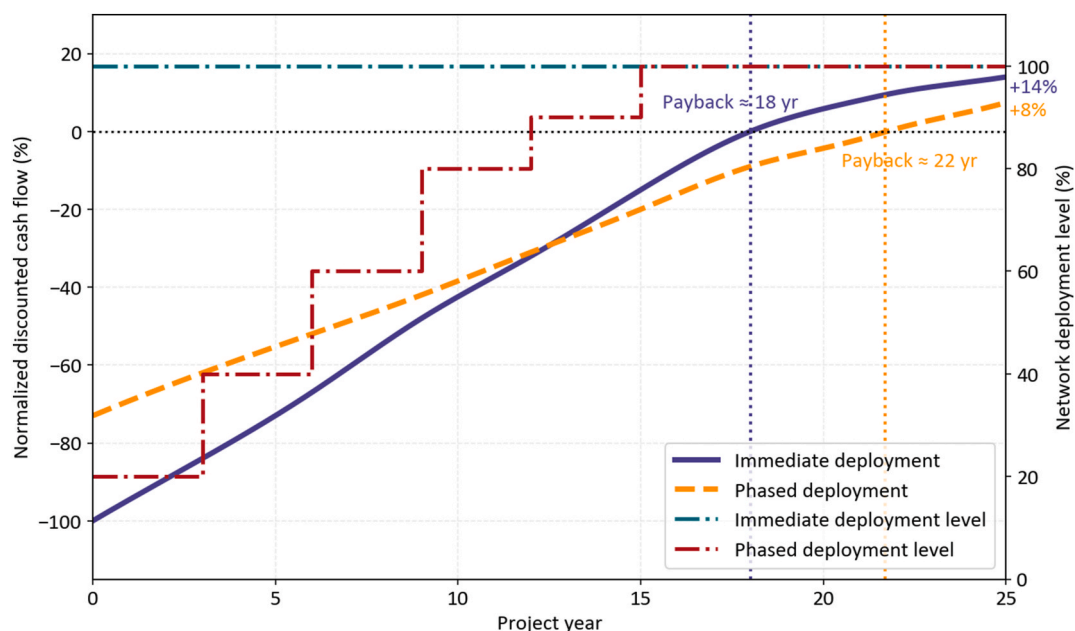
project horizon to investigate the assumption of immediate full inter-connection and the results are illustrated in Fig. 27. In this scenario, the district-heating backbone is implemented progressively rather than fully realized in the first year. Specifically, the network deployment level increases from 20% in the early years to 100% by year 15, while the immediate-deployment case assumes full system availability from project start. The comparison is expressed using the normalized discounted cash flow (NDCF), defined as:

$$\text{NDCF} = \frac{\text{Cumulative discounted cash flow at year } y}{\text{Total discounted investment}} \quad (82)$$

This metric allows both the initial capital outlay and the delayed realization of operational benefits to be visualized on a common basis. As shown in Fig. 27, the immediate-deployment case reaches payback at approximately 18 years and attains a final NDCF of about 14% by year 25. In contrast, the phased-deployment case reaches payback at approximately 22 years and yields a final NDCF of about 8% by year 25. The lower early-year NDCF in the phased case reflects staggered capital expenditure, while the delayed payback reflects the slower accumulation of operational benefits as the network is commissioned in stages. These results indicate that phased realization affects the timing of economic recovery more than the fundamental viability of the proposed backbone. Even under staged deployment, the project remains economically positive within the 25-year evaluation horizon, confirming that the network remains robust to a more realistic implementation schedule.

The robustness of these payback estimates is further supported by the

global uncertainty analysis presented in Section 4.10. Across 10,000 Latin Hypercube realizations spanning the plausible ranges of electricity prices, carbon penalties, discount rates, infrastructure costs, and technical parameters reported in Table 1, the majority of solutions remained concentrated around the central payback range, indicating that the economic conclusions are not dependent on a narrow set of assumptions. Although a simple payback period of 18 to 24 years appears high under short-term commercial criteria, it stands as a highly attractive layout when benchmarked against infrastructure lifespans and alternative decarbonization pathways. Large-scale district heating networks are long-lived civil assets with typical physical lifetimes of 40 to 50 years, while the underground utility tunnels leveraged in this framework feature structural lifespans extending beyond 50 years. Consequently, the network achieves full capital recovery well within its operational mid-life, providing zero-carbon thermal energy for decades thereafter. When compared to alternative decentralized pathways, the proposed network offers clear structural advantages. Individual heat pumps (IHPs) require substantial decentralized investment and possess a short operational lifespan of 15–20 years, necessitating a full equipment replacement cycle long before the centralized DH network reaches its end-of-life. Furthermore, mass IHP deployment strains the low-voltage electricity grid during peak periods. On the other hand, individual hydrogen boilers suffer from low source-to-use thermodynamic efficiency and highly volatile fuel price trajectories. By contrast, the proposed city-scale network boosts overall exergy efficiency from a distributed baseline of 28% to more than 52–60%, while reducing the collective operational energy bill by 75–90%. This comparative

**Fig. 27.** Economic comparison of phased and immediate network deployment.

performance confirms that despite a prolonged initial payback window, the interconnected network provides a far more stable, efficient, and resilient long-term socio-economic investment than decentralized alternatives.

4.13. Capacity utilization and source availability robustness

Although waste heat availability from data centers, industrial facilities, CHP plants, and power generation assets may fluctuate over time, the capacities used within the optimization framework were intentionally selected using conservative availability assumptions. For each source category, minimum annual available thermal capacity reported in the source datasets was adopted as the available recoverable heat capacity. As shown before, Fig. 9 in section 3.9 presents the statistical distribution of the available thermal resources across the city, including minimum, maximum, median, first quartile (Q1), and third quartile (Q3) values for each source category. These statistics are provided to illustrate the diversity of resource availability across Dublin and do not represent the capacities directly supplied to the optimization model. For the optimization itself, annual minimum available capacities were assigned individually to each source location based on the source-specific datasets obtained from the corresponding operators and public authorities. Consequently, the optimization was not supplied with nominal or peak capacities but rather with conservative source-specific minimum annual availability levels. Due to the large number of individual assets considered, the complete location-by-location statistics are not reported; however, they were incorporated directly into the optimization framework.

For environmental heat resources such as wastewater and surface-water systems, the limiting parameter is the source temperature rather than the thermal flow itself. Therefore, the minimum measured source temperature was adopted in the heat-pump calculations. This assumption ensures that the heat pumps remain capable of satisfying the required district-heating supply temperature under the least favorable operating conditions encountered during the year. This assumption is particularly appropriate for Dublin due to its maritime climate, which is characterized by relatively small seasonal temperature amplitudes compared with continental climates. As shown in Fig. 26 in section 4.11, surface-water (and wastewater treatment) temperatures exhibit limited annual variation throughout the study period. Consequently, the use of

minimum annual source temperatures provides a conservative estimate of heat-pump performance while remaining representative of actual operating conditions within the Dublin case study.

As shown in Fig. 28, the optimization results further indicate that the network does not require full utilization of the available source capacities. Across the selected network configurations, the average utilization of the available waste-heat sources remained below the conservative capacity limits adopted in the model. This occurs because the interconnected network can draw heat from multiple geographically distributed sources while simultaneously employing heat-pump boosting when required. Consequently, significant operational reserve margins remain available within the system. From a system-design perspective, this redundancy reduces the sensitivity of the optimized network to short-term fluctuations in individual waste-heat sources. Even if temporary reductions occur at a specific facility, the remaining sources and distributed heat-pump infrastructure provide alternative pathways for satisfying the thermal demand. Therefore, while temporal variability may influence short-term operational dispatch decisions, it is not expected to materially affect the viability, routing structure, or long-term techno-economic conclusions of the optimized district-heating backbone. The reported utilization values in Fig. 28 correspond only to sources selected in the optimal network configuration. Non-selected sources are excluded from the analysis, as they are not activated in the optimized topology despite being available in the underlying GIS dataset (see Fig. 28).

4.14. Practical implementation considerations and deployment barriers

Although the results demonstrate the technical, environmental, thermodynamic, and economic potential of the proposed city-scale district-heating backbone, practical implementation remains subject to several non-technical constraints that extend beyond the scope of the present optimization framework. A primary consideration is infrastructure ownership and access rights. Many underground utility tunnels and corridor assets are operated by different public authorities, utility companies, transportation agencies, or private stakeholders. Consequently, successful deployment of an interconnected district-heating backbone would require coordinated governance frameworks, long-term access agreements, and multi-stakeholder planning processes. While the GIS screening framework identifies technically suitable

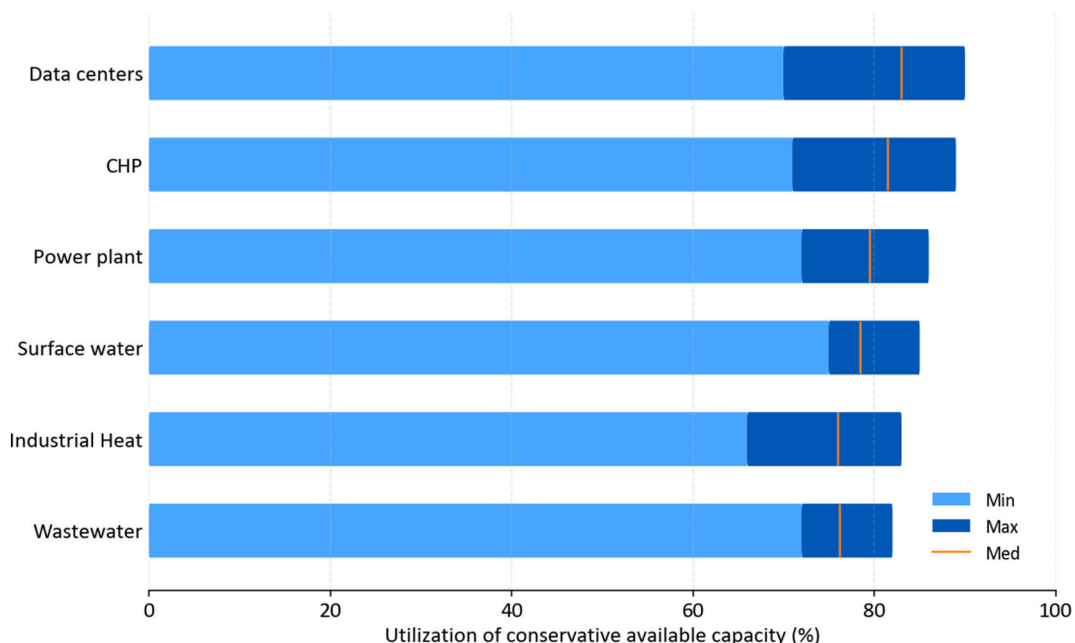


Fig. 28. Utilization range of connected waste-heat sources in the optimized district-heating network.

corridors, final implementation would depend on project-specific legal and institutional arrangements. Retrofit complexity represents a second challenge. Existing underground corridors were not originally designed for district-heating infrastructure and may require structural assessment, pipe-support modifications, ventilation upgrades, fire-safety evaluations, and integration with existing utility services. Although corridor reuse can substantially reduce excavation requirements and urban disruption compared with conventional street trenching, the practical retrofit requirements must be assessed on a corridor-by-corridor basis during detailed engineering design. Thermal losses and hydraulic performance also require consideration. While underground corridors provide protected routing environments and reduce construction costs, long-distance heat transport inevitably introduces thermal and pumping losses. These effects were incorporated into the optimization through the thermal-loss and hydraulic modelling framework; however, detailed transient operational studies would be required prior to implementation to evaluate seasonal operating conditions and future load growth. Maintenance accessibility and operational reliability constitute additional considerations. The presence of multiple utilities within shared corridors may influence maintenance scheduling, access restrictions, and operational coordination. Nevertheless, underground utility corridors generally provide superior accessibility for inspection, maintenance, and future expansion compared with buried pipelines requiring repeated excavation. As demonstrated by Yuan et al. [3], establishing dynamically optimized planning frameworks for building operations is essential to ensure that urban energy network expansions remain aligned with broader macro-level carbon budgets and long-term net-zero ambitions. Neglecting these multi-faceted socio-technical bottlenecks could lengthen project lead times and distort the idealized payback periods computed via pure techno-economic optimization. Finally, urban planning regulations, permitting procedures, environmental assessments, and future land-use developments may affect the feasibility of specific corridor segments. Although these factors were partially addressed through the GIS preprocessing and corridor-screening stages, the present work should be interpreted as a strategic planning framework rather than a detailed engineering design. Therefore, the optimized routes identify technically attractive and economically promising backbone configurations whose final implementation would require detailed stakeholder engagement, engineering assessment, and regulatory approval.

Despite these practical challenges, the use of existing underground infrastructure remains attractive because it substantially reduces civil construction requirements, minimizes disruption to dense urban environments, and enables the large-scale integration of distributed renewable and waste-heat resources that would otherwise remain inaccessible.

5. Conclusions

This study developed and demonstrated an integrated GIS–gravity–MCDA–MILP framework for the exergy-aware spatial optimization of a city-scale DH network integrating renewable and waste heat sources. Unlike conventional DH planning approaches that treat network expansion and source selection separately, the proposed methodology simultaneously optimizes routing, temperature hierarchy, source–sink matching, and infrastructure reuse under thermo-economic and carbon constraints. Applied to a case study in Dublin, the optimized configuration interconnected 17 existing district heating systems and 66 mapped thermal sources through a 148 km multi-temperature thermal grid comprising high-, medium-, and low-temperature corridors. The assessed heat demand of approximately $2.4 \text{ TWh}\cdot\text{yr}^{-1}$ was matched against an aggregated recoverable waste-heat potential of $2.0\text{--}2.8 \text{ GWh}\cdot\text{yr}^{-1}$. Direct utilization of high-grade sources enabled coverage of 13–28% of demand, whereas heat-pump-assisted integration increased potential coverage to 60–90%, depending on temperature lift and recovery efficiency. From a thermodynamic perspective, embedding exergy as an optimization criterion significantly improved system

performance. The optimized low-temperature cascading configuration increased overall exergy efficiency from approximately 28% in decentralized boiler-based heating to 52–60% in the integrated network. This improvement stems from reduced high-grade fuel consumption for low-temperature demand, smaller temperature lifts in heat production, cascaded distribution network with four-level temperature, and lower aggregate exergy destruction across generation and distribution i.e. nodes. Concurrently, central scenarios achieved operational CO_2 reductions of approximately 68–69%, with optimistic configurations approaching 90% decarbonization relative to baseline fossil-dominated heating. Economically, reuse of underground corridors substantially reduced trenching costs, enabling feasible investment scenarios with estimated simple payback periods in the range of 18–24 years under realistic heat pump deployment assumptions. The integration of multi-criteria corridor ranking prior to MILP optimization proved computationally efficient while preserving near-global optimality. The principal contribution of this work lies in coupling spatial planning, thermodynamic quality preservation, and system-level optimization within a unified framework applicable to large urban regions. To evaluate robustness beyond the deterministic optimization results, uncertainty propagation was performed using Latin Hypercube Sampling across 25 techno-economic and operational parameters. The results demonstrated that the environmental benefits remained consistently high across 10,000 realizations, while economic performance remained concentrated around the central payback range despite uncertainty in electricity prices, carbon penalties, infrastructure costs, and heat-pump performance. Furthermore, a phased-deployment analysis showed that progressive realization of the network delays economic recovery but does not alter the long-term viability of the proposed backbone, with payback increasing from approximately 18 years under immediate deployment to approximately 22 years under staged implementation. These findings indicate that the proposed framework remains robust under realistic market, operational, and implementation uncertainties. The results also demonstrate that renewable and low-grade waste heat sources, when strategically aggregated and temperature-matched, can transform fragmented district heating assets into a coherent city-scale thermal grid with substantial decarbonization potential.

CRedit authorship contribution statement

Mohammad Sameti: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Tao Fan:** Writing – review & editing, Resources. **Zili Li:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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